Measuring Institutional Pressure for Greenness: A Demand System Approach*

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Abstract

How should we quantify the institutional price pressure induced by demand for green stocks? We use the equity holdings of institutional investors and the demand system approach to answer this question. We devise and estimate a firm-level quantity, *institutional pressure for greenness*, that measures the price pressure a firm receives from its institutional owners to become more environment-friendly. We find that this quantity has a positive and significant relationship with future improvement in a firm's carbon intensity, but not with other measures of a firm's environment performance. We also find that investors with high portfolio-level environment scores do not necessarily contribute to higher institutional pressure. Instead, investors who are price-inelastic and display a positive portfolio tilt towards greenness – those who overweight greener stocks even after *controlling for other characteristics* – contribute the most to institutional pressure.

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1 Introduction

A recent survey estimates that global ESG ("Environmental, Social, and Governance") assets may exceed \$53 trillion by 2025, accounting for more than a third of the projected global assets under management (Bloomberg [2021]). While the trend encompasses all asset classes, ESG activity has been most pronounced in equity markets: ESG mutual funds and ETFs in Europe alone have reached the \$1.1 trillion milestone as of 2020Q3. A majority of these funds aim to influence corporations through price pressure either through threat of divestment via negative screening or through positive pressure by allocating more capital to "greener" firms, thereby bidding up their prices.[1] Recent studies find that greener firms indeed tend to have higher valuation ratios, perhaps due to this institutional demand for greenness.[2]

Measuring the price pressure, induced by investors and felt by corporations, is therefore key in evaluating the success of ESG investing, whose goal is to incentivize firms to adopt sustainable business practices. One often-used proxy for price pressure is the proportion of institutional ownership (Hong and Kacperczyk [2009], Dyck, Lins, Roth, and Wagner [2019]). If different institutional investors have heterogeneous demand for assets, however, this measure begets two concerns. First, if the institutional investors of a firm with high ownership shares do not demonstrate any taste for "greenness," this firm may not be subject to price pressure to become "greener." Second, if the majority of the institutional owners are very price elastic, divestment may not be able to produce much negative price pressure because a small drop in prices would induce the remaining owners to soak up the divested shares.

In this paper, we propose a method to quantify the institutional price pressure for greenness, taking into account the composition and heterogeneity of the institutional owners. Following the existing literature, we proxy greenness by the environment score from the third-party rater Sustainalytics. We then adapt the asset demand system developed by Koijen and Yogo [2019] and derive a closed-form expression for a firm-level quantity we call *institutional pressure*. Once we estimate the characteristics-based demand functions for each institutional investor using the 13F holdings data, institutional pressure can be computed empirically using the estimated demand coefficients. Specifically, it is defined as *the derivative of a firm's equilibrium price with respect to its own greenness*. This approach flexibly allows for heterogeneity in investors' demand for characteristics, and the effects of price elasticity of the owners are also reflected through the imposition of market clearing.

Our empirical strategy also circumvents some of the common concerns in the literature. 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, such as disclosed greenhouse gas (GHG) emissions. Second, we use equity holdings instead

[1]An alternative method is to embark on an activist campaign to promote ESG objectives, but such activities are not widespread.

[2]For example, see Koijen, Richmond, and Yogo [2019].

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 (Zerbib [2020]). For these reasons, we use equity holdings of institutional investors and employ the demand system approach to gauge each investor's demand for greenness.

The formula for institutional pressure resembles an elasticity-adjusted, share-weighted average of the owners' "portfolio tilts" toward greenness. As in Koijen, Richmond, and Yogo [2019], we refer to an investor's tendency to overweight stocks with a certain characteristic as a portfolio tilt towards this characteristic. In other words, if a firm's large shareholders are price inelastic and have large positive portfolio tilts towards greenness, this firm will have a higher value of institutional pressure.

It is important to note that while related, a positive portfolio tilt is different from a high portfolio-level greenness. For example, an investor may be holding a portfolio with high average environment score as a consequence of preferring other characteristics that happen to be correlated with the score, in which case this investor will be estimated to have a small portfolio tilt for greenness in the demand system. Consequently, investors with high portfolio-level greenness do not necessarily contribute to institutional pressure. This is the key insight underlying the recent complaints about green ETFs resembling technology ETFs too much[3]: investors who load up on the tech sector end up appearing superficially green.

Empirically, we find that institutional pressure is only weakly correlated with the proportion of institutional ownership. This finding hints at the importance of taking investor heterogeneity into account. We also find that average institutional pressure rises after the Paris Agreement in 2016 and is higher for the utilities sector.

As an application of our measure, we test whether institutional pressure predicts improvements in a firm's environmental performance. Assuming that a given firm cares about its stock price, institutional pressure should capture the strength of the firm's incentive to become greener. Interestingly, we find that while institutional pressure predicts a given firm's future improvements in carbon score, defined as within-industry performance in terms of carbon intensity (emissions scaled by revenue), it does not predict improvements in other measures of environmental performance. Also, we find in our placebo tests that the portfolio-level environment scores of a firm's owners or share of institutional ownership do not predict improvements even in carbon scores or do so only weakly.

One implication from our analysis is that crude alternative measures of institutional pressure that do not reflect investors' heterogeneous preferences may yield misleading conclusions. Measures such as the proportion of institutional ownership may lead to a null result and consequently understate the significance of the investor channel of ESG investing. Our approach highlights the importance of

[3]See https://www.bloomberg.com/news/articles/2021-04-14/blackrock-s-record-breaking-esg-fund-looks-just-like-a-big-tech-etf

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 investors with already-high portfolio-level scores. This result, while counter-intuitive, is crucial in designing investment mandates aimed at inducing desired firm behavior.

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 each investor's demand for greenness. We first show that not every investor with high portfolio-level greenness 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 larger improvements in environmental performance. We use measures of firm-level environmental performance from Sustainalytics as well as disclosed scope 1 greenhouse gas emissions from Trucost. For the Sustainalytics scores, a higher score suggests a firm is more environmentally friendly, respectively. In our baseline tests, 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 scores and the share of institutional ownership. We find that future firm environmental performance displays minimal or no significantly positive correlation with these measures.

Contribution to Literature

We add to the growing literature that examines the aggregate impact of ESG mandates and demand for green investments. The literature has mainly examined the response of investors and fund managers to climate risk and sustainability[4] as well as the implications for prices of climate risk-related assets[5]. 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

[4] 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].

[5] 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]

(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. On the theory side, Broccardo et al. [2020] considers the relative effectiveness of divestments and boycotts relative to engagement strategies in promoting socially desirable outcomes in firms. Empirically, 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 institutional pressure is particularly useful in that it can be generalized to *any* characteristic 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 Institutional Pressure

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 then discuss the concept of institutional pressure.

2.1 Incorporating Environment Scores 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 an 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 kth 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.[6] 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 Mth-order polynomial of this vector can be written as

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

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

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 Γ_{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:

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

where Φ_{it} and Ψ_{it} are vectors and ϕ_{it} and ψ_{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 kth 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[7]

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

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 kth 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*

[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.

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

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

the modified constant is given by

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

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 Φ_{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

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

Presumably, a public firm cares about its stock price. The quantity $\mathbf{M}_{n,n}$, which is the nth 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 kth characteristic.[8]

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 nth diagonal entry of the second term is

[8]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.

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

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.

2.3 Which Investors Contribute to Institutional Pressure?

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.[9] 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.[10] 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; we also augment this dataset with the greenhouse gas emissions data from Trucost. 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.

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

[10]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.

3.1 Firm Environmental Performance

We use firm-specific measures of environmental performance from Sustainalytics, which provides monthly normalized scores on environmental performance for predominantly publicly traded firms from 2009. Sustainalytics uses a number of sub-categories and evaluates each firm's score by comparing it to peers in the same industry. Therefore, 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. The environment score is used as one of the firm characteristics that enters investor demand. The carbon score is used as a measure of firms' efforts to become more environment-friendly. 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.

We also obtain firm level carbon and other greenhouse gas emissions from Trucost. We primarily use data on scope 1 emissions, which cover direct emissions over one year from company-owned or controlled resources.

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 numbers 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 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 exclude return variables because they violate our identifying assumption that characteristics other than price are exogenous to latent demand, as we discuss in Section 4.

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 51.4 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 firm response regressions.

The *owner environment* score is calculated in two steps. First, we calculate investor i's portfolio environment score as the holdings-weighted environment score of the stocks that constitute the portfolio, $\sum_m w_{it}(m)x_{kt}(m)$. Then for each firm n, 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 used during Sustainalytics' construction of the overall environment score.

4 Demand 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.[11]

4.1 Empirical Framework

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

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

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.

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

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.[12] 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,

[12] We use this terminology for brevity despite the fact that many green activist investors may actually demonstrate a portfolio tilt away from greener stocks, because they wish to improve the environmental laggards.

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 increasing trends from both of these 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 price inelastic 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 Environmental Performance

In this section, we examine the effect of institutional pressure for greenness on firm policies and performance, and juxtapose it to that of crude measures such as owner portfolio environment score and fraction of institutional ownership.[13]

[13] 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.

5.1 Predicting Environmental Performance with Institutional Pressure

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 intensity score from Sustainalytics. A higher score suggests a firm is more environmentally friendly. Our baseline tests examine the relation between firm's environmental performance and lagged institutional pressure for greenness:

$$y_t(n) = \alpha + \beta \cdot Pressure_{t-1}(n) + \gamma' X_t(n) + \Lambda + \epsilon_t(n) \tag{13}$$

where $y_t(n)$ is the measure of firm n's *improvement* in environmental performance at time t and $Pressure_{t-1}(n)$ is the institutional pressure for greenness, given as the ith diagonal element of $\mathbf{M}$. $X_t(n)$ is a set of firm-level control variables which include size, asset tangibility, leverage, Tobin's Q, and 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. Λ 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.[14] 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

[14] Ideally, we would like to include fixed effects using industry definitions employed by Sustainalytics. Unfortunately, our Sustainalytics data lacksthe industry definitions and therefore we employ the first two digits of the SIC code which represent the major industry sector to which a business belongs.

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 mitigates the aforementioned concern regarding potential biases.

In Table 6, we examine how other measures of firm-level environmental performance respond to lag institutional pressure in an identical empirical setting. As before, the main independent variable of interest is the lagged institutional pressure for greenness. As our dependent variables, we consider changes in three separate measures, all obtained form Sustainalytics, shown in columns (1) through (3): (1) Environmental Fines and Non-monetary Sanctions (E_1_4), (2) Operations Related Controversies or Incidents (E_1_12), and (3) Products & Services Related Controversies or Incidents (E_3_2). Interestingly, we do not find any significant coefficient on lagged institutional pressure. On the other hand, the coefficient on the lag score is negative and significant, which indicates that a higher score today is associated with deterioration in the same score next year.

To dive deeper into why institutional pressure affects next-year carbon intensity but not other measures of environmental performance, we repeat the regression by using scope 1 greenhouse gas emissions scaled by total assets as our main dependent variable. The results are shown in column (4) of Table 6: we do not find evidence of a significant association. Juxtaposing this result with the regression with carbon intensity score seems to imply either (1) that firm revenue, which enters the denominator of the carbon intensity calculation, responds to institutional pressure rather than emissions, or (2) that only within-industry relative emissions intensity responds while absolute emissions does not.

5.2 Placebo Tests

The careful, micro-founded construction of our institutional pressure measure is key to 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.

Tables 7 and 8 contain 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, and not just portfolio tilts, 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 9 shows the results using the lag owner environment score as the independent variable, and Table 10 using lag institutional ownership as the independent variable. We include all controls and fixed effects identically as our baseline. In column (4) of Table 9, we find a somewhat significant relationship between future firm environmental performance and lag owner environment score, albeit weaker than the results in Table 6.In the remaining columns of Table 9 as well as in Table 10, we do not find evidence of a significant relationship.

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

A natural 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 over time.

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 defer a more rigorous investigation to future studies.

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 by quantifying institutional price pressure through the lens of the asset demand system.

Our paper offers two unique insights. First, allocating capital to investors who are price-inelastic and have a positive tilt for greenness increases institutional pressure to firms while investing in those with high portfolio-level environment scores does not necessarily do so. Second, the institutional pressure of a firm is positively and significantly related to improvements in carbon scores; the environment score of its owners, on the other hand, is less so. Combined, these findings imply that naively investing in funds with high portfolio-level environment scores (e.g. ETFs with five Morningstar globes) may turn out to be fruitless.

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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

	Fines	Carbon	Operations Incidents	Product Incidents
Fines	1.000			
Carbon	0.126	1.000		
Operations Incidents	-0.192	-0.150	1.000	
Product Incidents	0.040	-0.050	-0.332	1.000

This table computes the bivariate correlations among measures of pressure induced by the institutional owners.

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: Institutional Pressure 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: Institutional Pressure and Other Firm-Level Environmental Performance

	(1)	(2)	(3)	(4)
Lag Inst. Pressure	0.00674	0.00893	-0.000483	0.00820
	(0.00531)	(0.00431)	(0.00271)	(0.0102)
lag_score	-0.320*	-0.309**	-0.144*	-0.0743**
	(0.0898)	(0.0584)	(0.0474)	(0.0164)
Constant	0.324	0.517**	0.211*	0.298
	(0.245)	(0.0945)	(0.0658)	(0.201)
Lag Score	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Observations	2969	3924	3928	3440
R-squared	0.332	0.665	0.200	0.0837

Standard errors in parentheses

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

This table reports the annual regression of the time-series change in measures of firm-level environmental performance on institutional pressure for greenness and control variables. The main independent variable of interest is the lagged institutional pressure for greenness, computed using equation (7). Each column shows the estimates for different measures as the dependent variable: (1) Environmental Fines and Non-monetary Sanctions (E_1_4), (2) Operations Related Controversies or Incidents (E_1_12), (3) Products & Services Related Controversies or Incidents (E_3_2), and (4) GHG1 emissions scaled by total assets. The estimates are for the time period 2010 to 2017. Standard errors are clustered at the industry and year level if applicable.

Table 7: Numerator of Approximated Institutional Pressure and Firm-Level Environmental Performance

	(1)	(2)	(3)	(4)	(5)
L.num_std_w	0.0108	0.00810	0.00249	0.0733	0.0151
	(0.00962)	(0.00593)	(0.00322)	(0.0411)	(0.00972)
lag_score	-0.320*	-0.309**	-0.144*	-0.154	-0.0743**
	(0.0898)	(0.0578)	(0.0475)	(0.101)	(0.0163)
Constant	0.336	0.514**	0.218*	-1.447**	0.320
	(0.246)	(0.0996)	(0.0683)	(0.297)	(0.216)
Lag Score	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Observations	2969	3924	3928	1613	3440
R-squared	0.332	0.665	0.200	0.238	0.0843

Standard errors in parentheses

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

This table reports the annual regression of the time-series change in measures of firm-level environment performance on the numerator of the approximated institutional pressure. Specifically, the main independent variable is the numerator of the institutional pressure for greenness from equation (10). Each column shows the estimates for different measures as the dependent variable: (1) Environmental Fines and Non-monetary Sanctions (E_1_4), (2) Operations Related Controversies or Incidents (E_1_12), (3) Products & Services Related Controversies or Incidents (E_3_2), (4) Carbon Intensity (E_1_9), and (5) GHG1 emissions scaled by total assets. The estimates are for the time period 2010 to 2017. Standard errors are clustered at the industry and year level if applicable.

Table 8: Denominator of Approximated Institutional Pressure and Firm-Level Environmental Performance

	(1)	(2)	(3)	(4)	(5)
L.denom_std_w	-0.0125	0.00367	-0.00405	-0.0149	-0.0128
	(0.00972)	(0.00367)	(0.00359)	(0.0218)	(0.0103)
lag_score	-0.320*	-0.310**	-0.144*	-0.150	-0.0744**
	(0.0897)	(0.0585)	(0.0476)	(0.100)	(0.0164)
Constant	0.339	0.491**	0.220*	-1.610**	0.304
	(0.252)	(0.0955)	(0.0672)	(0.344)	(0.216)
Lag Score	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Observations	2969	3924	3928	1613	3440
R-squared	0.333	0.664	0.201	0.234	0.0841

Standard errors in parentheses

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

This table reports the annual regression of the time-series change in measures of firm-level environment performance on the denominator of the approximated institutional pressure. Specifically, the main independent variable is the numerator of the institutional pressure for greenness from equation (10). Each column shows the estimates for different measures as the dependent variable: (1) Environmental Fines and Non-monetary Sanctions (E_1_4), (2) Operations Related Controversies or Incidents (E_1_12), (3) Products & Services Related Controversies or Incidents (E_3_2), (4) Carbon Intensity (E_1_9), and (5) GHG1 emissions scaled by total assets. The estimates are for the time period 2010 to 2017. Standard errors are clustered at the industry and year level if applicable.

Table 9: Owner Environment Score and Firm-Level Environmental Performance

	(1)	(2)	(3)	(4)	(5)
L.owner_escore	-0.00161	0.00564	-0.00226	0.0259*	0.00378
	(0.00223)	(0.00284)	(0.00155)	(0.00730)	(0.00336)
lag_score	-0.320*	-0.306**	-0.143*	-0.147	-0.0744**
	(0.0898)	(0.0555)	(0.0472)	(0.0998)	(0.0167)
Constant	0.368	0.311*	0.282*	-2.614***	0.150
	(0.288)	(0.111)	(0.108)	(0.374)	(0.301)
Lag Score	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Observations	2969	3924	3928	1613	3440
R-squared	0.332	0.667	0.202	0.238	0.0838

Standard errors in parentheses

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

This table reports the annual regression of the time-series change in measures of firm-level environment performance on owner environment score. The main independent variable – the owner environment score – is the AUM-weighted average environment score of the investors in each firm. Each column shows the estimates for different measures as the dependent variable: (1) Environmental Fines and Non-monetary Sanctions (E_1_4), (2) Operations Related Controversies or Incidents (E_1_12), (3) Products & Services Related Controversies or Incidents (E_3_2), (4) Carbon Intensity (E_1_9), and (5) GHG1 emissions scaled by total assets. The estimates are for the time period 2010 to 2017. Standard errors are clustered at the industry and year level if applicable.

Table 10: Institutional Ownership and Firm-Level Environmental Performance

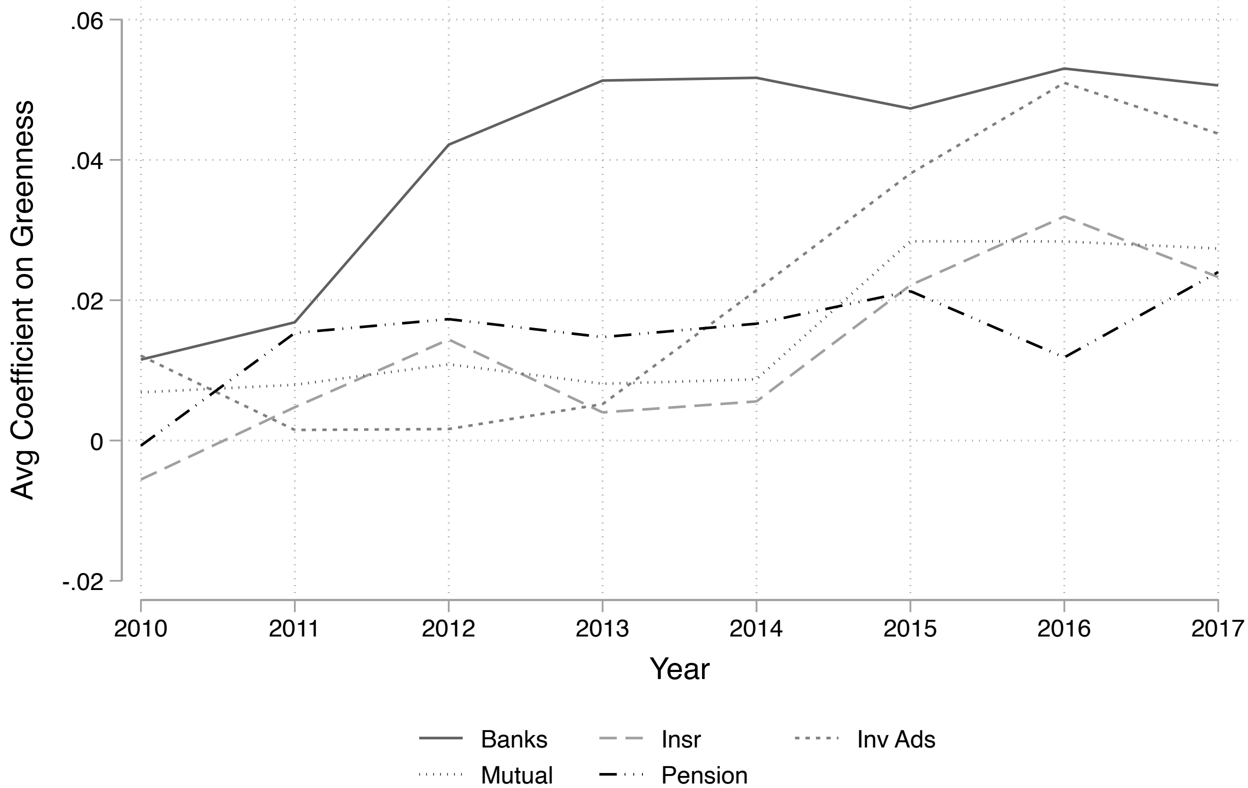
	(1)	(2)	(3)	(4)	(5)
L.inst_ownership	-0.0471	0.0128	-0.0129	-0.0306	-0.0311
	(0.0352)	(0.0102)	(0.0121)	(0.0793)	(0.0396)
lag_score	-0.320*	-0.310**	-0.144*	-0.150	-0.0745**
	(0.0898)	(0.0586)	(0.0475)	(0.102)	(0.0165)
Constant	0.366	0.483**	0.226*	-1.612**	0.314
	(0.262)	(0.0988)	(0.0741)	(0.326)	(0.231)
Lag Score	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Observations	2969	3924	3928	1613	3440
R-squared	0.333	0.664	0.201	0.234	0.0837

Standard errors in parentheses

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

This table reports the annual regression of the time-series change in measures of firm-level environment performance on institutional ownership. Each column shows the estimates for different measures as the dependent variable: (1) Environmental Fines and Non-monetary Sanctions (E_1_4), (2) Operations Related Controversies or Incidents (E_1_12), (3) Products & Services Related Controversies or Incidents (E_3_2), (4) Carbon Intensity (E_1_9), and (5) GHG1 emissions scaled by total assets. The estimates are for the time period 2010 to 2017. Standard errors are clustered at the industry and year level if applicable.

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:

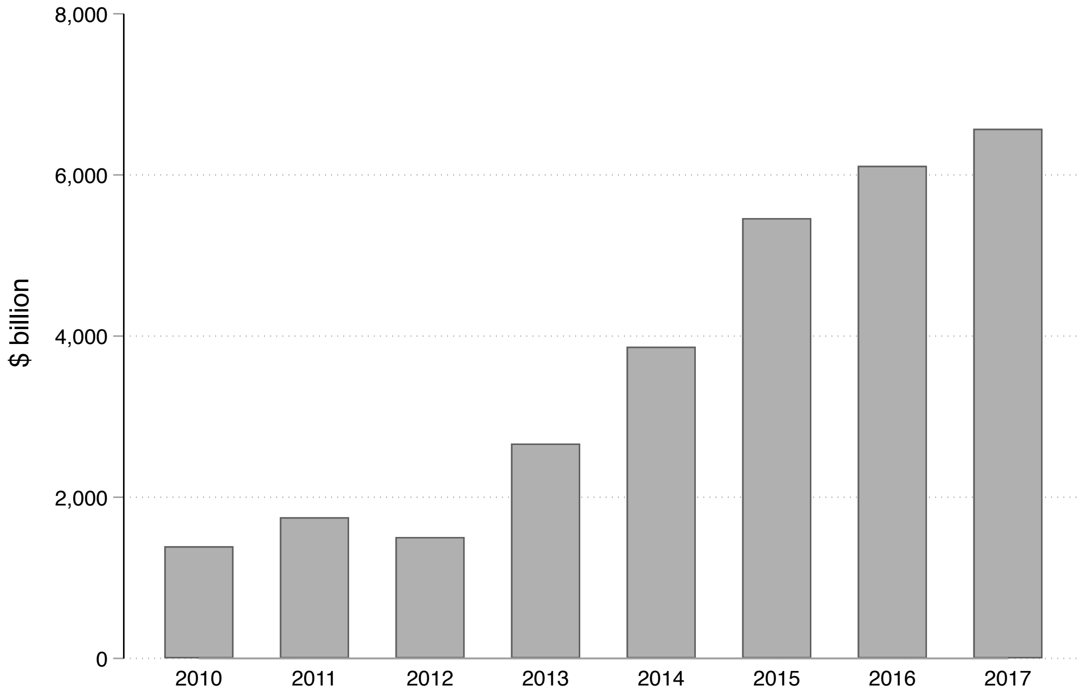
$$\forall i, \forall t : \frac{w_{it}(n)}{w_{it}(0)} = \exp\left(b_{0,it} + \beta_{0,it} me_t(n) + \beta_{1,it} es_t^*(n) + \beta_{2,it}' \mathbf{x}_t^*(n)\right) \epsilon_{it}(n)$$

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 thatv characteristics are exogenous to latent demand:

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

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:

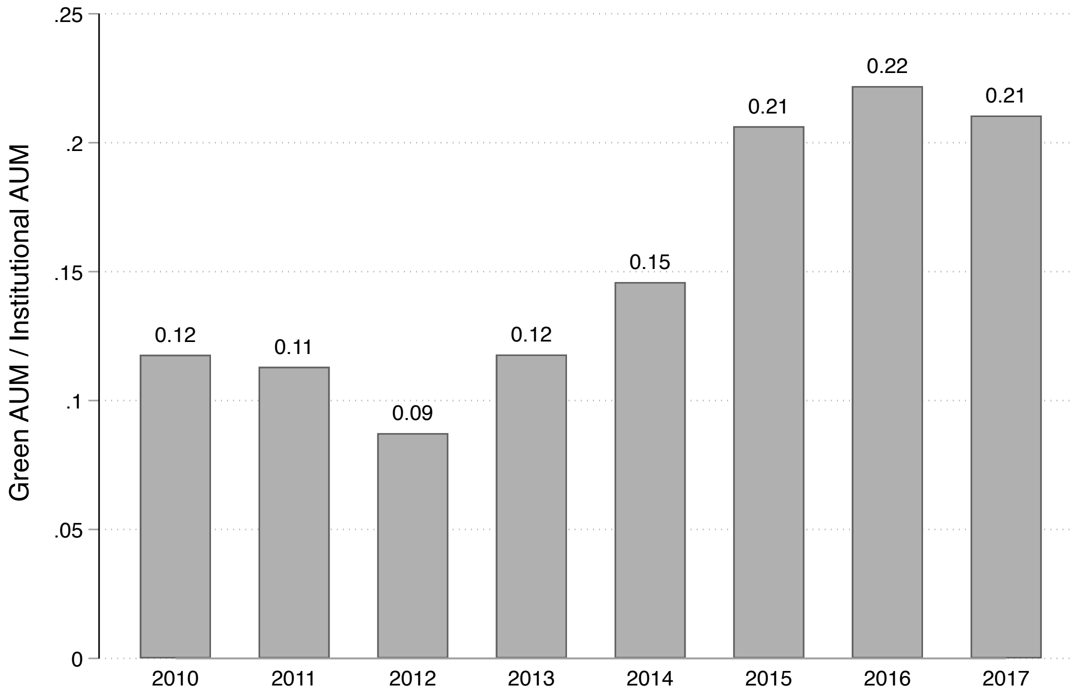
$$\forall i, \forall t : \frac{w_{it}(n)}{w_{it}(0)} = \exp\left(b_{0,it} + \beta_{0,it} me_t(n) + \beta_{1,it} es_t^*(n) + \beta_{2,it}' \mathbf{x}_t^*(n)\right) \epsilon_{it}(n)$$

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:

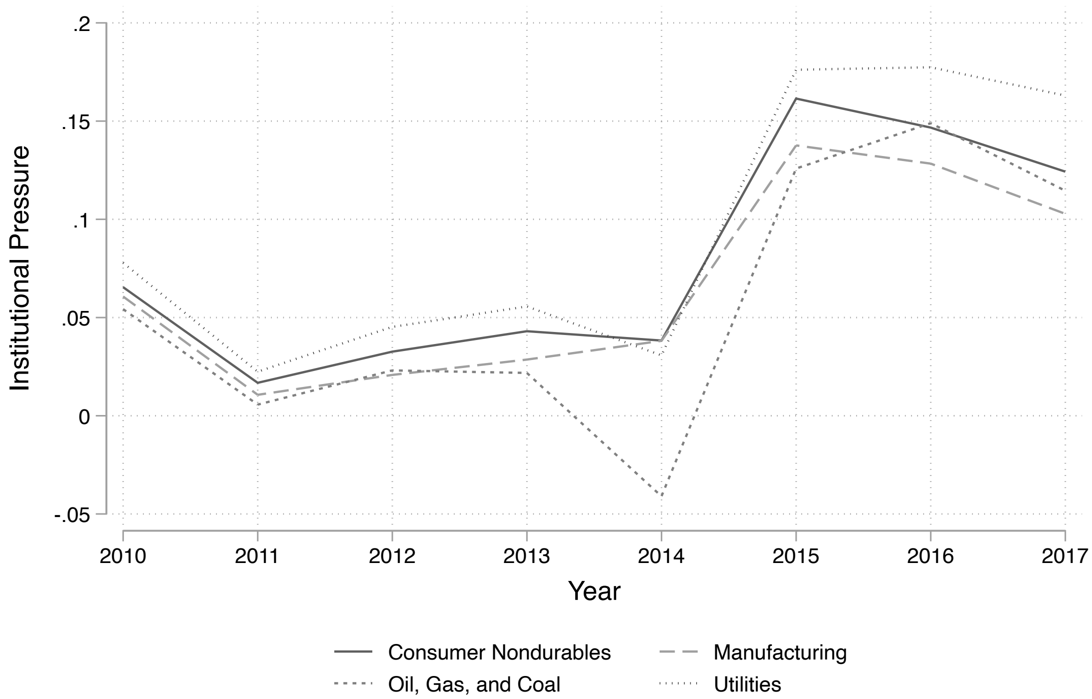
$$\forall i, \forall t : \frac{w_{it}(n)}{w_{it}(0)} = \exp\left(b_{0,it} + \beta_{0,it} me_t(n) + \beta_{1,it} es_t^*(n) + \beta_{2,it}' \mathbf{x}_t^*(n)\right) \epsilon_{it}(n)$$

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 $\mathbf{M}$ 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 kth 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 $\mathbf{p}$:

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

where

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

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

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

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 (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 kth 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.[15] 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 λ 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[16] 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.

The results of the estimation are shown in Figures 5 and 6. In Figure 5, we present the average

[15] 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.

[16] 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.

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.[17] 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 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):

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

[17] 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 for liquidity, we use the ratio of current assets to total assets:

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

B.2.2 Empirical Results

Table 11 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 11: Green-Inducing Investors and Corporate Policy

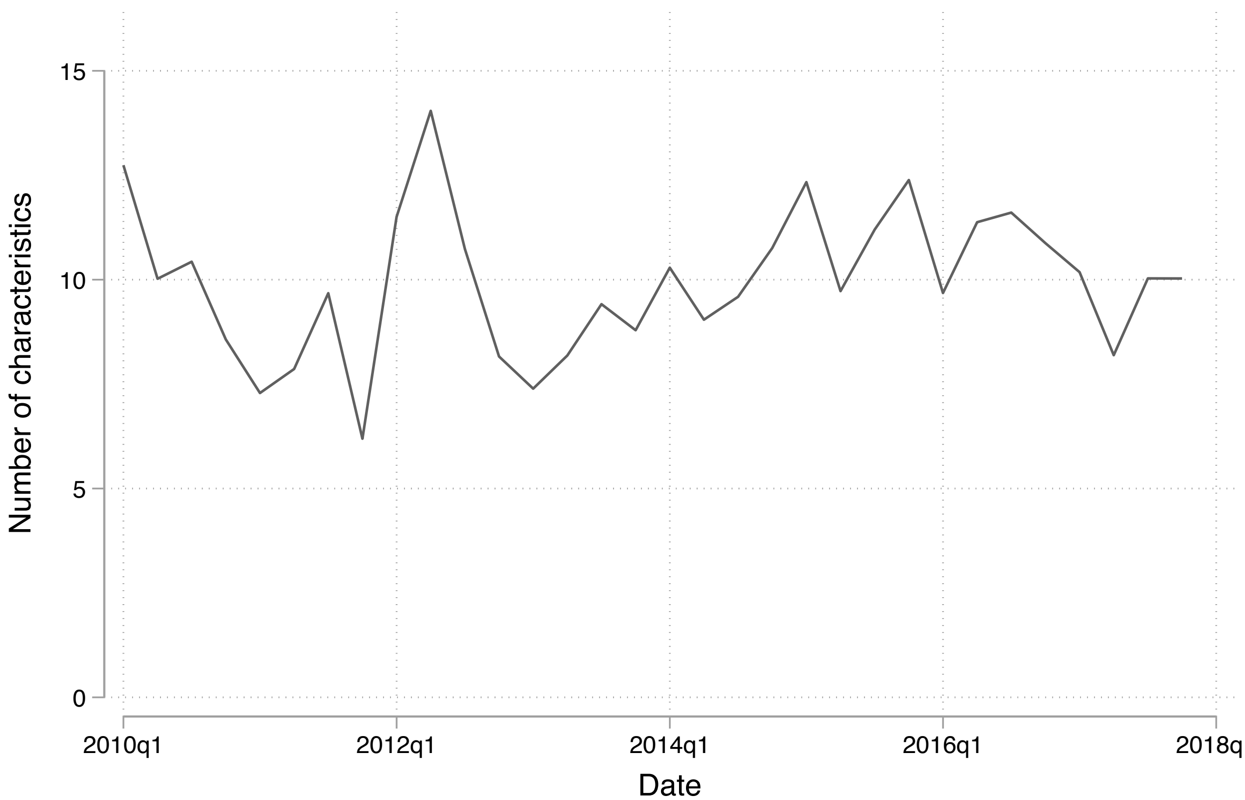
	(1) Investment	(2) Leverage	(3) Cash Holdings	(4) Payout
Lag Inst. Pressure	-0.0176*	-0.00880	0.0134*	0.00369*
	(0.00652)	(0.00503)	(0.00398)	(0.00147)
Tobin's Q	0.00503		0.234***	
	(0.00454)		(0.0295)	
Lag Cash	0.252*			
	(0.0765)			
Profitability		-0.640**		
		(0.148)		
Tangibility		0.0386		
		(0.0676)		
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 kth characteristic of stock n at time t. The penalty parameter λ 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 kth characteristic of stock n at time t. The penalty parameter λ is chosen through 5-fold cross validation.