# Are Green Investors Green-Inducing? A Demand System Approach*

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**Abstract**

Despite the growing interest in green investing among academics and industry professionals alike, there is little consensus on whether it successfully incentivizes firms to adopt eco-friendly business practices. Using the equity holdings of institutional investors and the "demand system approach" to asset pricing, we provide evidence that institutional demand for greener stocks encourages firms to improve their environmental performances. Specifically, we devise and estimate a firm-level quantity, *institutional pressure* for greenness, that measures the price pressure a firm receives from its institutional owners. We find that this quantity has a positive and significant relationship with future improvement in a firm's environmental performance. Together with results from placebo tests, we conclude that *green* investors, those with high portfolio-level environment scores, are not necessarily *green-inducing* investors, those who encourage better environmental performance. Instead, green-inducing investors are institutions who contribute to higher institutional pressure, i.e. investors who are price-inelastic and display a positive portfolio tilt towards greener assets.

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# 1 Introduction

Efforts to promote Environmental, Social, and Governance (ESG) considerations in finance started over 30 years ago and have gained significant traction during the past decade. There are currently over 40 ESG-related associations, standards and codes in place, the most notable of which include the UN Principles for Responsible Investment launched in 2006 and the Paris COP21 Agreement signed in 2015.[1] Accordingly, the growth of ESG-dedicated funds have also accelerated, most of which are equity funds totaling $560 billion as of 2019.

Despite the growth in academic literature accompanying this trend, there is little consensus on whether ESG investing is effective in meeting its goal: incentivizing firms to carry out investment in eco-friendly technologies and implement business practices that help reduce negative externalities. Also unanswered is the question of where the marginal dollar of investors should be invested in order to maximize impact. Such questions should be of primary interest to investors and policymakers who genuinely believe in ESG investing's potential to bring about change.

Among different reasons for which firms may respond to ESG investing, we focus on the price pressure generated by institutional investors' demand. Firms have an incentive to improve their business practices if institutional investors prefer to hold firms with better ESG performance, thereby bidding up the prices of "greener" firms. To examine such a hypothesis, one must fix a model of asset demand because asset prices are equilibrium objects. Thus, we adapt the asset demand system pioneered in Koijen and Yogo [2019] to rigorously examine this institutional price pressure mechanism. We extend the characteristics-based demand by adding the firm's "greenness," which we proxy by Sustainalytics environment scores, to the original list of characteristics – market equity, book equity, profitability, investment, dividends, and market beta.

Using the extended demand system, we construct a model-driven firm-level quantity we call *institutional pressure*, defined as the derivative of a firm's equilibrium price with respect to its own greenness. Assuming that a given firm cares about its stock price, institutional pressure should capture the strength of the firm's incentive to become greener. We therefore define *green-inducing investors* to be investors who contribute positively to the firms' institutional pressures. The model suggests that they are investors who are price-inelastic and have a positive portfolio weight tilt towards greener stocks. Consistent with the model, our main empirical test verifies that institutional pressure indeed predicts a given firm's future improvements in environmental performance.

A key subsequent question is then whether *green* investors, whose portfolios' average environment scores are high, are *green-inducing*. A high portfolio environment score need not necessarily imply a positive portfolio tilt towards greener stocks. Instead, the investor may be holding a high scored portfolio for other reasons (e.g. preferring larger stocks) that happen to be correlated with

[1] IMF, "Global Financial Stability Report" (2019)

greenness. In a placebo test, we demonstrate that the portfolio environment scores of a firm's owners or share of institutional ownership do not predict improvements in environmental performance or does so only weakly.

A juxtaposition of our main and placebo tests therefore reveals a key insight: green investors are not necessarily green-inducing. In other words, having green owners does not impact firm behavior, while having green-inducing owners does. In reaching this conclusion, the extra step of estimating each investor's institutional demand is crucial.

Empirically, two aspects of our methodology allow us to get around the challenges that limited the efficacy of existing approaches. First, we exclusively focus on environment-related (green) concerns and avoid confounding E, S, and G. Our focus on green investing is motivated by the better availability of quantifiable measures related to the environment as well as the surprising lack of academic and industry consensus on green investing. Second, we use equity holdings instead of stock returns in our analysis. While still informative, returns have two shortcomings in analyzing the efficacy of green investing. The first is that it masks interesting heterogeneity across institutions, and the second is that regime-switching and investor learning can induce a spurious risk-return profile during periods of transition. For these reasons, we use equity holdings of institutional investors and employ a demand system approach to construct each investor's demand for greenness.

In Section 2, we first show how greenness enters as a relevant characteristic the characteristics-based institutional investor demand. Theoretically, we show that adding a minimum greenness constraint, similar to one imposed in Pastor et al. [2019], to a mean-variance investor's portfolio choice problem yields a characteristics-based demand that includes greenness. This result allows us to extend the framework in Koijen and Yogo [2019].

We estimate the demand system in Section 4 and document interesting heterogeneity across investors' demand for greenness. We first show that things are easier said than done – not every investor who was deemed green demonstrate a portfolio tilt towards greener stocks. Furthermore, we show that banks and investment advisors have taken the most aggressive tilts towards greener stocks.

In Section 5, we then examine in a reduced form setting whether higher institutional pressure leads to improvements in firms' environmental performances. As our main measures of environmental performance we use the carbon score and environment score from Sustainalytics. For both measures, a higher score suggests a firm is less carbon intense and more environmentally friendly, respectively. We find that a one standard deviation increase in institutional pressure leads to around a 13.7% greater increase in the carbon score, a finding that is significant at the 1% level. The finding is robust to controls as well as year and industry fixed effects.

We repeat the analysis by replacing institutional pressure with two other proxies that may plausibly lead to better performance: ownership-weighted average of the owners' portfolio-level environment score and the share of institutional ownership. We find that future firm environmental performance displays minimal or no significantly positive correlation with these measures.

One implication from our results is that crude alternative measures of institutional pressure do not reflect investors' heterogeneous preferences. Measures such as the proportion of institutional ownership may lead to a null result and thereby understate the significance of the investor channel of ESG investing. Our approach therefore highlights the importance of explicitly accounting for the heterogeneity in investors' demands. Another implication is that a marginal investor may not successfully incentivize better firm behavior by naively investing in green investors. This result, while counter-intuitive, is crucial in designing investment mandates aimed at inducing desired firm behavior.

## Contribution to Literature

Our paper contributes to four strands of literature. First, it adds to the growing literature that examines the aggregate impact of growing ESG mandates and demand for green investments. The literature has mainly examined the response of investors and fund managers to climate risk and sustainability[2] as well as the implications for prices of climate risk-related assets[3]. For corporate response to ESG investing, Dyck et al. [2019] document that current institutional ownership is positively associated with better future ESG performance and Ginglinger and Moreau [2019] find that greater climate risk leads to lower leverage in the post-2015 (Paris Agreement) period. Naaraayanan et al. [2019] take advantage of quasi-experimental setting of the Boardroom Accountability Project (BAP) and provide empirical evidence that environmental activist investing leads to reduced polluting activities at the firm level. Li and Wu [2020] use firms' participation in the UN Global Compact program as a proxy of their CSR engagement and find that public firms are more likely than private firms to engage in sustainable actions with no subsequent real impact. Our paper is the first to measure demand for greenness at each investor level in examining subsequent corporate policies and outcomes.

We also contribute to the literature that explores institutional investors' impact on corporate finance. Researchers have documented the effect of institutional ownership on transparency (Boone and White [2015]), payout policy (Crane et al. [2016]), tax avoidance (Khan et al. [2017]) and governance choices (Appel et al. [2016]). While they use exogenous variation from index rebalancing and share of institutional ownership as an empirical proxy, we explicitly measure each institution's demand separately and micro-found the institutional pressure. Our idea of refining the measure of

[2]Some examples include Alok et al. [2020], Andersson et al. [2016], Barko et al. [2018], Bolton and Kacperczyk [2019], Engle et al. [2020], Geczy et al. [2005], Hartzmark and Sussman [2019], Hirshleifer [2001], Pedersen et al. [2019].

[3]See Baker et al. [2018], Bernstein et al. [2019], Daniel et al. [2015], Hsu et al. [2019], Kruttli et al. [2019], Lins et al. [2017], Pastor et al. [2019]

institutional pressure is particularly useful in that it can be generalized to characteristics other than greenness.

Our paper is also related to the literature on the role of specific demand for assets and its real implications. One particular line of research examines how firms react to changes in investor demand (Baker and Wurgler [2004], Becker et al. [2011], DellaVigna and Pollet [2007], Greenwood and Hanson [2013], Avdjiev et al. [2019]). Our paper formalizes the investor's preference for greenness and tests the fundamental assumption of green investing, which is that institutional investors can incentivize firms to become greener through their presence as major shareholders. As in van Binsbergen and Opp [2019], we are establishing a possible mechanism through which the financial market has real effects.

Finally, our paper contributes to a nascent literature on demand system asset pricing. The demand system approach developed in Koijen and Yogo [2019], and further refined in Koijen et al. [2019] and Koijen and Yogo [2020], bridges the gap between traditional portfolio theory and heterogeneity in investors' holdings through heterogeneous beliefs. Our paper provides a novel way of leveraging the demand system to investigate corporate finance issues. Our approach can be analogously applied to investigate firm's reactions to institutional demand for other characteristics such as dividend policies. Similar to the aforementioned works, our paper highlights the importance of accounting for heterogeneity in investors' demands.

# 2 The Asset Demand System and Key Concepts

In this section, we motivate our decision to include greenness in the characteristics-based demand. We also briefly review the characteristics-based demand system developed by Koijen and Yogo [2019] and introduce key concepts that we utilize in our later empirical analyses.

Investors may care about greenness either for pecuniary or non-pecuniary reasons, and evidence can be found for both (e.g. Barber et al. [2019] and Bansal et al. [2018]). While we remain agnostic on what the more prominent motivation is, we show in Section 2.1 that greenness should enter the characteristics-based demand in at least two cases: greenness is informative about expected returns or investors are constrained to hold a green portfolio (e.g. due to investment mandates or pressure from clients). Section 2.2 and Section 2.3 then discuss the concepts of institutional pressure and green-inducing investors.

## 2.1 Incorporating Environment Score into Characteristics-Based Demand

We adapt the setting and notation used in Koijen and Yogo [2019], which we partly introduce here while omitting some details to avoid repeating the entire setup. With this in mind, consider a economy with $N$ assets indexed by $n = 1, \ldots, N$ and $I$ investors indexed by $i = 1, \ldots, I$. We denote the outside asset as the 0th asset.

**Assets and Characteristics** Let $P_t(n)$ and $S_t(n)$ denote the price and shares outstanding of asset $n$ at time $t$ respectively. We denote the logarithms of these variables in lowercase letters and the $N$-dimensional vectors in boldface. Suppose each asset has $K$ characteristics indexed by $k = 1, \ldots, K$ so that the $k$th characteristics of asset $n$ at time $t$ is denoted $x_{kt}(n)$ and the vector of characteristics is denoted $\mathbf{x}_t(n)$.

**Investor Decisions** Investor $i$ optimally chooses at each time $t$ her weights on these assets $\mathbf{w}_{it}$. Denoting the asset under management of investor $i$ at time $t$ by $A_{it}$, investor $i$ maximizes expected terminal wealth $\mathbb{E}_{it}[\log(A_{iT})]$ under the intertemporal budget constraint.[4] Investors face short-sale constraints, $\mathbf{w}_{it} \geq \mathbf{0}$ and $\mathbf{1}'\mathbf{w}_{it} < 1$. Investors have heterogeneous beliefs about expected returns of assets, which they form by considering the observed characteristics. Investor $i$'s unobserved latent demand for asset $n$ is denoted $\log(\epsilon_{it}(n))$. Investor $i$'s information set for asset $n$ can be written as

$$\hat{\mathbf{x}}_{it}(n) = \begin{bmatrix} me_t(n) \\ x_t(n) \\ \log(\epsilon_{it}(n)) \end{bmatrix} \tag{1}$$

and an $M$th-order polynomial of this vector can be written as

$$\mathbf{y}_{it}(n) = \begin{bmatrix} \hat{\mathbf{x}}_{it}(n) \\ vec(\hat{\mathbf{x}}_{it}(n)\hat{\mathbf{x}}_{it}(n)') \\ \vdots \end{bmatrix}, \tag{2}$$

which determines the investors' beliefs about expected returns.

**Factor Structure** We maintain Assumption 1 of Koijen and Yogo [2019], so that the covariance of log excess returns, relative to the outside asset, is $\Sigma_{it} = \Gamma_{it}\Gamma_{it}' + \gamma_{it}\mathbf{I}$, where $\Gamma_{it}$ is a vector of factor loadings and $\gamma_{it} > 0$ is idiosyncratic variance, and that expected excess returns and factor loadings are polynomial functions of characteristics:

$$\begin{aligned} \mu_{it}(n) &= \mathbf{y}_{it}(n)'\Phi_{it} + \phi_{it} \\ \Gamma_{it}(n) &= \mathbf{y}_{it}(n)'\Psi_{it} + \psi_{it} \end{aligned} \tag{3}$$

[4]As in Pastor et al. [2019], we can make greenness enter the utility directly, but we derive our results without doing so for now.

where $\Phi_{it}$ and $\Psi_{it}$ are vectors and $\phi_{it}$ and $\psi_{it}$ are scalars that are constant across assets. In other words, returns have a one-factor structure and an asset's own characteristics are sufficient for its factor loadings.

**Greenness as a Characteristics** Importantly, we further assume that greenness is the $k$th characteristic of an asset. In other words:

$$\mathbf{g}_t = \mathbf{x}_{kt} \tag{4}$$

In the remaining parts of this subsection, we show that greenness enters the investor's characteristic-based demand if either it is informative about the expected returns or the investor faces a "minimum greenness constraint." If greenness 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 greenness is not informative about the expected returns, but investors face a minimum greenness constraint instead, similar to Pastor et al. [2019]. More concretely, suppose for some $c > 0$ investor $i$ faces, on top of short-sale constraints, an extra constraint[5]

$$\mathbf{b}_{it}'\mathbf{w}_{it} = (d_i\mathbf{g}_t)'\mathbf{w}_{it} > c \tag{5}$$

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' greenness. Let $\nu_{it} \geq 0$ be the Lagrange multiplier associated with this new constraint. Also, let us denote the $k$th elementary vector by $\mathbf{e}_k$. Then we have the following result:

**Proposition 1.** *If an investor faces a greenness 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*

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

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

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

[5]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.

*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 greenness*

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

Proposition 1 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 greenness, $\nu_{it}\mathbf{b}_{it}$. This addition comes from the fact that green assets are valuable beyond their expected returns because they relax the greenness 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 greenness is informative about expected returns (the factor loading on greenness is zero in $\Phi_{it}$), the optimal portfolio weights will still be positively related to greenness.

Appendix A of Koijen and Yogo [2019] shows that a particular coefficient restriction, together with Proposition 1, implies that the investors' optimal portfolio weights follow logit functions of prices, characteristics, and latent demand. In other words, optimal portfolio weight for stock $n$, for investor $i$, at a given period $t$ satisfies:

$$\frac{w_{it}(n)}{w_{it}(0)} = \exp\left(b_{0,it} + \beta_{0,it} me_t(n) + \beta_{1,it}' \mathbf{x}_t(n)\right) \epsilon_{it}(n) \tag{6}$$

with greenness entering as one of the characteristics $\mathbf{x}_t(n)$. In Section B.1 of the Appendix, we provide some suggestive evidence supporting that greenness should enter the logit demand function: variable selection using Lasso picks up environment score as often as other major firm characteristics known to explain investors' portfolio holdings.

## 2.2 Institutional Pressure

We define the institutional pressure of firm $n$ for characteristic $k$ as the equilibrium price impact of changing the value of characteristic $k$ for firm $n$:

$$\frac{\partial \mathbf{p}(n)}{\partial \mathbf{x}_k(n)}. \tag{7}$$

This can be computed analytically from the demand system as below.

**Proposition 2.** *The price impact of a change in the value of characteristic k for firm n, denoted as* $\mathbf{M}$*, is given as the nth diagonal element of the matrix*

$$\mathbf{M} := \frac{\partial \mathbf{p}}{\partial \mathbf{x}_k} = \left(\mathbf{I} - \sum_i \beta_{0i} A_i \mathbf{H}^{-1} \mathbf{G}_i\right)^{-1} \left(\sum_i \beta_{ki} A_i \mathbf{H}^{-1} \mathbf{G}_i\right) \tag{8}$$

*where*

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

Presumably, a public firm cares about its stock price. The quantity $\mathbf{M}_{n,n}$, which is the $n$th diagonal entry of $\mathbf{M}$, can be interpreted as the price pressure that a firm receives through institutional demand. Put differently, it represents the firm's marginal benefit derived from increasing its $k$th characteristic.[6]

In a sense, the measure of institutional pressure derived is a lower bound on the actual institutional pressure that a firm may receive. If substantial variation in holdings operates through the extensive margin, then the current methodology understates $\partial \mathbf{p}(n) / \partial \mathbf{x}_k(n)$ as new investors would start to hold the stock if the firm improves sufficiently. While interesting, this possibility is not a first-order concern in our setup, as Koijen and Yogo [2019] shows that the set of stocks that institutions invest in is usually small and highly persistent.

As also discussed in Koijen and Yogo [2019], the matrix inside the inverse in equation (8) is the aggregate demand elasticity. Therefore, assets held by less price elastic investors react more sensitively. The $n$th diagonal entry of the second term is

$$\frac{\sum_i \beta_{ki} A_i w_i(n)(1 - w_i(n))}{\sum_i A_i w_i(n)} \tag{9}$$

This quantity can be viewed as an AUM weighted average of the coefficients on the environment score. Therefore, institutional pressure for a given firm $n$ is a weighted average of environment score coefficients of its institutional owners, adjusted for their price elasticity. If a firm faces a representative owner who is price inelastic and exhibits a high coefficient on the environment score, this firm faces a large institutional pressure. In other words, a set of investors is considered to be green-inducing for a given firm if their collective institutional pressure for the firm is high.

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

### 2.3 Who are the Green-inducing Investors?

Through an approximation, we can also gauge how much a specific investor $i$ contributes to institutional pressure. Specifically, we consider the following approximate expression which assumes that $w_i(n)$ are small, thereby allowing us to ignore the second order terms:

$$M_{n,n} \approx \frac{\sum_i s_i(n)\beta_{ki}(1 - w_i(n))}{1 - \sum_i s_i(n)\beta_{0i}(1 - w_i(n))} \tag{10}$$

where $s_i(n) = A_i w_i(n) / \sum_j A_j w_j(n)$ is $i$'s ownership share in asset $n$.[7] From expression (10), we see more clearly that larger owners with a large greenness coefficient ($\beta_{ki} \uparrow$) and lower price elasticity ($\beta_{0i} \uparrow$) contribute more to this quantity.[8] The intuition is that if a firm's representative owner demonstrates a strong tilt, the firm has a higher institutional pressure; and the effect is amplified if the owner is price-inelastic because prices have to adjust more to counterbalance the propensity to overweight.

# 3 Data

Our empirical analysis combines three sources of data. First, we use firm-level environment and carbon scores from Sustainalytics. Second, we use institutional holdings from the Thomson Reuters Institutional Holdings Database. Finally, we use data on stock characteristics and firm variables from Compustat and CRSP.

### 3.1 Firm Environmental Performance

For a firm-specific measure of environmental performance, we use the environment and carbon score provided by Sustainalytics, which provides monthly normalized scores on environmental performance for predominantly publicly traded firms from 2009. Sustainalytics uses a number of subcategories and evaluates each firm's score by comparing it to peers in the same industry. Therefore,

[7] The approximation is not perfect, but yields a 0.7 correlation coefficient with the actual institutional pressure across the entire firm-quarter sample.

[8] Unfortunately, the above term cannot be approximated by some simpler sum $M_{n,n} \approx \sum_i a_i$ for some quantities $a_i$. It is tempting to claim that we can rank investors in terms of

$$a_i = \frac{s_i(n)\beta_{ki}(1 - w_i(n))}{1/I - s_i(n)\beta_{0i}(1 - w_i(n))}$$

to find the most green-inducing investor. However, it is not difficult to come up with counterexamples where one can increase the $a_i$ for some investor $i$ and but actually decrease the overall institutional pressure. Thus, we only claim that $M_{n,n}$ is increasing in the overall portfolio tilt towards greener stocks and decreasing in the overall demand elasticity of the owners.

the provided scores are only comparable within industry. A higher score suggests a firm is more environmentally friendly, relative to its industry peers. The environment score is computed based on a large number of environment-related indicators that Sustainalytics compiles, and the carbon score is based on the publicly disclosed carbon emissions. We often refer to the environment score as greenness in the remainder of the paper.

We choose Sustainalytics for several reasons. Importantly, Morningstar bases its sustainability ratings for mutual funds and ETFs on Sustainalytics' company-level ESG analysis. Given the saliency of the rating, Sustainalytics is a natural place to start for third-party ratings on sustainability. MSCI KLD is also a widely used sustainability ratings agency. Berg et al. [2019], however, find that among popular ratings, the divergence in scores is most pronounced for KLD data ratings. Therefore, we only use Sustainalytics in our exercise and potentially consider MSCI KLD as an extension.

## 3.2 Institutional Holdings

The data on institutional common stock holdings are from the Thomson Reuters Institutional Holdings Database (s34 file), which are compiled from the quarterly filings of Securities and Exchange Commission Form 13F. All institutional investment managers exceeding $100 million in total market value must file the form. Form 13F reports only long positions and not short positions. Following Koijen and Yogo [2019], we merge the institutional holdings data with the CRSP-Compustat data by CUSIP number and drop any holdings that do not match (i.e., 13(f) securities whose share codes are not 10, 11, 12, or 18). We compute the dollar holding for each stock that an institution holds as price times shares held. Assets under management is the sum of dollar holdings for each institution. We compute the portfolio weights as the ratio of dollar holdings to assets under management. We also follow the authors' classification of institutions into six types: banks, insurance companies, investment advisors, mutual funds, pension funds, and other 13F institutions. The group of other 13F institutions includes endowments, foundations, and non-financial corporations.

## 3.3 Stock Characteristics and Firm Variables

The data on stock prices, dividends, returns, and shares outstanding are from the Center for Research in Security Prices (CRSP) Monthly Stock Database. We restrict our sample to ordinary common shares (i.e., share codes 10, 11, 12, and 18) that trade on NYSE, AMEX, and Nasdaq (i.e., exchange codes 1, 2, and 3). We further restrict our sample to stocks with non-missing price and shares outstanding. Accounting data are from the Compustat North America Fundamentals Annual and Quarterly Databases.

For the other stock characteristics, we use the 70+ financial ratios provided by WRDS grouped into following seven categories: capitalization, efficiency, financial soundness/solvency, liquidity, profitability, valuation, and others. We stay away from return variables because they could violate our identifying assumption that characteristics other than price are exogenous to latent demand, as we discuss in Section IV.

### 3.4 Summary Statistics

Table 1 contains summary statistics for the independent and dependent variables used in the reduced form regressions. The average environment score for a given firm is 75.7 with standard deviation of around 12.8. The mean of the carbon score is much smaller around 0.317, which implies that the two scores are not directly comparable against each other. This discrepancy in units is acceptable for our empirical exercise as we use the environment score in estimating the demand system and the carbon score in our reduced-form regressions.

The owner environment score is calculated in two steps. First, we calculate each institutional portfolio environment score as the holdings-weighted environment score of the stocks that constitute the portfolio. Then for each firm, we take the weighted average of the investor environment scores of its owners' portfolio environment scores using the ownership share in that firm as weights. The mean is 40.2 with a standard deviation of around 3.69. The mean is much lower than that of firm environment score, as we assign unrated firms the lowest score in each quarterly cross-section.

Table 2 compares the key variables in terms of correlation. We find that none of the pairs exhibit high correlation. As expected, the environment score and the carbon score are positively related with magnitude of 0.235 because the carbon score is presumably used during Sustainalytics' construction of the overall environment score.

## 4 Demand System Estimation and Stylized Facts

We estimate the demand system and obtain each investor's demand function coefficients. In particular, the coefficient on the environment score captures the portfolio tilt towards greener stocks. The data period is from 2010 to 2017.[9]

### 4.1 Empirical Framework

We estimate the demand model for investor $i$ for a given quarter $t$, which can be written as:

$$\forall i, \forall t : \frac{w_{it}(n)}{w_{it}(0)} = \exp\left(b_{0,it} + \beta_{0,it} me_t(n) + \beta_{1,it} es_t^*(n) + \beta_{2,it}' \mathbf{x}_t^*(n)\right) \epsilon_{it}(n) \tag{11}$$

[9] This is the period for which we can obtain the Sustainalytics data.

where $me_t(n)$ is the log market equity of asset $n$ at time $t$, $es_t^*(n)$ is the cross-sectionally standardized e-score, and $\mathbf{x}_t^*(n)$ denotes other cross-sectionally standardized characteristics. We assume throughout that characteristics are exogenous to latent demand:

$$\mathbb{E}_t\left[\epsilon_{it}(n) \mid \mathbf{x}_t(n), es_t^*(n)\right] = 1 \tag{12}$$

where the expectations is taken across the stocks in a given period. We do not use the linear version of Equation (11) in order to account for zero holdings.

Following Koijen et al. [2019], we focus on the set of largest firms that constitutes 90% of market capitalization to ameliorate the bias in estimates caused by firms with missing environment scores. In 2016, this set corresponds of a universe of 761 firms, and approximately 80% of firms are rated once we filter by market capitalization. For the remaining set of firms without any ratings, we assign the lowest environment score in each quarter by appealing to information asymmetry concerns. Furthermore, we estimate the coefficients by institution whenever there are more than 500 strictly positive holdings in the cross-section. For those with less than 500 holdings, we pool them with similar institutions in order to estimate their coefficient where the groups are determined by institution type and quantiles of assets under management conditional on type as in Koijen and Yogo [2019].

It is important to note that we are estimating the equation across all industries. If investors care about the scores themselves – possibly because Sustainalytics score is used by Morningstar – then pooling across industries is the correct approach. Rather, if we interpret the scores to approximate how each investor views each firm's greenness, then we are making the following two implicit assumptions in our estimation. First is that investment of any given investor is not concentrated in a single or few industries. This assumption is not too strong given that we are pooling the holdings of different funds for a given investor (e.g. Blackrock). Second is that the cross-industry allocation stays relatively stable across our sample period for a given investor. One approach to circumvent these assumptions is to estimate a nested logit model a la Koijen et al. [2019], which we leave for future extensions.

## 4.2 Estimation Results

In our analysis, $\beta_{1,it}$ is our parameter of interest; it is the portfolio tilt toward greener stocks. If $\beta_{1,it}$ is positive and significant, then at time $t$ investor $i$ allocates more weight to stocks with higher environment scores, controlling for other stock characteristics. Below we also discuss results that are most pertinent to our exercise in question, namely constructing firm-specific institutional pressure.

### 4.2.1 Heterogeneity in Loadings

We first illustrate how the coefficients differ across investors and through time. For convenience, we label investors with a positive and significant, negative and significant, and statistically insignificant coefficient on greenness as *green*, *brown*, and *neutral* respectively.[10] At the end of 2010, 12% of institutional investors were green, 5% were brown, and 83% were neutral. By the end of 2017, the numbers had changed to 26%, 11%, and 63%. These numbers do not take into account the size of the institutions but simply use counts. We see increases in both proportions of green and brown investors, but we see a larger increase in the proportion of green investors.

The transition probabilities between green, brown, and neutrals at the quarterly frequency are shown in Table 3. The estimates appear fairly stable, as we can see that each status demonstrates reasonable amount of persistence and that investors never transition directly from brown to green or vice versa. Still, the magnitude and sign of the coefficients suggest that the past decade has been a period of transition towards a new regime in which large investors to show portfolio tilts toward greener stocks.

We next examine loadings on environment scores with respect to investor types. In Table 4, we first list the largest green investors in the US by AUM for each investor type at the end of 2017. To provide insight into the time-series trend, we also compute an annual average of coefficients on environment scores for each institution and plot the averages in Figure 1. We see that while the coefficients appear to be increasing over time, consistent with the increasing popularity of ESG investing, banks and investment advisors appear to have the strongest tilts towards greener stocks in the recent years. This is surprising as insurance companies and pension funds, typically considered to be longer-term investors, are not necessarily those with higher coefficients. Perhaps banks and investment advisors are quicker to satisfy the recent changes in the preferences of the clients. Alternatively, they may be anticipating higher future valuation of green stocks stemming from the regime switch.

### 4.2.2 Size of Green AUM

We provide further results consistent with the increasing popularity of green investing by calculating the fraction of green assets under management using the same classification as above. For each quarter, we sum the AUM of all green investors and compute its proportion relative to the total institutional AUM among the 13F institutions. We average these numbers and report at the annual frequency so that the trend is more apparent. Figure 2 plots the trend of total green AUM for our sample, and Figure 3 plots the proportion of green AUM relative to the total AUM of large institutions. Consistent with the popular belief, we see a general increasing trend from both of these

[10] For brevity we use the terminology "green" here despite the possibility of confusion with the terminology used in the Introduction.

figures.

Interestingly, the proportion of green AUM around year 2016 does not experience rapid growth, contrary to conventional wisdom and papers documenting significant inflows into ESG funds. This suggests that a large fraction of such influx went to investors whose portfolios do not demonstrate a tilt towards greener assets. Instead, as documented in Hartzmark and Sussman [2019], the investor flow is likely to be concentrated in green investors holding portfolios with high environment scores. As we elaborate in the next section, such investments do not necessarily lead to increased institutional pressure and may not be impactful in incentivizing firms to adopt more environment-friendly practices. What matters is the flow to green-inducing, not green, investors who exhibit a large tilt towards greener assets.

#### 4.2.3 Institutional Pressure by Industry

Given the coefficients $\beta_{0,it}$ and $\beta_{1,it}$, we can calculate the firm-level institutional pressure on greenness at each period. This institutional pressure serves the role of the independent variable in our subsequent regressions, but its trend may be of interest in itself. We may see that some industries experience different degrees of change over time as various global agreements and regulations are introduced. In Figure 4, we plot the industry average of institutional pressures for a few notable industries. We observe that on average, institutional pressure has been increasing with a sharp jump in years 2014 and 2015. Qualitatively, the timing corresponds to the adoption of the Paris Agreement in 2015, but we do not have further empirical results to corroborate this claim. Also, we do not see noticeable differences across different industries.

# 5 Effect of Institutional Pressure on Firms

In this section, we examine the effect of institutional pressure for greenness on firm policies and performance. [11]

## 5.1 Does institutional pressure work?

We first examine whether high institutional pressure translates into better environmental performance at the firm-level. As our main measure of firm's environmental performance, we use the carbon score from Sustainalytics. A higher score suggests a firm is more environmentally friendly.

[11] For theoretical models that illustrate the efficacy of impact investing, see Heinkel et al. [2001], Chowdhry et al. [2019], Oehmke and Opp [2019], and Landier and Lovo [2020]. In all these models, presence of ESG investors forces companies to (partially) internalize externalities.

Our baseline tests examine the relation between firm's environmental performance and lagged institutional pressure for greenness:

$$y_{it} = \alpha + \beta \cdot Pressure_{i,t-1} + \gamma' X_{it} + \Lambda + \epsilon_{it} \tag{13}$$

where $y_{it}$ is the measure of firm $i$'s environmental performance at time $t$ and $Pressure_{i,t-1}$ is the institutional pressure for greenness, given as the $i$th diagonal element of $\mathbf{M}$. $X_{it}$ is a set of firm-level control variables which include size, asset tangibility, leverage, Tobin's Q, profitability. The choice of control variables is motivated by that in Dyck et al. [2019], and all variables are winsorized at the 1th and 99th level. We also include lagged log carbon score to account for a possible mechanical relationship between the change and the level in the carbon score. $\Lambda$ includes year and industry fixed effects, and standard errors are clustered at industry-year level.

It is important to mention that firms may increase green investment – and therefore lower carbon emissions – because the cost of green improvements might have gone down. While we do not explicitly account for this mechanism in our regressions, we assume that the rate of such improvement is similar across industries and thereby focus on within-industry variation.

Table 5 reports the results of the panel regression of year-on-year change in firm-level log carbon score on lag institutional pressure and control variables. We standardize the institutional pressure measure for each year. Column (1) shows the baseline estimate in which we include the lag carbon score, controls, year fixed effects and industry fixed effects.[12] Columns (2) – (5) relaxes each control or fixed effect to examine the stability of our estimates.

Across the different specifications, we find that the coefficient on lagged institutional pressure is positive with an estimate around 0.129 and highly significant at the 1% level. Given the log transformation and the standardization, the estimate implies that a unit standard deviation increase in lagged institutional pressure is associated with a $\exp(0.129) - 1 = 13.7\%$ higher change in carbon score for a given firm, holding other control variables fixed. The coefficients on the other control variables are also insignificant, which implies that the carbon score exhibits little correlation with other firm characteristics.

One may be worried about possible simultaneity bias in which a firm's high carbon score, which is used to construct the firm's environment score, may be driving the magnitude of the institutional pressure, not vice versa. We argue that this concern can be discounted for two reasons. First is that we use lagged institutional pressure, not its contemporaneous counterpart. Furthermore, institutional pressure depends not only on an investor's loading on the environment score but also on its price elasticity. This additional dimension in the construction of institutional pressure therefore mitigates

[12] Ideally, we would like to include fixed effects using industry definitions employed by Sustainalytics. Unfortunately, Sustainalytics does not disclose their definitions and therefore we employ the first two digits of the SIC code which represent the major industry sector to which a business belongs.

the aforementioned concern regarding potential biases.

## 5.2 Placebo Tests

The careful, micro-founded construction of our institutional pressure measure is key in our result. To provide further support for this argument, we conduct two sets of placebo tests.

In the first, we repeat the previous analysis by replacing institutional pressure with the numerator and the denominator of equation (10). The numerator approximates the average loading on greenness across all investors for a given firm, and the denominator approximates the average demand elasticity across all investors. We also repeat the regression using equation (10) as our main independent variable.

Table 6 contains the results of the regressions. In all specifications, we find no evidence of a relationship between future firm environmental performance and the approximated measure of institutional pressure. The results speaks to the importance of estimating $\mathbf{M}$ jointly across all firms and investors rather than taking linearized approximations focusing on a single firm and its owners. It also emphasizes the fact that price elasticity needs to be taken into account.

In the second set of placebo tests, we repeat the previous analysis by replacing institutional pressure with more crude measures of green institutional ownership. Specifically, we consider two measures. First is the owner environment score, which is the ownership-weighted average environment score of the investors in each firm. We calculate this in two steps: (1) we calculate each institutional portfolio's environment score by holdings-weighting the environment scores of the assets that consist that portfolio, (2) then for each firm we take the weighted average of the investor environment scores of its owners using ownership share in that firm as weights. The second measure is the share of institutional ownership of each firm, which is used in Dyck et al. [2019].

Table 7 contains the results of the regressions. Columns (1) and (2) illustrate results using the lag owner environment score as the independent variable, and (3) and (4) using lag institutional ownership as the independent variable. We include all controls and fixed effects identically as our baseline. We find a somewhat significant relationship between future firm environmental performance and lag owner environment score, albeit weaker than the results in Table 5. This result, however, may possibly be spurious since it is legitimately subject to the aforementioned simultaneity bias. In columns (3) and (4), we find no significant relationship for lagged institutional ownership.

In sum, both sets of placebo tests highlight the importance of micro-founding the measure of institutional pressure from an asset demand system in evaluating the efficacy of green investing.

### 5.3 Learning about Institutional Pressure

The economic mechanism behind our results is that the price pressure of institutional investors increases the firm's future investment in green technology and lowers carbon emissions. For firms to respond to institutional pressure, they must observe or learn the degree of pressure from tangible quantities.

One such channel is the equity market reaction to events associated with firm's ESG disclosures. For example, Grewal et al. [2019] finds that there is significant heterogeneity across firms in the market's reaction to ESG disclosure. Firms may also learn about the institutional pressure they face through boardroom or investor meetings. As Naaraayanan et al. [2019] find, institutional investors appear to wield tangible influence through methods such as proxy access proposals. Although we conjecture that the propensity to engage in activism may be connected to our measure of institutional pressure, we do not provide direct evidence here.

## 6 Conclusion

The ultimate goal of green investing is to shape firms' behavior towards more environment-friendly practices. Evaluating the efficacy of green investing is therefore of first-order importance for both investors and policymakers. Where should the marginal dollar be spent in order to maximize the impact of green investing? Has green investing led to substantial changes on firm operations and environmental performance? In this paper, we provide new ways to tackle these questions through the lens of the asset demand system.

Our paper's findings are twofold. First, investing in *green-inducing* investors – those with price-inelastic and positive demand for environment score – increases institutional pressure to firms, thereby incentivizing them to adopt environment-friendly practices. Investing in *green* investors – those with high portfolio environment scores – do not necessarily do so. Second, the institutional pressure of a firm is positively and significantly related to better future environmental performance; the environment score of its owners, on the other hand, is less so. Combined, these insights imply that investing in green-inducing investors is more effective than investing in green investors in incentivizing firms to become more environment-friendly.

# References


Shashwat Alok, Nitin Kumar, and Russ Wermers. Do fund managers misestimate climatic disaster risk. *The Review of Financial Studies*, 33(3):1146–1183, 2020.

Mats Andersson, Patrick Bolton, and Frédéric Samama. Hedging climate risk. *Financial Analysts Journal*, 72(3):13–32, 2016.

Ian R Appel, Todd A Gormley, and Donald B Keim. Passive investors, not passive owners. *Journal of Financial Economics*, 121(1):111–141, 2016.

Stefan Avdjiev, Wenxin Du, Catherine Koch, and Hyun Song Shin. The dollar, bank leverage, and deviations from covered interest parity. *American Economic Review: Insights*, 1(2):193–208, 2019.

Malcolm Baker and Jeffrey Wurgler. A catering theory of dividends. *The Journal of Finance*, 59(3): 1125–1165, 2004.

Malcolm Baker, Daniel Bergstresser, George Serafeim, and Jeffrey Wurgler. Financing the response to climate change: The pricing and ownership of us green bonds. Technical report, National Bureau of Economic Research, 2018.

Ravi Bansal, Wu Di, and Amir Yaron. Is Socially Responsible Investing A Luxury Good? 2018.

Brad Barber, Adair Morse, and Ayako Yasuda. Impact Investing. dec 2019. URL `http://www.nber.org/papers/w26582.pdf`.

Tamas Barko, Martijn Cremers, and Luc Renneboog. Shareholder engagement on environmental, social, and governance performance. 2018.

Bo Becker, Zoran Ivković, and Scott Weisbenner. Local dividend clienteles. *The Journal of Finance*, 66 (2):655–683, 2011.

Florian Berg, Julian F Koelbel, and Roberto Rigobon. Aggregate confusion: The divergence of esg ratings. 2019.

Asaf Bernstein, Matthew T Gustafson, and Ryan Lewis. Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics*, 134(2):253–272, 2019.

Patrick Bolton and Marcin T Kacperczyk. Do investors care about carbon risk? *Available at SSRN 3398441*, 2019.

Audra L Boone and Joshua T White. The effect of institutional ownership on firm transparency and information production. *Journal of Financial Economics*, 117(3):508–533, 2015.

Jacob Boudoukh, Roni Michaely, Matthew Richardson, and Michael R Roberts. On the importance of measuring payout yield: Implications for empirical asset pricing. *The Journal of Finance*, 62(2): 877–915, 2007.

Alex Chinco, Adam D. Clark-Joseph, and Mao Ye. Sparse Signals in the Cross-Section of Returns. *Journal of Finance*, 2019. ISSN 15406261. doi: 10.1111/jofi.12733.

Bhagwan Chowdhry, Shaun William Davies, and Brian Waters. Investing for impact. *The Review of Financial Studies*, 32(3):864–904, 2019.

Michael J Cooper, Huseyin Gulen, and Michael J Schill. Asset growth and the cross-section of stock returns. *the Journal of Finance*, 63(4):1609–1651, 2008.

Alan D Crane, Sébastien Michenaud, and James P Weston. The effect of institutional ownership on payout policy: Evidence from index thresholds. *The Review of Financial Studies*, 29(6):1377–1408, 2016.

Kent D Daniel, Robert B Litterman, and Gernot Wagner. Applying asset pricing theory to calibrate the price of climate risk: A declining optimal price for carbon emissions. *Columbia Graduate School of Business working paper*, 2015.

Stefano DellaVigna and Joshua M Pollet. Demographics and industry returns. *American Economic Review*, 97(5):1667–1702, 2007.

Olivier Dessaint and Adrien Matray. Do managers overreact to salient risks? evidence from hurricane strikes. *Journal of Financial Economics*, 126(1):97–121, 2017.

Alexander Dyck, Karl V Lins, Lukas Roth, and Hannes F Wagner. Do institutional investors drive corporate social responsibility? international evidence. *Journal of Financial Economics*, 131(3):693–714, 2019.

Robert F Engle, Stefano Giglio, Bryan Kelly, Heebum Lee, and Johannes Stroebel. Hedging climate change news. *The Review of Financial Studies*, 33(3):1184–1216, 2020.

Christopher Geczy, Robert F Stambaugh, and David Levin. Investing in socially responsible mutual funds. *Available at SSRN 416380*, 2005.

Edith Ginglinger and Quentin Moreau. Climate risk and capital structure. *Available at SSRN 3327185*, 2019.

Robin Greenwood and Samuel G Hanson. Issuer quality and corporate bond returns. *The Review of Financial Studies*, 26(6):1483–1525, 2013.

Jody Grewal, Edward J Riedl, and George Serafeim. Market reaction to mandatory nonfinancial disclosure. *Management Science*, 65(7):3061–3084, 2019.

Samuel M Hartzmark and Abigail B Sussman. Do investors value sustainability? a natural experiment examining ranking and fund flows. *The Journal of Finance*, 74(6):2789–2837, 2019.

Robert Heinkel, Alan Kraus, and Josef Zechner. The effect of green investment on corporate behavior. *Journal of financial and quantitative analysis*, 36(4):431–449, 2001.

David Hirshleifer. Investor psychology and asset pricing. *The Journal of Finance*, 56(4):1533–1597, 2001.

Po-Hsuan Hsu, Kai Li, and Chi-Yang Tsou. The pollution premium. *J. Financ. Econ. forthcoming*, 2019.

Mozaffar Khan, Suraj Srinivasan, and Liang Tan. Institutional ownership and corporate tax avoidance: New evidence. *The Accounting Review*, 92(2):101–122, 2017.

Ralph SJ Koijen and Motohiro Yogo. A demand system approach to asset pricing. *Journal of Political Economy*, 127(4):1475–1515, 2019.

Ralph SJ Koijen and Motohiro Yogo. Exchange rates and asset prices in a global demand system. Technical report, National Bureau of Economic Research, 2020.

Ralph SJ Koijen, Robert J Richmond, and Motohiro Yogo. Which investors matter for global equity valuations and expected returns? *Available at SSRN*, 2019.

Mathias Kruttli, Brigitte Roth Tran, and Sumudu W Watugala. Pricing poseidon: extreme weather uncertainty and firm return dynamics. 2019.

Augustin Landier and Stefano Lovo. Esg investing: How to optimize impact? *HEC Paris Research Paper No. FIN-2020-1363*, 2020.

Jonathan Lewellen et al. The cross-section of expected stock returns. *Critical Finance Review*, 4(1): 1–44, 2015.

Jun Li and Di Wu. Do corporate social responsibility engagements lead to real environmental, social, and governance impact? *Management Science*, 2020.

Karl V Lins, Henri Servaes, and Ane Tamayo. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance*, 72(4):1785–1824, 2017.

S Lakshmi Naaraayanan, Kunal Sachdeva, and Varun Sharma. The Real Effects of Environmental Activist Investing. *SSRN Electronic Journal*, 2019. doi: 10.2139/ssrn.3483692.

Martin Oehmke and Marcus M Opp. A theory of socially responsible investment. *Available at SSRN 3467644*, 2019.

Berardino Palazzo. Cash holdings, risk, and expected returns. *Journal of Financial Economics*, 104(1): 162–185, 2012.

Lubos Pastor, Robert F Stambaugh, and Lucian A Taylor. Sustainable investing in equilibrium. Technical report, National Bureau of Economic Research, 2019.

Lasse Heje Pedersen, Shaun Fitzgibbons, and Lukasz Pomorski. Responsible investing: The esg-efficient frontier. *Available at SSRN 3466417*, 2019.

Jules H. van Binsbergen and Christian C. Opp. Real Anomalies. *Journal of Finance*, 2019. ISSN 15406261. doi: 10.1111/jofi.12771.

Table 1: Summary Statistics of Firm Response and Performance Variables

| | Mean | 5th | 95th | SD | N |
|---|---|---|---|---|---|
| Institutional Ownership | 0.749 | 0.060 | 0.989 | 0.24 | 6,523 |
| Owner Environment Score | 40.167 | 34.004 | 45.031 | 3.69 | 6,523 |
| Institutional Pressure | 0.064 | -0.047 | 0.189 | 0.09 | 6,523 |
| Environ. Score | 51.368 | 34.000 | 75.667 | 12.77 | 5,394 |
| Carbon Score | 0.317 | 0.000 | 1.083 | 0.42 | 4,267 |
| Investment | 0.122 | -0.100 | 0.506 | 0.37 | 6,396 |
| Leverage | 0.409 | 0.000 | 0.835 | 0.26 | 6,382 |
| Cash Holdings | 0.142 | 0.005 | 0.478 | 0.15 | 6,401 |
| Payout | 0.035 | -0.011 | 0.118 | 0.06 | 6,007 |

This table summarizes the firm response and environmental performance variables used in Section 5. The data on environmental performance is from Sustainalytics, and firm response variables are computed from Compustat data.

Table 2: Correlations of Firm Response and Performance Variables

| | pressure | owner_escore | inst_ownership | E_score | carbon |
|---|---|---|---|---|---|
| pressure | 1.000 | | | | |
| owner_escore | 0.400 | 1.000 | | | |
| inst_ownership | -0.006 | 0.253 | 1.000 | | |
| E_score | 0.230 | 0.376 | -0.016 | 1.000 | |
| carbon | -0.004 | -0.248 | -0.029 | 0.235 | 1.000 |

This table computes the bivariate correlations for firm response and environmental performance variables used in Section 5. The data on environmental performance is from Sustainalytics, and firm response variables are computed using Compustat data.

Table 3: Transition Probabilities between Green, Brown, and Neutral

| | Brown | Neutral | Green |
|---|---|---|---|
| Brown | 0.71 | 0.29 | 0.00 |
| Neutral | 0.03 | 0.90 | 0.07 |
| Green | 0.00 | 0.20 | 0.80 |

This table reports the transition probabilities among investors with a positive, negative, and statistically insignificant coefficient on the environment score. We label each as *green*, *brown*, and *neutral* respectively. For each investor, the estimated demand system yields a time-series of quarterly coefficients. We pool the observations and compute the transition probabilities.

Table 4: Top Investors by Greenness

| Type | Manager Name | AUM ($bn) |
|---|---|---|
| Banks | STATE STR CORPORATION | 1164 |
| Banks | NORTHERN TRUST CORP | 343 |
| Banks | MELLON BANK NA | 333 |
| Banks | NORGES BK INVT MGMT (NBIM) | 256 |
| Banks | BANK OF AMERICA CORPORATION | 194 |
| Insurance companies | LEGAL & GENERAL GROUP PLC | 130 |
| Investment advisors | GEODE CAPITAL MGMT, L.L.C. | 280 |
| Investment advisors | PARAMETRIC PORTFOLIO ASSOC LLC | 77 |
| Investment advisors | RHUMBLINE ADVISERS LTD. PTNR | 47 |
| Investment advisors | ASSET MANAGEMENT ONE CO., LTD. | 40 |
| Investment advisors | GUGGENHEIM INVESTMENTS | 36 |
| Mutual funds | VANGUARD GROUP, INC. | 2150 |
| Mutual funds | GOLDMAN SACHS & COMPANY | 247 |
| Mutual funds | CREDIT SUISSE SECS (USA) LLC | 67 |
| Mutual funds | UBS ASSET MGMT (AMERICAS) INC. | 55 |
| Mutual funds | PANAGORA ASSET MANAGEMENT INC. | 25 |
| Pension funds | NEW YORK STATE COMMON RET FD | 79 |
| Pension funds | CALIFORNIA PUBLIC EMP' RET SYS | 69 |
| Pension funds | CALIFORNIA STATE TEACH RET SYS | 46 |
| Pension funds | NEW YORK STATE TEACH' RET SYS | 41 |
| Pension funds | FLORIDA STATE BD ADMINISTRATIO | 36 |
| Other | GREAT-WEST LIFE ASSURANCE CO | 40 |
| Other | CREDIT AGRICOLE | 29 |
| Other | BNP PARIBAS ARBITRAGE SA | 18 |

This table lists the largest green investors in the US by assets under management for each type at the end of 2017. Green investors are those with a positive significant coefficient on environment score from the estimated asset demand system. Investor are classified as banks, insurance companies, investment advisors, mutual funds, and pension funds following Koijen and Yogo [2019].

Table 5: Green-Inducing Investors and Changes in Firm-Level Carbon Score

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Lag Inst. Pressure | 0.129*** | 0.112*** | 0.128*** | 0.137*** | 0.157*** |
| | (0.0149) | (0.0123) | (0.0166) | (0.0329) | (0.0160) |
| Size | 0.0664* | 0.0711* | 0.0534* | 0.0753*** | |
| | (0.0208) | (0.0211) | (0.0186) | (0.0166) | |
| Tangibility | -0.411 | -0.309 | -0.155 | -0.447 | |
| | (0.178) | (0.197) | (0.150) | (0.236) | |
| Leverage | 0.111 | 0.0813 | -0.00693 | 0.210 | |
| | (0.125) | (0.116) | (0.105) | (0.152) | |
| Tobin's Q | 0.216 | 0.167 | 0.114 | 0.302 | |
| | (0.180) | (0.154) | (0.198) | (0.204) | |
| Profitability | 0.401 | 0.296 | 0.494 | 0.543 | |
| | (0.412) | (0.372) | (0.391) | (0.514) | |
| Lag Carbon Score | -0.161 | | -0.0931 | -0.262*** | -0.158 |
| | (0.0988) | | (0.0831) | (0.0529) | (0.102) |
| Constant | -1.451** | -1.308* | -1.153** | -1.778*** | -0.535*** |
| | (0.391) | (0.369) | (0.297) | (0.412) | (0.0787) |
| Lag Score | Y | N | Y | Y | Y |
| Controls | Y | Y | Y | Y | N |
| Year FE | Y | Y | Y | N | Y |
| Industry FE | Y | Y | N | Y | Y |
| Observations | 1613 | 1613 | 1616 | 1613 | 1792 |
| R-squared | 0.243 | 0.226 | 0.193 | 0.160 | 0.230 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports the annual regression of changes in firm-level carbon scores on institutional pressure for greenness and control variables. The dependent variable is the changes in natural logarithm of the carbon score obtained from Sustainalytics. A high score implies a lower carbon intensity. The main independent variable of interest is the institutional pressure for greenness, computed using equation (7). The estimates are for the time period 2010 to 2017. Standard errors are clustered at the industry and year level if applicable.

Table 6: Approximated Institutional Pressure and Changes in Firm-Level Carbon Score

| | (1) | (2) | (3) |
|---|---|---|---|
| Lag Numerator | 0.0733 | | |
| | (0.0411) | | |
| Lag Denominator | | -0.0149 | |
| | | (0.0218) | |
| Lag Approximated Inst. Pressure | | | 0.0625 |
| | | | (0.0272) |
| Size | 0.0724** | 0.0854** | 0.0940** |
| | (0.0179) | (0.0193) | (0.0212) |
| Tangibility | -0.430 | -0.400 | -0.371 |
| | (0.199) | (0.191) | (0.187) |
| Leverage | 0.106 | 0.122 | 0.131 |
| | (0.136) | (0.132) | (0.131) |
| Tobin's Q | 0.206 | 0.233 | 0.247 |
| | (0.163) | (0.176) | (0.181) |
| Profitability | 0.429 | 0.392 | 0.395 |
| | (0.429) | (0.421) | (0.420) |
| Lag Carbon Score | -0.154 | -0.150 | -0.146 |
| | (0.101) | (0.100) | (0.0986) |
| Constant | -1.447** | -1.610** | -1.723** |
| | (0.297) | (0.344) | (0.370) |
| Lag Score | Y | Y | Y |
| Controls | Y | Y | Y |
| Year FE | Y | Y | Y |
| Industry FE | Y | Y | Y |
| Observations | 1613 | 1613 | 1613 |
| R-squared | 0.238 | 0.234 | 0.236 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports the annual regression of changes in firm-level carbon scores on institutional pressure for greenness and control variables. The dependent variable is the changes in natural logarithm of the carbon score obtained from Sustainalytics. A high score implies a lower carbon intensity. The main independent variable of interest is the numerator, denominator, and the approximation of the institutional pressure for greenness from equation (10). The estimates are for the time period 2010 to 2017. Standard errors are clustered at the industry and year level if applicable.

Table 7: Green Investors and Changes in Firm-Level Carbon Score

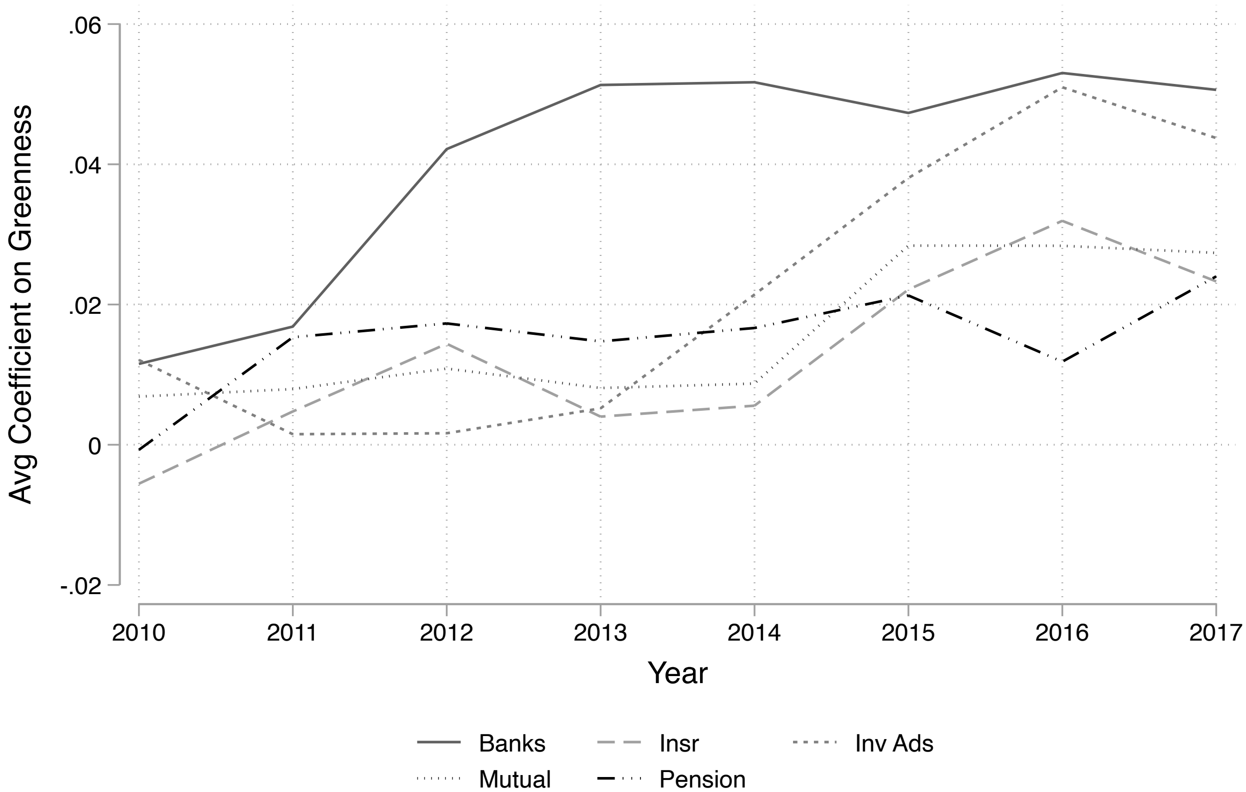
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Lag Owner E-Score | 0.0259* | 0.0271** | | |
| | (0.00730) | (0.00603) | | |
| Lag Inst. Ownership | | | -0.0306 | 0.00163 |
| | | | (0.0793) | (0.0800) |
| Size | 0.0769* | 0.0779* | 0.0873** | 0.0904** |
| | (0.0232) | (0.0293) | (0.0194) | (0.0205) |
| Tangibility | -0.352 | -0.259 | -0.395 | -0.298 |
| | (0.223) | (0.222) | (0.196) | (0.204) |
| Leverage | 0.138 | 0.109 | 0.125 | 0.0973 |
| | (0.121) | (0.111) | (0.134) | (0.121) |
| Tobin's Q | 0.252 | 0.205 | 0.237 | 0.192 |
| | (0.177) | (0.146) | (0.175) | (0.152) |
| Profitability | 0.205 | 0.102 | 0.389 | 0.288 |
| | (0.399) | (0.400) | (0.418) | (0.384) |
| Lag Carbon Score | -0.147 | | -0.150 | |
| | (0.0998) | | (0.102) | |
| Constant | -2.614*** | -2.502*** | -1.612** | -1.498** |
| | (0.374) | (0.359) | (0.326) | (0.307) |
| Lag Score | Y | N | Y | N |
| Controls | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y |
| Observations | 1613 | 1613 | 1613 | 1613 |
| R-squared | 0.238 | 0.223 | 0.234 | 0.219 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports the annual regression of firm-level environment performance on measures of green institutional ownership. The dependent variable is the changes in natural logarithm of the carbon score obtained from Sustainalytics. A high score suggests a firm is more environmentally friendly. We consider two main independent variables of interest. First is the AUM-weighted average environment score of the investors in each firm, which we denote as the Owner E-Score. Second is the share of institutional ownership of each firm. The estimates are for the time period 2010 to 2017. Standard errors are clustered at the industry and year level.

Figure 1: Time-Series of Average Coefficients by Investor Type




This figure plots the time-series of average coefficient on environment score by investor type. The coefficients are obtained from the demand system in which we treat the unrated firms as having the lowest environment score in the cross-section. We estimate the demand model for investor $i$ for a given quarter $t$, which can be written as:

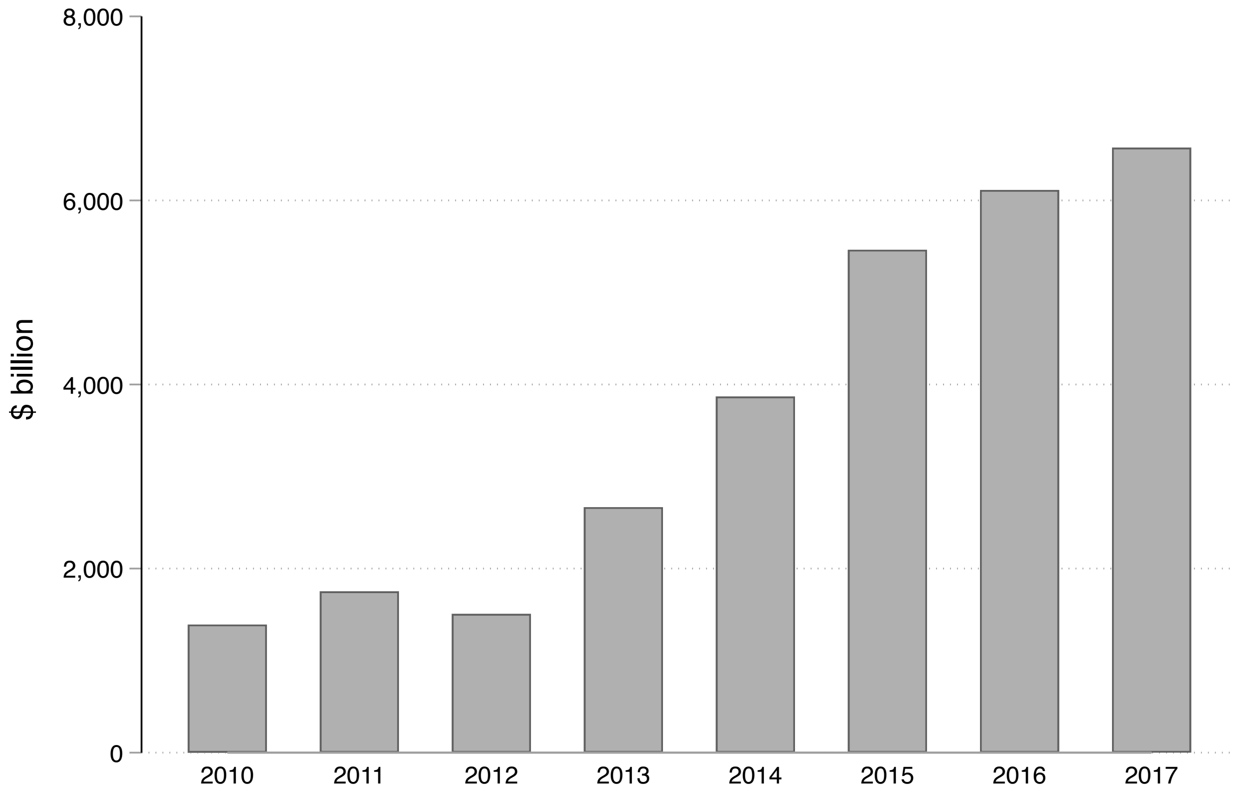
$$\forall i, \forall t: \frac{w_{it}(n)}{w_{it}(0)} = \exp\left(b_{0,it} + \beta_{0,it} me_t(n) + \beta_{1,it} es_t^*(n) + \beta_{2,it}' \mathbf{x}_t^*(n)\right) \epsilon_{it}(n)$$

where $me_t(n)$ is the log market equity of asset $n$ at time $t$, $es_t^*(n)$ is the cross-sectionally standardized e-score, and $\mathbf{x}_t^*(n)$ denotes other cross-sectionally standardized characteristics. We assume throughout that characteristics are exogenous to latent demand:

$$\mathbb{E}_t\left[\epsilon_{it}(n) \,|\mathbf{x}_t(n), es_t^*(n)\right] = 1$$

where the expectations is taken across the stocks in a given period. We instrument $me_t(n)$ with $\widehat{me}_t(n)$ as detailed in Section 4.1.

Figure 2: Time-Series of Green AUM




This figure plots the time-series of total green AUM in our universe. Green AUM is computed by combining the AUM of investors who have a positive loading on environment score in each quarter and then averaging across four quarters for each year. The coefficients are obtained from the demand system in which we treat the unrated firms as having the lowest environment score in the cross-section. We estimate the demand model for investor $i$ for a given quarter $t$, which can be written as:

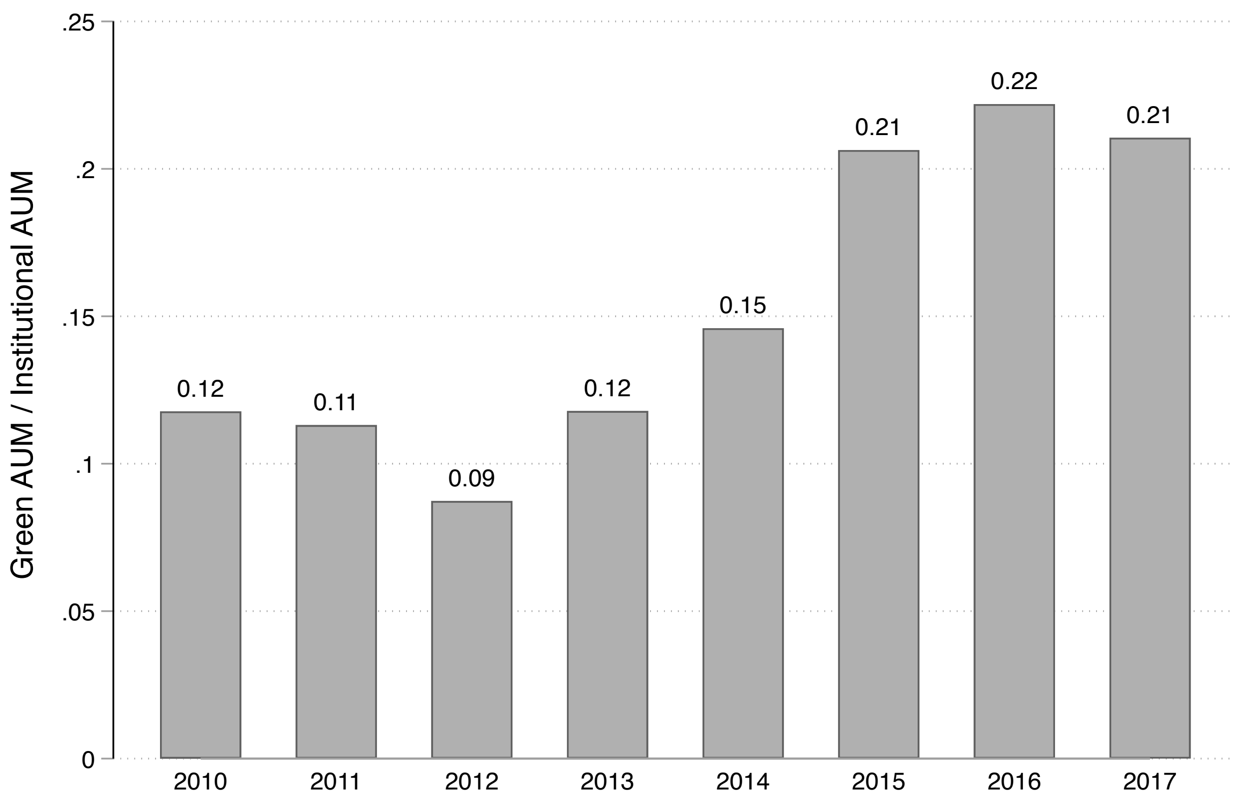
$$\forall i, \forall t : \frac{w_{it}(n)}{w_{it}(0)} = \exp\left(b_{0,it} + \beta_{0,it} me_t(n) + \beta_{1,it} es_t^*(n) + \beta_{2,it}' \mathbf{x}_t^*(n)\right) \epsilon_{it}(n)$$

where $me_t(n)$ is the log market equity of asset $n$ at time $t$, $es_t^*(n)$ is the cross-sectionally standardized e-score, and $\mathbf{x}_t^*(n)$ denotes other cross-sectionally standardized characteristics. We assume throughout that characteristics are exogenous to latent demand:

$$\mathbb{E}_t\left[\epsilon_{it}(n) \,|\mathbf{x}_t(n), es_t^*(n)\right] = 1$$

where the expectations is taken across the stocks in a given period. We instrument $me_t(n)$ with $\widehat{me}_t(n)$ as detailed in Section 4.1.

Figure 3: Time-Series of Proportion of Green AUM




This figure plots the time-series of the proportion of green AUM in our universe. Green AUM is computed by combining the AUM of investors who have a positive loading on environment score in each quarter and then averaging across four quarters for each year. We compute the proportion with respect to total AUM in each quarter. The coefficients are obtained from the demand system in which we treat the unrated firms as having the lowest environment score in the cross-section. We estimate the demand model for investor $i$ for a given quarter $t$, which can be written as:

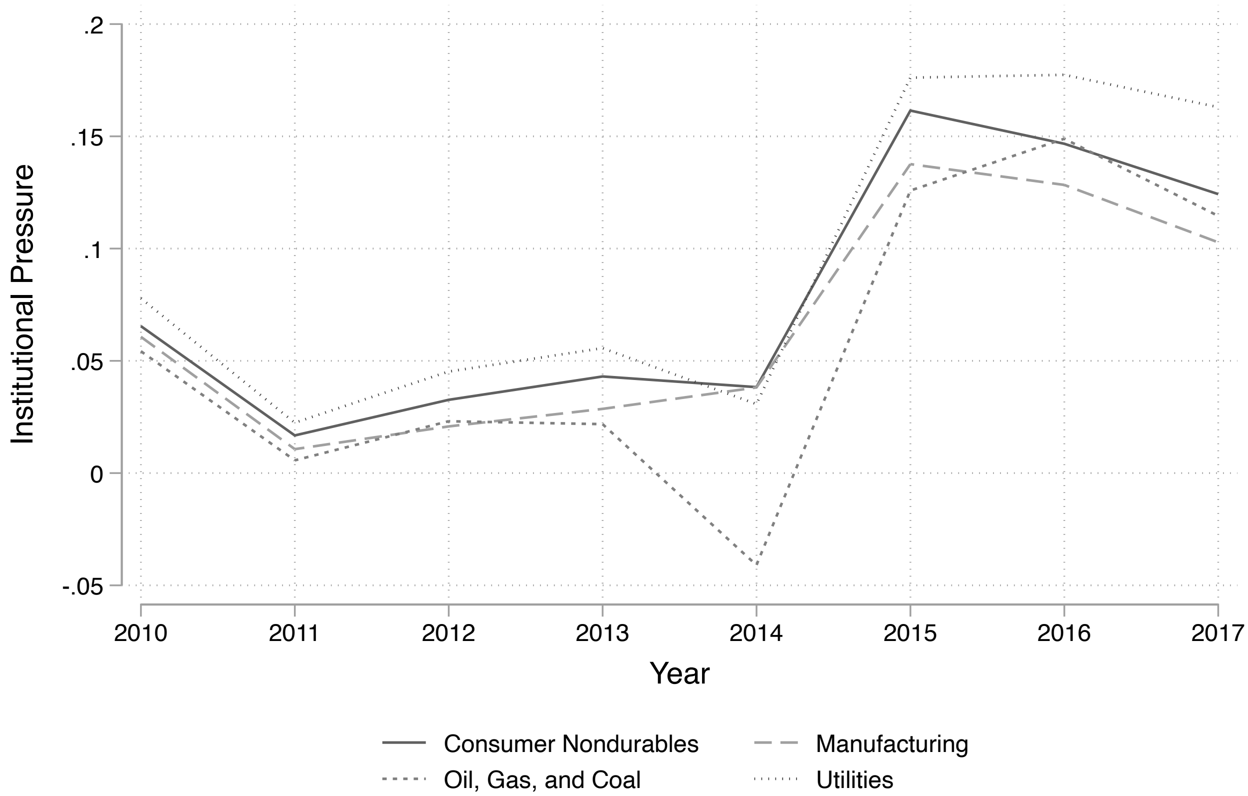
$$\forall i, \forall t : \frac{w_{it}(n)}{w_{it}(0)} = \exp\left(b_{0,it} + \beta_{0,it} me_t(n) + \beta_{1,it} es_t^*(n) + \beta_{2,it}' \mathbf{x}_t^*(n)\right) \epsilon_{it}(n)$$

where $me_t(n)$ is the log market equity of asset $n$ at time $t$, $es_t^*(n)$ is the cross-sectionally standardized e-score, and $\mathbf{x}_t^*(n)$ denotes other cross-sectionally standardized characteristics. We assume throughout that characteristics are exogenous to latent demand:

$$\mathbb{E}_t\left[\epsilon_{it}(n) \,|\mathbf{x}_t(n), es_t^*(n)\right] = 1$$

where the expectations is taken across the stocks in a given period. We instrument $me_t(n)$ with $\widehat{me}_t(n)$ as detailed in Section 4.1.

Figure 4: Time-Series of Institutional Pressure for Selected Industries




This figure plots the time-series of industry average of the firms' institutional pressures. For each firm, we compute the institutional pressure given as the diagonal entries of **M** from Proposition 2. We then compute an equal-weighted average across the stocks within each industry.

# A Proof of Propositions

**Proof of Proposition 1** With the new constraint, the FOC yields the new approximate solution

$$w_{it}^{(1)} \approx \Sigma_{it}^{(1,1)-1}[\mu_{it}^{(1)} - \lambda_{it}1 + \nu_{it}b_{it}^{(1)}].$$

Suppose we define $\tilde{\mu}_{it}$, expected returns after adjusting for shadow benefit, as

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

Notice that because $g_{it}(n)$ is simply the $k$th entry of $y_{it}(n)$, we can write

$$\nu_{it}b_{it} = \nu_{it}d_i g_t = \nu_{it}d_i y_{it}e_k.$$

Putting this together, we can rewrite

$$\mu_{it}^{(1)} - \lambda_{it}1 + \nu_{it}b_{it}^{(1)} = \tilde{\mu}_{it}^{(1)} - \lambda_{it}1$$

and proceed exactly as in the proof provided in the appendix of Koijen and Yogo [2019] to arrive at the desired claim. □

**Proof of Proposition 2** To compute this, recall the following identity that holds by market clearing:

$$\mathbf{p} = \log\left(\sum_i A_i \mathbf{w}_i\right) - \mathbf{s} \tag{14}$$

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

$$\begin{aligned}
\mathrm{I} &= \begin{pmatrix} \left(\frac{1}{\sum_i A_i w_i(1)}\right)\left(\frac{\partial}{\partial \mathbf{p}(1)} \sum_i A_i w_i\,(1)\right) & \cdots & \left(\frac{1}{\sum_i A_i w_i(1)}\right)\left(\frac{\partial}{\partial \mathbf{p}(n)} \sum_i A_i w_i\,(1)\right) \\ \\ \left(\frac{1}{\sum_i A_i w_i(n)}\right)\left(\frac{\partial}{\partial \mathbf{p}(1)} \sum_i A_i w_i\,(n)\right) & \cdots & \left(\frac{1}{\sum_i A_i w_i(n)}\right)\left(\frac{\partial}{\partial \mathbf{p}(n)} \sum_i A_i w_i\,(n)\right) \end{pmatrix} \\
&= \begin{pmatrix} \frac{1}{\sum_i A_i w_i(1)} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \frac{1}{\sum_i A_i w_i(n)} \end{pmatrix} \begin{pmatrix} \frac{\partial(\sum_i A_i w_i(1))}{\partial \mathbf{p}(1)} & \cdots & \frac{\partial(\sum_i A_i w_i(1))}{\partial \mathbf{p}(n)} \\ \vdots & & \vdots \\ \frac{\partial(\sum_i A_i w_i(n))}{\partial \mathbf{p}(1)} & \cdots & \frac{\partial(\sum_i A_i w_i(n))}{\partial \mathbf{p}(n)} \end{pmatrix} \\
&\equiv \mathbf{H}^{-1} \frac{\partial}{\partial \mathbf{p}} \left(\sum_i A_i \mathbf{w}_i\right)
\end{aligned} \tag{15}$$

where

$$\mathbf{H} := \text{diag}\left(\sum_i A_i \mathbf{w}_i\right) = \sum_i A_i \text{diag}\left(\mathbf{w}_i\right) \tag{16}$$

Furthermore, it can be shown that:

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

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

which can be rewritten as

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

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

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

Now going back to the market clearing condition (14) 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:

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

□

# B Addendum on Empirical Strategy

## B.1 Variable Selection with Lasso

We empirically examine whether the environment score enters investors' characteristics-based demand. Specifically, we consider a Lasso regression with the following linear specification:

$$\forall i, \forall t : y_{it}(n) = \log\left(\frac{w_{it}(n)}{w_{it}(0)}\right) = \sum_{k=0}^{K} \beta_{itk} x_{kt}(n) \tag{17}$$

where $x_{kt}(n)$ is the $k$th characteristic of stock $n$ at time $t$. $w_{it}(0)$ is investor $i$'s portfolio weight on the outside asset and $y_{it}(n)$ is the logarithm of the portfolio weight on asset $n$ relative to the weight on the outside asset.[13] This log-linear relationship is motivated by the asset demand model in Koijen and Yogo [2019]. This leads to the estimates:

$$\hat{\beta}(\lambda) = \arg\min_{\beta} \|\mathbf{y}_{it} - \mathbf{x}_{it}'\beta\|_2^2 + \lambda\|\beta\|_1. \tag{18}$$

where $\lambda$ is a penalty parameter that is chosen through 5-fold cross validation. In interpreting the results, we consider the characteristics that have nonzero estimated coefficients to be relevant for investor's demand.

As characteristics, we start from 70 financial ratios from the WRDS Industry Financial Ratio dataset, the Sustainalytics environment score, and the five characteristics used in Koijen and Yogo [2019]. We then take out valuation ratios to avoid endogeneity problems caused by using market prices and arrive at a total of 62 relevant firm characteristics. To address the endogeneity of prices in market equity, we use an instrument[14] from Koijen and Yogo [2019] for market equity and exclude valuation ratios.

The regression is estimated for each investor at each quarter. For example, if there are 100 institutions and 10 quarters, we are running $100 \times 10 = 1000$ different linear models indexed by $i$ and $t$. For each run, we count whether a given stock characteristic is selected or not, and later divide the frequency selected by the number of all institution-quarter pairs. If log book equity was included in 500 out of 1,000 models, the selection frequency is 0.5. It should be noted that we are imposing the restriction that instrument for market equity and log book equity always enter the model.

[13] We define inside assets to be common shares of largest US stocks that collectively comprise 90% of total US market capitalization. Outside asset represents all wealth outside the assets that are the subject of our study.

[14] The instrument is defined as

$$\widehat{me}_i(n) = \log\left(\sum_{j \neq i} A_j \frac{\mathbb{I}_j(n)}{1 + \sum_{m=1}^{N} \mathbb{I}_j(m)}\right)$$

where $\mathbb{I}_j(n)$ is the indicator function that is equal to one if asset $n$ is in investor $i$'s investment universe. The instrument justified if each institution's investment universe is exogenous.

The results of the estimation are shown in Figures 5 and 6. In Figure 5, we present the average number of characteristics included when we run Lasso on the institutional holdings. We find that relatively sparse models of around 10 characteristics are chosen on average. Chinco et al. [2019] uses a similar idea to identify a sparse set of relevant signals out of a large set of possible predictors.

Figure 6 reports the selection frequencies. We see that all the characteristics that were originally included in Koijen and Yogo [2019] – log book equity, profitability, investment, dividends to book equity, and market beta – appear in the list of top ten most frequently selected characteristics. We also see that the environment score from Sustainalytics is selected at a frequency that is comparable to that of investment. Although a frequency of less than 0.5 may appear low, this is explained by the existence of passive institutions whose portfolio weights only depend on market and book equity.

## B.2 Institutional Pressure and Corporate Policy

In this section, we also examine key corporate policy variables in response to institutional pressure for greenness. We focus on four variables: investment, leverage, cash holdings, and payout. The empirical specification is identical to that in (13) with a different set of control variables for each.

As background, Ginglinger and Moreau [2019] show that greater climate risk leads to lower firm leverage with firms decreasing their demand for debt and lenders reducing their lending to firms with the greatest risk. Dessaint and Matray [2017] also shows that sudden shock to perceived liquidity risk leads managers to increase corporate cash holdings. We are not aware of papers that directly examine investment and payout responses to climate risk. Given that both variables are tightly linked to the firm's investment decision, we may reasonably expect changes in their levels after a sudden increase in institutional pressure.

### B.2.1 Construction of Corporate Policy Variables

**Investment** For our dependent variable, we use the definition from Cooper et al. [2008]:

$$y_{it} = \frac{AT_{it} - AT_{i,t-1}}{AT_{i,t-1}}$$

i.e. the percentage quarter-on-quarter growth in total assets. The control variables known to affect investment include Tobin's Q ($Q_{it}$) and cash-to-assets ratio ($CHE_{it}/AT_{it}$). For Tobin's Q, we use the following definition

$$\frac{AT_{it} + PRCC_{it} \times CSHO_{it} + CEQ_{it} - TXDB_{it}}{AT_{it}}$$

**Capital Structure and Leverage** For our dependent variable, we use the definition from Lewellen et al. [2015]:

$$y_{it} = \frac{DLTT_{it} + DLC_{it}}{DLTT_{it} + DLC_{it} + SEQ_{it}}$$

where $DLTT_{it}$ is the amount of long-term debt exceeding a maturity of one year, $DLC_{it}$ is the debt in current liabilities and $SEQ_{it}$ is the stockholder's equity.[15] The control variables known to affect the leverage decision include profitability, asset tangibility, lagged sales growth, and firm size. For profitability, we follow Ball et al. (2015) and use gross profits divided by equity:

$$\frac{GP_{it}}{SEQ_{it} + TXDITC_{it} - PSTK_{it}}$$

For asset tangibility, we use:

$$\frac{PPENT_{it}}{AT_{it}}$$

For sales growth, we use the percentage growth sale in annual sale (SALE) following Lakonishok, Shleifer, and Vishny (1994). For firm size, we use log total assets $(AT_{it})$.

Ginglinger and Moreau [2019] show that greater climate risk leads to lower firm leverage with firms decreasing their demand for debt and lenders reducing their lending to firms with the greatest risk.

**Cash Holdings** For our dependent variable, we use the definition from Palazzo [2012] and Dessaint and Matray [2017] :

$$y_{it} = \frac{CHE_{it}}{AT_{it}}$$

where $CHE_{it}$ is the cash and short-term investments and $AT_{it}$ is total assets for firm $i$ at quarter $t$. The control variables known to affect the cash-holding decisions of firms include net income $(NI_{it})$, Tobin's Q $(Q_{i,t})$ , firm size $(SIZE_{i,t})$, and lagged leverage $(LEV_{i,t})$. where the denominator is our measure of book equity.

**Payouts** For our dependent variable, we use the definition from Boudoukh et al. [2007]:

$$y_{it} = \frac{DVC_{it} + PRSTKC_{it} - SSTK_{it}}{CSHO_{it} \times PRCC_{it}}$$

where $DVC_{it}$ is common dividends; $PRSTKC_{it}$ is the purchase of common and preferred stock; $PSTKRV$ is the sale of common and preferred stock; $CSHO_{it}$ is the number of shares outstanding

[15] In a contemporaneous paper, Ginglinger and Moreau (2019) exclude $DLC_{it}$ due to the long-term nature of climate risks. Our results are robust to alternate definitions.

and $PRC_{it}$ is the stock price. The control variables known to affect payout decisions include return on assets, size, lagged sales growth, and liquidity. For return on assets, we use the definition from Balakrishnan, Bartov, and Faurel (2010):

$$\frac{IB_{it}}{AT_{it}}$$

and for liquidity, we use the ratio of current assets to total assets:

$$\frac{ACT_{it}}{AT_{it}}$$

#### B.2.2 Empirical Results

Table 8 reports the annual regression of corporate policy variables on institutional pressure and control variables. We find that lagged institutional pressure is negatively associated with investment and positively associated with cash holdings and payout, the significance of which is at the 5% level. For investment, a one standard deviation increase in lagged institutional pressure leads to a 1.8 p.p. decline in investment but 1.34 p.p. increase in cash holdings and 0.37 p.p. increase in payouts.

Table 8: Green-Inducing Investors and Corporate Policy

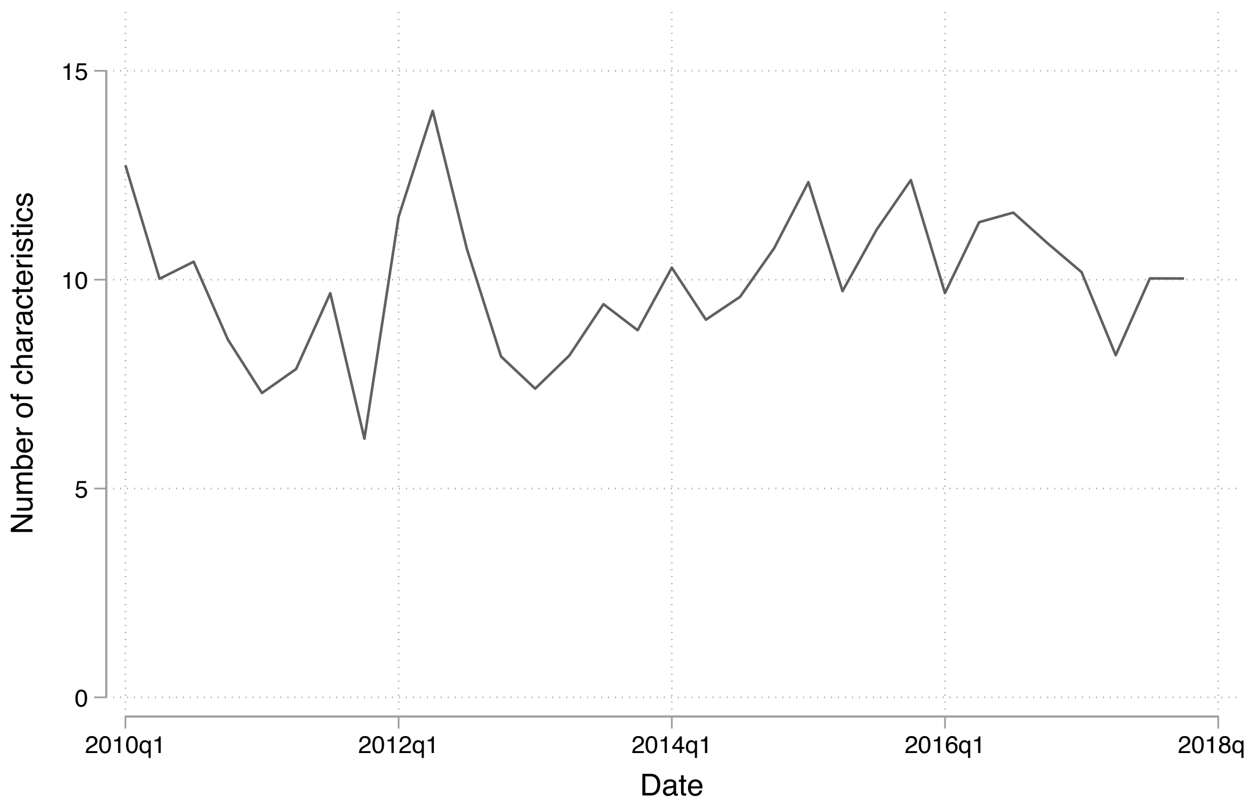
| | (1) Investment | (2) Leverage | (3) Cash Holdings | (4) Payout |
|---|---|---|---|---|
| Lag Inst. Pressure | -0.0176* | -0.00880 | 0.0134* | 0.00369* |
| | (0.00652) | (0.00503) | (0.00398) | (0.00147) |
| Tobin's Q | 0.00503 | | 0.234*** | |
| | (0.00454) | | (0.0295) | |
| Lag Cash | 0.252* | | | |
| | (0.0765) | | | |
| Profitability | | -0.640** | | |
| | | (0.148) | | |
| Tangibility | | 0.0386 | | |
| | | (0.0676) | | |
| Lag Sales Growth | | -0.120 | | -0.0464* |
| | | (0.0530) | | (0.0154) |
| Size | | 0.0350*** | -0.0209* | 0.00440* |
| | | (0.00523) | (0.00599) | (0.00123) |
| Net Income (Loss) | | | 0.00000767* | |
| | | | (0.00000238) | |
| Lag Leverage | | | 0.0602* | |
| | | | (0.0188) | |
| Return on Assets | | | | 0.132* |
| | | | | (0.0410) |
| Liquidity | | | | 0.000288 |
| | | | | (0.0114) |
| Constant | 0.0585*** | 0.129* | -0.0300 | -0.00714 |
| | (0.00418) | (0.0493) | (0.0441) | (0.0152) |
| Controls | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y |
| Observations | 4709 | 5008 | 4698 | 4107 |
| R-squared | 0.0412 | 0.275 | 0.385 | 0.141 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports the annual regression of corporate policy variables on institutional pressure for greenness and control variables. The dependent variables are investment, leverage, cash holdings, and payouts. Definitions and construction of the variables are detailed in Appendix B.2.1. The main independent variable of interest is the institutional pressure for greenness, computed using equation (7). The estimates are for the time period 2010 to 2017. Standard errors are clustered at the industry and year level.

Figure 5: Average Number of Selected Characteristics (2009:Q3 – 2018:Q4)




This figure plots the average number of characteristics included in the Lasso estimation of holdings on characteristics. Specifically, we consider a Lasso regression with the following linear specification:

$$\forall i, \forall t : y_{it}(n) = \log\left(\frac{w_{it}(n)}{w_{it}(0)}\right) = \sum_{k=0}^{K} \beta_{itk} x_{kt}(n)$$

where $x_{kt}(n)$ is the $k$th characteristic of stock $n$ at time $t$. The penalty parameter $\lambda$ is chosen through 5-fold cross validation.

Figure 6: Variable Selection from Lasso Regression (2009:Q3 – 2018:Q4)


This figure plots the frequency of characteristics selected in the Lasso estimation of holdings on characteristics. Specifically, we consider a Lasso regression with the following linear specification:

$$\forall i, \forall t : y_{it}(n) = \log\left(\frac{w_{it}(n)}{w_{it}(0)}\right) = \sum_{k=0}^{K} \beta_{itk} x_{kt}(n)$$

where $x_{kt}(n)$ is the $k$th characteristic of stock $n$ at time $t$. The penalty parameter $\lambda$ is chosen through 5-fold cross validation.