Unpacking the Demand for Sustainable Equity Investing*

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Abstract

We investigate the heterogeneity in investor demand for sustainable equity investing and study its implications. We measure firm-level sustainability across three dimensions: third-party environment scores, emissions, and green patents. Separately estimated institutional investor demands are sensitive to scores and emissions, but not to green patents. We then aggregate these heterogeneous demands in an equilibrium framework to draw implications for the effectiveness of sustainable investing: (i) price-elastic investors do not "undo" effects of sustainable investors, (ii) investor pressure for sustainability only weakly predicts future improvements in firm sustainability, and (iii) incorporating green patents into ESG ratings can be a valuable adjustment.

JEL Codes: G12, G23, Q54

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1 Introduction

Sustainable investing seeks to direct capital towards companies with positive environmental and social impact and away from those with negative impact, thereby affecting their cost of capital. Interest in sustainable investing has grown significantly in the last decade with ESG (Environmental, Social, and Governance) assets predicted to reach over $53 trillion by 2025 (Bloomberg, 2021). This trend has been particularly pronounced in equity markets, resulting in a plethora of academic research attempting to understand equity investors' demand for sustainability (Coqueret, 2021).

While existing research shows that the demand for sustainable assets in financial markets has strengthened enough in aggregate to affect equity valuations (van der Beck, 2021; Pástor et al., 2022), this trend alone masks the underlying heterogeneity in demand for sustainability across investors. Often-cited threats to sustainable investing include concerns about price-elastic investors picking up "brown" stocks divested by sustainable investors and political backlash against ESG such as Florida's banning of ESG considerations from state pension investments (Bloomberg, 2022).[1] Not every investor shares the enthusiasm for sustainability.

Taking this heterogeneity into account is of first-order importance for the outstanding questions related to sustainable investing. Can investors meaningfully affect firms' cost of capital even if the hedge fund sector collectively invests in divested brown firms? If states or countries ban ESG considerations, how will the cross-section of stock valuations be affected? Do firms improve environmental performance in response to price pressure from sustainable shareholders?[2] Answers to these questions cannot be deduced from valuation patterns alone as they depend on the joint distribution of price elasticities, strength of demand for sustainability, and the specific dimensions of sustainability that investors care about.

In this paper, we investigate the heterogeneity in investor demand for sustainability and study its implications for firm decisions and asset prices. Not only do we estimate each investor's demand separately, but we also incorporate various dimensions of sustainability that a particular investor may care about. As a result, we go beyond a simple dichotomy of "green" vs. "brown" investors and provide a more nuanced classification of who green investors are. We then apply an equilibrium asset pricing framework to derive model-based empirical quantities and to consider counterfactual scenarios that allow us to answer policy-relevant questions.[3]

[1] Popular media outlets often report hedge funds and private equity firms purchasing stakes in polluting firms that are being divested by climate-conscious institutions (Fletcher and Brower, 2021; Gilbert, 2021). The usual story is that institutional investors who face fewer constraints or less pressure from their clients happily scoop up divested shares, thereby attenuating the effectiveness of sustainable investment mandates.

[2] In our framework, the first question will be the concern that price-elastic investors absorbing the excess supply (demand) of brown (green) assets. A perfectly price-elastic market will completely "undo" the valuation effect of sustainable investing, which also implies zero impact on the cost of capital of green and brown firms. The second question will be a counterfactual scenario in which we "turn off" the demand coefficient on sustainability for a subset of investors.

[3] Many existing equilibrium asset-pricing models on sustainable investing are based on one or two sources of investor heterogeneity. Pástor et al. (2021), Pedersen et al. (2021), and Goldstein et al. (2022) all present models that feature investors with different preferences or beliefs about ESG stocks. Zerbib (2022) offers a model that has investors with both different ESG preferences and investment universes. Our paper builds on these works by analyzing multiple sources of investor heterogeneity.

Our findings reveal both the merits and limitations of sustainable equity investing. On one hand, we show that the demand for firm sustainability has been rising for both active and passive investors and is not driven by potential correlation of sustainability with other firm characteristics. In addition, we find that investors not only demand firms with high third-party sustainability ratings but also those with low emissions intensity. On the other hand, they do not demand firms that innovate in sustainable technologies, which are the firms that could benefit the most from cost of capital reductions. In addition, investor pressure generated by these demand patterns seem to translate into only limited improvements in firm sustainability.

As the first step in understanding the investor demand for sustainability, we start by measuring three key dimensions of firm-level sustainability: emissions intensity, environment score, and green patents. To measure emissions intensity, we gather data on Scope 1 greenhouse gas emissions from S&P Trucost , which are emissions that come directly from sources controlled or owned by the firm. Next, we create environment scores using data from the MSCI ESG ratings database. Since these scores are correlated with greenhouse gas emissions among firms, we extract the component of the score that is unrelated to emissions. Finally, we use data from PatentsView to create company-level production of green patents. By adopting this comprehensive approach, we obviate the need to assume a specific perspective on how investors perceive sustainability, thus improving upon existing studies that typically examine only one dimension.

Using the firm sustainability measures, we present initial evidence that the three aspects of sustainability are valued differently by investors. Our cross-sectional valuation regressions from 2013 to 2021 reveal that third-party environment scores have been consistently valued by investors over this period, and emissions intensity has been negatively valued only after 2018. In particular, during the post-2018 period, a one standard deviation lower emission intensity is associated with 6.45% lower market-to-book ratio, and one standard deviation higher environmental score is associated with 11.5% higher market-to-book ratio. On the other hand, the production of green patents is not valued by investors. These results suggest that different aspects of sustainability may be valued heterogeneously in the equity market.

To gain a deeper understanding of this heterogeneity, we construct an asset demand system that incorporates our sustainability measures into investor demand curves, along with traditional stock characteristics that are known to influence investor demand. We model and estimate investor demand using the approach in Koijen and Yogo (2019), which provides a tractable model of investor demand that allows for rich heterogeneity. We also illustrate that sustainability can enter investor demand in two ways: when sustainability is informative about expected returns and when the investor faces a minimum sustainability constraint.

We document substantial heterogeneity in demand for sustainability across investors. On average, investors have a positive preference for higher environment score and emissions intensity but not for green patents. Comparing across investors, we find that active investors—those who deviate more from the market benchmark weights—exhibit not only higher price elasticities but also stronger demand for sustainability. This finding suggests that active investors are not counteracting sustainable investing as commonly assumed, but rather playing a crucial role along with passive investors in shaping the valuation patterns in equity markets.

The trend of increasing overall demand for low-emissions firms can come from two sources: (i) a within-investor preference shift towards low-emission stocks, or (ii) a shift of AUM away from "brown" investors who prefer high-emission stocks, towards "green" investors who prefer low-emission stocks. By examining trends based on estimated coefficients, we provide evidence that this trend is mainly driven by within-investors shifts in preferences rather than shifts in capital across investors. We also confirm this evidence through counterfactuals based on the estimated demand system.

Having documented the heterogeneity across investors, we then examine the implications of these patterns in investor demand. We first consider implications for firm decisions. We use the estimated demand curves to quantify investor pressure for sustainability, which captures the price pressure a firm receives, through investor demand, to become more sustainable. Our closed-form expression shows that the pressure is determined by the average demand for sustainability of the firm's investors, adjusted for their collective price elasticity. Our estimated demand parameters also suggest that, on average, firms have faced increased pressure to improve sustainability. However, we find that higher investor pressure today only weakly predicts future improvements in firm sustainability.

We next consider the asset pricing implications of two counterfactual scenarios that reflect important developments in sustainable investing. In the first, we study the impact of introducing ESG-agnostic mandates by analyzing the valuation patterns when certain investors "shut off" their demand for sustainability. This exercise shows that active and passive investors contribute roughly equally to the valuation patterns, challenging the often held belief that active investors may "undo" sustainable investing.[4]

In the second scenario, we examine the effect of introducing hypothetical ESG ratings. Specifically, we consider how leading sustainability score providers could adjust their methodology to incorporate firm-level green productivity. We find that such a change leads to a meaningful increase in the valuation of top green patent producers while maintaining the valuation gap between low- and high-emission stocks. These results suggest that the proposed change in rating methodology can be implemented without compromising the objective of sustainable investing.

Related Literature and Contribution

Our paper contributes to four main strands of literature in sustainable equity investing and asset pricing. First, our paper contributes to the literature on the asset-pricing implications of sustainable investing, to which Giglio et al. (2021) and Coqueret (2021) provide a comprehensive review. Our focus is on the equity market, and existing papers in this literature study the return gap between green and brown stocks both

[4]In the language of demand system asset pricing, this would be the concern that price-elastic investors absorbing the excess supply (demand) of brown (green) assets. A perfectly price-elastic market will completely "undo" the valuation effect of sustainable investing, which also implies zero impact on the cost of capital of green and brown firms.

through the lens of a theoretical framework (Heinkel et al., 2001; Pástor et al., 2021; Pedersen et al., 2021 Zerbib, 2022) and through empirical analyses based on realized returns (Görgen et al., 2020; Bolton and Kacperczyk, 2021; Derrien et al., 2021; ; Glossner, 2021; Hsu et al., 2022; Pástor et al., 2022).[5] To this literature, we provide two contributions. First, we provide new evidence on how three different measures of environmental performance are priced in the cross-section of stock valuations and how these pricing relationships have evolved over time. Our findings complements Choi et al. (2022) who find that carbon emissions intensity is negatively correlated with stock valuation in 26 countries as well as Cohen et al. (2020) who show that ESG investors lack incentive to invest in firms with high green innovation capacity. The coverage of our results on all three green characteristics also adds to the discussion regarding "ESG confusion" in Berg et al. (2022) that highlights the low correlation between different sustainable metrics. Our second contribution is to illustrate how different changes in sustainable demand could affect these valuation relationships via counterfactuals, which add to the analysis of green-brown expected returns in Berk and van Binsbergen (2021) and the analysis of realized returns in van der Beck (2021).

Second, our paper contributes primarily to the growing literature that directly studies investor demand for sustainable assets. While some papers use the survey instruments (Krueger et al., 2020; Gormsen et al., 2023), most papers analyze their portfolio choice decisions directly. For institutional investors, Gibson et al. (2020) computes a portfolio-level sustainability measure for all 13F investors and shows that institutions with high portfolio sustainability earned higher returns after 2010. Others have focused on subsets of institutional investors by studying inflows into sustainable mutual funds (Hartzmark and Sussman, 2019; van der Beck (2021); Baker et al. (2022)) or the greenwashing behaviors of hedge funds and active mutual funds (Liang et al., 2021; Kim and Yoon, 2022). We contribute to this literature by providing a comprehensive estimate of sustainable demand for institutional investors in the U.S. stock market. The estimates of investor demand thus shed new light on both the cross-sectional differences in sustainable demand across investors as well as the time-series evolution of sustainable demand for each characteristic. While our paper shares the same focus on asset demand as in Koijen et al. (2022), we provide more richness by analyzing a comprehensive set of sustainability metrics, studying more counterfactual scenarios, and providing real impact analysis through our model-based investor pressure measure.

Third, our paper contributes to the literature on the real impact of sustainable equity investing. Theoretically, Broccardo et al. (2022) shows in a model of firm incentives that divestment ("exit") tends to be less effective than engagement ("voice"), and Edmans et al. (2022) highlights the limits of blank exclusion of such full divestment strategies. Berk and van Binsbergen (2021) also argues based on a CAPM calibration that even a large substitution from brown to green stocks would only marginally increase the cost of capital for brown firms. The empirical evidence is also generally mixed regarding the impact of sustainable investing on real firm decisions (Heath et al., 2021, Gantchev et al., 2022; Hartzmark and Shue, 2023). We contribute to this literature by deriving a new measure of a firm's incentive to improve its environmen-

[5]There also exists work with respect to demand for other types of assets such as bonds (Flammer, 2021) and options (Ilhan et al., 2021).

tal performance and showing that while firms on average have positive incentive from investor pressure to reduce carbon emission, the correlation between a firm's investor pressure and future environmental performance is only weakly positive.

Finally, our paper contributes to the burgeoning literature that studies questions in asset pricing based on estimation of asset demand in markets ranging from equity, corporate bonds, and country-level assets (Koijen and Yogo (2019), Koijen et al. (2022), Koijen and Yogo (2020), Bretscher et al. (2020), Jiang et al. (2022)). In particular, our paper relates to studies that apply demand estimation to specific asset-pricing questions, including Gabaix et al. (2022) on the asset demand of U.S. households, Huebner (2022) on the source of equity momentum, Jansen (2021) on long term bond demand, and van der Beck and Jaunin (2021) on retail investor demand.[6] Our paper contributes to the latter part of this literature by providing a structural analysis of sustainable equity investing through our emphasis on asset demand of individual investors.

Roadmap

We first describe the data as well as stylized facts from valuation regressions (Section 2). We then set up the asset demand system that includes sustainability characteristics in investor demand curves (Section 3), which we estimate and highlight key patterns (Section 4). With the estimated demand system, we explore implications for both firm decisions and asset prices. In Section 5, we quantify investor pressure for sustainability and examine whether higher pressure today leads to greater future sustainability. In Section 6, we consider three counterfactual scenarios related to investor preferences and measures of sustainability to examine how valuation patterns changes.

2 Data and Stylized Facts

We measure firm sustainability in three ways, an approach that improves upon the previous literature that usually focuses on one of the three dimensions (Section 2.1). We then show that each sustainability characteristic is priced differently in the cross-section of stocks, indicating that these characteristics may enter investor demand curves in different ways (Section 2.2).

2.1 Data

We construct three measures that capture different dimensions of firm-level sustainability: (i) emissions intensity using data from S&P Trucost, (ii) environment score using data from MSCI, and (iii) green patents

[6] Another strand of the literature focuses on asset demand elasticity: Gabaix and Koijen (2021) estimates low "macro elasticity" of equity demand and proposes the inelastic market hypothesis, Davis et al. (2022) proposes an explanation of inelastic demand based on a model of information acquisition, and Haddad et al. (2021) estimates moderate strategic substitution in the price elasticity of investors.

using data from PatentsView. We later combine this data with detailed holdings of institutional investors from FactSet as well as stock characteristics and firm-level variables from CRSP and Compustat.

2.1.1 Measuring Firm Sustainability

Emissions Intensity We use firm-level Scope 1 greenhouse gas emissions from S&P Trucost. We choose carbon emission as our primary measure because it is one of the most important objectives for sustainable investing and also the most quantifiable. We also focus on Scope 1 emissions, which are the emissions that emanate directly from sources controlled or owned by the firm. For our measure, we use the logarithm of Scope 1 emissions intensity, which is defined as a company's annual Scope 1 emissions divided by annual revenue[7]. We henceforth refer to this measure as *emissions intensity*.

Environment Score We obtain firm-specific measures of environmental performance from MSCI ESG Ratings database, which succeeds the MSCI KLD database used in previous studies related to ESG investing. We choose MSCI ESG ratings over other ESG rating datasets with a similar motivation as in Pástor et al. (2022): MSCI covers more firms than other raters, exhibits the least noise (Berg et al., 2019), and is based on a comprehensive set of corporate documents, government data, and news media.

Following Pástor et al. (2022), we use a combination of the Environment Pillar Score and Environment Pillar Weight from MSCI to measure sustainability for asset n at time t. Specifically, let $E_t(n)$ be the asset n's most recent Environment Pillar Score before month t, looking back no more than 12 months, and let $w_t^E(n)$ be the most recent Environment Pillar Weight before month t, looking back no more than 12 months.

We define $g_t(n)$ as the following, which we call the *raw environment score*:

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

The product is a combination of how far the asset's rating is from a perfect score $(10 - E_t(n))$ and the relative importance of environmental issues for the firm $\left(w_t^E(n)\right)$. Due to the minus sign, $g_t(n)$ is always negative and a value close to zero implies higher level of sustainability. Appendix A.1 illustrates the importance of adjusting MSCI Environmental Pillar Scores by the Environmental Pillar Weights by comparing the scores between oil & gas and banking stocks. Appendix B.2 shows that our main results are robust to two alternative definitions of environmental score, based on different transformations of environmental pillar scores and weights.

The quarterly average cross-sectional correlation between $g_t(n)$ and log Scope 1 emissions intensity is -0.58, which suggest that emission is an important part in MSCI's environmental ratings. In order to improve precision and interpretability of our analysis, we regress environmental score on log emissions intensity in each quarter and use this residual in all cross-sectional analyses. This residual thus captures

[7] Fewer than 0.1% of all firm-year observations in the Trucost data have zero Scope 1 emission. We add the minimum positive level of Scope 1 emissions intensity to the actual values before taking the logarithm.

the component of environmental score orthogonal to current level of carbon emission, and we henceforth refer to this residual as the *environment score.*

GREEN PATENTS We construct firm-specific measures of green technology innovation based on data of granted U.S. patents from PatentsView. We follow the method developed by Haščič and Migotto (2015) and used in Cohen et al. (2020) to identify "green patents" related to technologies for reducing emission, mitigating pollution, or improving environmental performance in general. We use the firm identifier links provided by Autor et al. (2020) and the WRDS Patents database to merge PatentsView data with our stock universe.

For cross-sectional analyses, we take the number of green patents that each firm develops in the past five years, and scale the number of patents by the firm's total asset. We henceforth refer to this measure as *green patents* and define *non-green patents* analogously using the number of non-green patents[8]. Appendix A.2 provides further details on processing the PatentsView data.

2.1.2 PORTFOLIO HOLDINGS, ASSET PRICES, AND CHARACTERISTICS

We use quarterly institutional portfolio holdings of U.S. stocks from the FactSet database, which sources its data primarily from Securities and Exchange Commission Form 13-F filings. All institutional investment managers with more than $100 million of asset under management must file the form every quarter. The data comes at the investment manager level rather than individual fund level (e.g. Vanguard files its aggregated holdings as one institution) and reports only long positions. We use the data from 2013Q1 to 2021Q3 and merge the data with our quarterly stock universe from CRSP and Compustat via CUSIP. Appendix A.3 provides additional details.

2.1.3 SUMMARY STATISTICS

Table 1 provides summary statistics of investor and stock characteristics. Panel (a) first provides the distribution of stock characteristics. In an average quarter, 10.1% of stocks by market cap does not have environmental score data, and 3.9% of stocks by market cap does not have emissions data. For these observations with missing data, we impute the environmental scores or emission intensities based on industry-quarter averages using Fama-French 12-industry classifications. Among observations with non-missing annual emissions intensity, the median and mean are 13.6 and 189.7 tons per million dollars of revenue. In an average quarter, 64.8% of stocks (constituting 67.3% of total market cap) have at least one non-green patent granted in the previous 5 years, and 33.0% of stocks (constituting 29.6% of total market cap) have at least one green patent granted in the previous 5 years. In panel (b), we summarize the investors by type. Institutional investors constitute 69.3% of total AUM in an average quarter and the top 25 largest investment

[8]The correlation between the two measures is 0.54, which highlights the importance of including non-green patents as a control variable that captures a firm's overall innovation capacity. The correlations between all other stock characteristics are below 0.1.

advisors constitute 30.7% of the total AUM. Hedge funds have highest average portfolio active share at 0.711. In Appendix B.1, we also summarize the relationship between the three measures of firm sustainability and show that the environment score has real information content with respect to future emissions and green innovation.

2.2 Stylized Facts: Evidence from Valuation Regressions

Next we provide results from cross-sectional valuation regressions during the period from 2013 to 2021. We find that environment score is consistently positively priced; the emissions intensity is negatively priced only after 2018; and green patents is not priced. These results imply that different aspects of sustainability may be demanded differently by investors, thereby motivating a more structural analysis via the asset demand system in subsequent sections.

Specifically, we estimate the following valuation regressions:

$$mb_t(n) = a_t + \boldsymbol{\lambda}'\mathbf{x}_t(n) + \epsilon_t(n) \tag{1}$$

where the dependent variable $mb_t(n)$ is the market-to-book ratio of firm n at time t and $\mathbf{x}_t(n)$ is a vector of time-varying firm characteristics that includes both sustainability and non-sustainability characteristics that are cross-sectionally standardized in each quarter.

Table 2 summarizes the coefficients from the regressions. Column (1) shows the results based on the entire sample. First, among the three green characteristics, only the environmental score is significantly reflected in the cross-section of valuations: a one standard deviation higher environmental score is associated with 10.7% higher market-to-book ratio, with t-statistic of 8.2 based on clustered standard errors. Second, emissions intensity is negatively related to valuation, but the coefficient is not statistically significant over the entire sample. Finally, although a firm's overall innovation capacity is positively reflected in valuations (strongly positive coefficient for the non-green patents), green patents are not reflected in the cross-sectional of valuations.

Columns (2) - (3) of Table 2 provides subsample analyses based on data from 2013-2017 and 2018-2021 separately. First, the results for environmental score are similar over the two sample periods, i.e., the environmental score is consistently valued in the cross-section. Second, the coefficient for emissions intensity is not significant for the 2013-2017 subsample but is strongly negative and significant for the 2018-2021 subsample. In the 2018-2021 sample, one standard deviation higher emissions intensity is associated with 6.45% lower market-to-book ratio in the cross-section. This difference across two sample periods suggests a significant shift in investor demand that prefers low-emission over high-emission stocks in the recent years.

Figure 1 plots the coefficients from estimating Equation (1) cross-sectionally for each quarter. The time series of coefficients confirm both a consistent valuation gap for environmental score and a strengthening valuation gap against emissions intensity. In fact, the valuation regression coefficient for emissions intensity was positive and statistically significant from 2013 to 2014 and then turned negative and statistically significant since 2018.

Overall, we find that the three sustainability characteristics are priced differently in the cross-section of stocks and also for different time periods. These results suggest that characteristics may enter investor demand curves in different ways, which we explore next.

3 The Asset Demand System with Sustainability

We set up the asset demand system that includes sustainability characteristics in investor demand curves. We allow heterogeneity across both investors and time, which allows us to examine how each of the sustainability measures are demanded differently across investors.

3.1 Setup and Notation

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. A key addition is the introduction of sustainability characteristics. Investors may care about sustainability either for pecuniary or non-pecuniary reasons, and evidence can be found for both (e.g. Barber et al., 2021 and Bansal et al., 2018). While we remain agnostic on what the more prominent motivation is, we show that sustainability should enter the characteristics-based demand in at least two cases: sustainability is informative about expected returns or investors are constrained to hold a sustainable portfolio (e.g. due to investment mandates or pressure from clients).

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. Furthermore, 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.[9] 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

[9] As in Pástor et al. (2021), we can have sustainability enter the utility directly, but we derive our results without doing so for now.

denoted $\log(\epsilon_{it}(n))$. Then investor i's information set for asset n can be written as

$$\hat{\mathbf{x}}_{it}(n) = \begin{bmatrix} me_t(n) \\ x_t(n) \\ \log(\epsilon_{it}(n)) \end{bmatrix} \tag{2}$$

and an Mth-order polynomial of this vector can be written as

$$\mathbf{y}_{it}(n) = \begin{bmatrix} \hat{\mathbf{x}}_{it}(n) \\ vec(\hat{\mathbf{x}}_{it}(n)\hat{\mathbf{x}}_{it}(n)') \\ \vdots \end{bmatrix}, \tag{3}$$

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:

$$\begin{aligned} \mu_{it}(n) &= \mathbf{y}_{it}(n)'\Phi_{it} + \phi_{it} \\ \Gamma_{it}(n) &= \mathbf{y}_{it}(n)'\Psi_{it} + \psi_{it} \end{aligned} \tag{4}$$

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.

SUSTAINABILITY AS CHARACTERISTICS Importantly, we further assume that firm-level sustainability metrics are included in the vector of characteristics $\mathbf{x}_t(n)$. In Appendix C.1, we use an example of one sustainability metric to show that sustainability can enter an investor's characteristic-based demand function if either it is either informative about the expected returns or the investor faces a "minimum sustainability constraint". Moreover, Appendix A of Koijen and Yogo (2019) shows that a particular coefficient restriction 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:

$$\frac{w_{it}(n)}{w_{it}(0)} = \exp\left(b_{0,it} + \beta_{0,it} me_t(n) + \beta_{1,it}'\mathbf{x}_t(n)\right)\epsilon_{it}(n) \tag{5}$$

with sustainability entering as part of the characteristics $\mathbf{x}_t(n)$.

3.2 Implementation

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

$$\forall i, \forall t : \frac{w_{it}(n)}{w_{it}(0)} = \exp\left(b_{0,it} + \beta_{0,it} mb_t(n) + \beta'_{1,it}\mathbf{s}_t(n) + \beta'_{2,it}\mathbf{x}^*_t(n)\right)\epsilon_{it}(n) \tag{6}$$

where $mb_t(n)$ is the log market-to-book ratio of asset n at time t. $\mathbf{s}_t(n)$ denotes the cross-sectionally standardized sustainability characteristics: emissions intensity, environmental score, and green patents. $\mathbf{x}^*_t(n)$ denotes other cross-sectionally standardized characteristics: log book equity, profitability, investment, dividend to book equity, market beta, and non-green patents. Note that we follow Koijen et al. (2022) to use log market-to-book ratio as the measure for price. The coefficients $\beta'_{1,it}$ measure investor i's demand for the three sustainability characteristics, after controlling for all other stock characteristics.

We use the same identification assumption as Koijen and Yogo (2019) for estimating Equation (6): we assume the latent demand $\epsilon_{it}(n)$ is exogenous to all stock characteristics except log market-to-book ratio, all investors' AUM A_{it}, and all investors' investment universes $\mathcal{N}_{it}$. Under these assumptions, $mb_t(n)$ is the only endogenous regressor in (6) as $mb_t(n)$ is correlated with latent demand $\epsilon_{it}(n)$ through market clearing.

To instrument for $mb_t(n)$ in the demand estimation for investor i, we construct counterfactual log market capitalization of stock n if all investors other than i or the household sector holds an equal-weighted portfolio of their investment universes:

$$\widetilde{me}_{i,t}(n) = \log\Big(\sum_{j\neq i,HH} A_{jt}\frac{1\{n\in\mathcal{N}_{it}\}}{1+|\mathcal{N}_{it}|}\Big) \tag{7}$$

Based on the identification assumptions above, the instrument $\widetilde{me}_{i,t}(n)$ for investor i is exogenous to the investor's latent demand $\epsilon_{it}(n)$, and thus the instrument satisfies the exclusion restriction:

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

The instrument satisfies the relevance condition because all else equal, stocks held by more and larger investors tend to have higher market capitalization and thus higher market-to-book ratio. Koijen and Yogo (2019) documents that the instrument has high first-stage t-statistics that pass the Stock and Yogo (2005) test for weak instruments. We use non-linear GMM to estimate the demand equation (6) based on the instrument $\widetilde{me}_{i,t}(n)$ and all non-price characteristics.

4 Estimated Demand for Sustainability

In this section, we summarize the estimated demand curves and highlight three key patterns. First, we document strong heterogeneity in demand for sustainability across investors—in particular, more price-elastic investors exhibit higher demand for sustainability in terms of both environmental score and emission intensity. Second, we show that the increasingly negative demand for emissions intensity is primarily driven by within-investor demand shifts rather than across-investor shifts in AUM. Third, we find that higher active share, and lower portfolio turnover are associated with stronger sustainability demand, while indicators for value investors or signatories of the United Nations Principles for Responsible Investment (UNPRI) are not significantly correlated with sustainability demand.

4.1 Summary Statistics of Estimated Demand Coefficients

The estimated demand system reveals a strong heterogeneity in demand for sustainability across investors behind the valuation patterns. In particular, active investors are more price-elastic and exhibit higher demand for sustainability, which suggests that they are not "undoing" sustainable investing but rather playing a key role in driving and maintaining the valuation gap.

Table 3 provides summary statistics of our estimated demand coefficients. We compute the summary statistics across investors in every quarter, and then take an equal-weighted average across quarters. First, the demand for environmental score is positive on average, with an AUM-weighted average coefficient of 0.031. The demand for emissions intensity is negative on average, with an AUM-weighted average coefficient of -0.023. These coefficients mean that an average investor increases its demand by 3.1% per one standard deviation higher environmental score, and decreases its demand by 2.3% per one standard deviation higher emissions intensity. Therefore, investors have positive demand for sustainability on average, and they have positive preference for two orthogonal measures of environmental performance—emissions intensity and environmental score. Moreover, the demand coefficients for these two green characteristics have comparable magnitudes with coefficients for the five non-green characteristics.

The demand for green patents is near zero on average, with an AUM-weighted average coefficient of -0.003 for green patents. In comparison, the demand for a firm's overall innovation (measured by non-green patents) is positive, with an AUM-weighted average coefficient of 0.02. Therefore, the average investor in our sample does not have specific preference for green patents. In addition, we observe strong heterogeneity of demand across investors: the equal-weighted 10th/90th percentile of demand coefficients are -0.287/0.343 for environmental score, and -0.394/0.190 for emissions intensity. In line with Koijen and Yogo (2019) and Koijen et al. (2022), this result highlights the importance of allowing cross-investor heterogeneity for understanding demand for sustainability.

Figure 2 summarizes the relationship between pairs of demand coefficients across investors through binscatter plots. Panel (a) shows that price-elastic investors have higher demand for sustainability on average for both environment score and emissions intensity. Because active investors tend to be more price-elastic[10], these results provide the first evidence that active investors are not "undoing" sustainable demand by aggressively buying brown stocks. In contrast, the stronger sustainable demand for price-

[10]The average quarterly cross-sectional correlation between active share and price inelasticity is -0.30.

elastic investors suggests that they play an important role in creating the valuation gap between green and brown stocks, as the demand of price-elastic investors have higher relative impact on valuation (Koijen et al., 2022). Furthermore, panel (b) of shows that investors with higher demand for environment score also tend to have larger negative demand for emissions intensity. These results suggest that "green investors" consider both the actual emission of a firm and its third-party environmental rating when making sustainable investment decisions.

Finally, in Figure 3, we study the time trends in the AUM-weighted average coefficients for all investors as well as by broad investor types, which provides a validation of our exercise with respect to the valuation regression results. First, across all investor types, the average demand coefficient for environmental score is positive and stable over time, while the average demand coefficient for emissions intensity is negative and increasing in magnitude over time. These results are consistent with the time series of valuation regression coefficients in Figure 1, where the valuation gap between stocks with high and low environmental scores is positive and stable over time, and the valuation gap between high- and low-emission stocks is negative and opening up over time.

Second, we observe that the increasing demand for low-emission stocks is driven by both active and passive institutional investors. For active institution types, the average demand coefficient for emissions intensity decreased from -0.013 in 2013Q1 to as low as -0.105 in 2020Q2. For passive institution types, this coefficient decreased from -0.008 in 2013Q1 to -0.040 in 2021Q3. These results suggest that the shift in asset demand towards low-emission firms is a broad-based trend across different investor types.

4.2 Within-Investor Demand or Across-Investor AUM Shift?

The trend of increasing overall demand for low-emission firms could come from two sources: (i) a within-investor preference shift towards low-emission stocks, or (ii) a shift of AUM away from "brown" investors who prefer high-emission stocks, towards "green" investors who prefer low-emission stocks. We next show that the increasingly negative demand for emissions intensity is primarily driven by within-investor demand shifts rather than across-investor shifts in AUM.

To quantify the relative importance of each in driving the shift in overall demand, Figure 4 plots the time series of average demand coefficient for emissions intensity against a counterfactual series where there is no within-investor preference shift. To construct this counterfactual, let $T_{0,i}$ be the first quarter when investor i appears in our sample, and let $\beta_{i,GHG,t}$ be investor i's demand coefficient for emission in quarter t. With these notations, $\beta_{i,GHG,T_{0,i}}$ is investor i's demand coefficient for emission in its earliest quarter in our sample. In each quarter, we compare the AUM-weighted average of demand coefficients $\beta_{i,GHG,t}$ against the counterfactual coefficients if there was no preference shift over time, $\beta_{i,GHG,T_{0,i}}$:

$$\bar{\beta}_{GHG,t} := \frac{\sum_i A_{i,t}\beta_{i,GHG,t}}{\sum_i A_{i,t}} \text{ (Actual Data)}$$

$$\bar{\beta}^*_{GHG,t} := \frac{\sum_i A_{i,t}\beta_{i,GHG,T_{0,i}}}{\sum_i A_{i,t}} \text{ (No Within-Investor Preference Shift)}$$

Figure 4 shows that the decrease of $\bar{\beta}_{GHG,t}$ over time—from -0.009 in 2013Q1 to -0.035 in 2021Q3—is almost entirely driven by preference shift within investor. If each investor's demand coefficient had stayed constant over time, the average demand coefficient for emissions intensity would only decrease from -0.009 in 2013Q1 to -0.014 in 2021Q3. Therefore, the overall demand shift towards low-emission stocks is mostly driven by portfolio rebalancing decisions of each investor, rather than a shift of AUM from "brown" to "green" investors.

To formally test the analysis above, we also regress the emission demand coefficient $\beta_{i,GHG,t}$ on a time trend with investor fixed effects. Within each quarter, the investors are weighted by their AUM. If the time trend of decreasing coefficients is purely driven by the shift of AUM across different investors, the time trend should not be significant after controlling for investor fixed effects. On the other hand, if the time trend is driven by within-investor change of demand, the time trend should remain significant after controlling for investor fixed effects.

Table 4 displays the regression results. Column (1) shows the time trend without controlling for investor fixed effects, and column (2) show the time trend after controlling for investor fixed effects. We observe that adding investor fixed effects has little impact on the time trend coefficient: the time trend coefficients in columns (1) and (2) are not statistically significantly different from each other. Therefore, these results further bolster our finding that the time trend of increasing demand towards low-emission stocks is mainly driven by within-investor demand shifts, rather than a shift of AUM across investors. In Appendix B.3, we further confirm this finding using a counterfactual analysis where we reverse the investor-changes in demand for sustainability as well as the changes in AUM.

We note that our results here are complementary to and independent from the finding of van der Beck (2021) that the outperformance of sustainable stocks from 2016 to 2021 can be entirely attributed to the flow-driven price pressure from end investors' portfolio reallocation from non-sustainable to sustainable mutual funds. The finding of van der Beck (2021) shows that the AUM shift between mutual funds is important, but in our institution-level data, shift of AUM between funds provided by a same institution will be reflected as a within-institution demand shift in our analysis. For example, if many retail investors shifted their investment from a Vanguard value-stock fund into a Vanguard sustainable fund, the total AUM of Vanguard would not change, but Vanguard's green demand coefficients will increase. Therefore, as long as most flows from non-sustainable to sustainable mutual funds occur among funds provided by a same institution, our results are consistent with van der Beck (2021). Furthermore, our sample of all 13F institutional investors is much larger than the equity mutual funds and thus our findings provide new insights on the recent growth of sustainable investing.

4.3 Cross-sectional Patterns

In this section, we examine the relationship between green demand and investor characteristics via cross-sectional regressions. In the cross-section of investors, we find that higher price elasticity, higher active share, and lower portfolio turnover are all associated with stronger sustainability demand. On the other hand, value investors and signatories of the UNPRI do not have significantly different demand for sustainability.

4.3.1 Investor Characteristics

For each of our three sustainability measures, we regress the investor-quarter level demand coefficients on four continuous (price inelasticity, log AUM, active share, and quarterly portfolio turnover) and seven investor style of type indicators. For the indicators, we include one dummy variable for non-US investors, two investment style indicators for value and growth, and four investor type indicators for hedge funds, private banking, long-term, and broker-dealer (the left-out type is investment advisors). We control for time fixed effects to make the comparison across investors within each quarter, and we exclude the household sector from this analysis.

Table 5 reports the cross-sectional regression results. First, columns (1) and (2) of the table show that higher price elasticity, higher active share, and lower portfolio turnover are all associated with stronger sustainability demand, for both environmental score and emissions intensity. Also, growth investors have stronger sustainability demand than "generalist" investors who do not classify as either value or growth. We also find that foreign (non-U.S.) investors have stronger sustainability demand than U.S. investors, which complements the findings in Dyck et al. (2019) and may reflect Krueger et al. (2020) which highlights the importance of geographical origins for investors' sustainability preferences.

Second, compared with investment advisors, hedge funds have higher demand coefficients for both environmental score and emissions intensity—i.e., hedge funds have stronger preference for stocks with higher environmental score and *higher* emission. On one hand, to the extent that emission is a cleaner measure of firms' current environmental performance than environmental scores, these result could be interpreted as evidence of "green window dressing" for hedge funds. Hedge funds might buy more high-environmental score stocks to boost their portfolio score, but at the same time buy more high-emission stocks[11]. On the other hand, because higher environmental score predicts lower future emission in the cross-section of stocks (Table A1), we can also interpret the results as evidence that hedge funds prefer stocks that have high current emission but better emission reduction potential in the future.

Finally, investors classified as "value" by FactSet do not have significantly different sustainability demand compared with "generalist" investors. Together with our finding that price-elastic investors tend

[11]We only propose "green window dressing" as one potential explanation of the hedge fund coefficients in Table 5. While we do not seek to prove the existence of "green window dressing", we note that this proposition is in line with the finding of Liang et al. (2021) that many hedge funds engage in "green washing"—i.e., holding a brown portfolio while advertising themselves as green investors.

to have stronger green demand, this result alleviates the popular concern of value investors "undoing" sustainable investing by buying up brown stocks.

4.3.2 UNPRI Signatory

We also examine whether signatories of the United Nations Principles for Responsible Investment (UNPRI) have stronger sustainable demand. The UNPRI describes itself as the "leading proponent of responsible investment" and one of its six main principles is that "[investors] will be active owners and incorporate ESG issues into our ownership policies and practices."[12] We use fuzzy string matching to match the UNPRI signatory list with the institutional investors in FactSet data. In an average quarter in our sample, 9.9% of institutional investors are UNPRI signatories, but they constitute 38.9% of total institutional AUM. The fraction of institutional AUM controlled by UNPRI signatories has grown from 18.1% in 2013Q1 to 52.1% in 2021Q3.

However, we show from cross-sectional and time-series regressions that UNPRI signatory status is not associated with higher sustainable demand. Table A2 shows that after controlling for other investor characteristics, UNPRI signatories do not exhibit higher sustainable demand than non-signatories[13]. Table A3 further shows that signing the UNPRI is not significantly associated with any within-investor demand change, after controlling for within-investor time trends. Our results are consistent with the findings of Kim and Yoon (2022) and Liang et al. (2021) that investors who signed the UNPRI have not necessarily increased their sustainable portfolio holdings.

5 Investor Pressure for Sustainability and Real Effects

Using the estimated demand system, we next study the real effects of sustainable investing. To achieve this goal, we first use the estimated demand curves to quantify investor pressure for sustainability, which captures the price pressure a firm receives, through investor demand, to become more sustainable. While the average firm has experienced greater investor pressure to become more sustainable, we find that higher investor pressure today predicts greater future sustainability only to a limited extent, thus highlighting the limited real impact of sustainable equity investing.

5.1 Quantifying Investor Pressure

We first derive a closed-form expression for investor pressure and show that the average firm has experienced greater investor pressure to become more sustainable. Importantly, we show that the investor

[12] See UNPRI's website for these descriptions of the main principles (`https://www.unpri.org/about-us/about-the-pri`) and the signatory list (`https://www.unpri.org/signatories/signatory-resources/signatory-directory`), last accessed in December 2022.

[13] Without controls, UNPRI signatories have statistically significant higher demand only for environmental score.

pressure is the average of the coefficients on sustainability of the firm's investors adjusted for their price elasticity.

We define the investor pressure of firm n for the kth sustainability characteristic $s_{k,t}(n)$ as the equilibrium price impact of a small change in $s_{k,t}(n)$, holding all other stock characteristics and all investor demand curves constant:

$$\frac{\partial mb_t(n)}{\partial s_{k,t}(n)}. \tag{8}$$

This can be computed analytically from the demand system as below, with the proof in Appendix C:

Proposition 1. *The price impact of a change in the value of sustainability characteristic k for firm n, denoted as* $\mathbf{M}$*, is given as the nth diagonal element of the matrix*

$$\mathbf{M} := \frac{\partial \mathbf{p}}{\partial \mathbf{s}_k} = \left(\mathbf{I} - \sum_i \beta_{0i} A_i \mathbf{H}^{-1} \mathbf{G}_i\right)^{-1} \left(\sum_i \beta_{ki} A_i \mathbf{H}^{-1} \mathbf{G}_i\right) \tag{9}$$

where β_{ki} is investor i's demand coefficient for sustainability characteristic s_k, and we omit time subscripts for simplicity. The matrices $\mathbf{H}$ *and* $\mathbf{G}_i$ *are defined as follows:*

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

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 investor demand. Put differently, it represents the firm's marginal benefit in terms of stock valuations derived from increasing its sustainability characteristic $s_{k,t}(n)$.[14] Public firms have incentive to increase their stock valuations as they are related to both equity cost of capital and value of share-based compensations.

Because we hold latent demand constant in the calculations above, the measure of investor pressure only captures the intensive margin of investor demand and thus is a lower bound on the actual investor pressure that a firm may receive. If substantial variation in holdings operates through the extensive margin, then the current methodology understates how $mb_t(n)$ could change with $s_t(n)$ as new investors would start to hold the stock if the firm improves sufficiently. We note, however, that such response on the extensive margin 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.

[14] 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.

The matrix inside the inverse in Equation (9) is the aggregate demand elasticity. Therefore, the valuation of a stock reacts more to a change in characteristic if the stock is held by less price-elastic investors[15]. In addition, the nth diagonal entry of the second term is

$$\frac{\sum_i \beta_{ki} A_i w_i(n)(1 - w_i(n))}{\sum_i A_i w_i(n)}. \tag{10}$$

This quantity can be viewed as an AUM weighted average of the coefficients on the sustainability characteristic. Therefore, investor pressure for a given firm n is a weighted average of sustainability demand 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 sustainability characteristic, this firm faces a large investor pressure on that dimension of sustainability.

Table A4 reports the summary statistics for investor pressure of each sustainability characteristic. The average investor pressure for environmental score is 0.063: an average firm could expect its valuation to increase by 0.63% if it improves environmental score by 0.1 standard deviation. The average pressure for emissions intensity is -0.084: an average firm could expect its valuation to increase by 0.84% if it improves Scope 1 carbon emissions intensity by 0.1 standard deviation. The average pressure for green innovation is close to zero. In addition, the investor pressure for each characteristic shows strong heterogeneity across stocks. For example, the investor pressure for emission is -0.192 at 10th percentile and 0.004 at 90th percentile.

Figure 5 plots the average of investor pressure across stocks for each sustainability characteristic in each quarter. The investor pressure for environmental score is positive and roughly constant over time, and the investor pressure for carbon emissions intensity is negative and increasing over time in magnitude (a near twofold increase from -0.039 in 2013Q1 to -0.110 in 2021Q3). The investor pressure for green innovation is around zero for the entire sample. These results are in line with the time series evolution of sustainable demand coefficients, as discussed in Section 4.2.

The increasing investor pressure against carbon emission complements our previous finding in Section 4.3 that the trend towards higher sustainable demand has not been "undone" by price-elastic investors. Because investor pressure for a characteristic is increasing in the demand for that characteristic but decreasing in investors' price elasticity, one might be concerned *ex ante* that if investors have become more price-elastic over time, the increasing demand for low-emission stocks we documented in Section 4.2 may not translate into higher investor pressure. Figure A1 shows that this concern is not realized: the investors on average has in fact become more price inelastic during our sample period, as the average price inelasticity coefficient ($\beta_{0,i,t}$) increased from 0.67 in 2013Q1 to 0.72 in 2021Q3. Therefore, both the increasing demand for low-emission stocks and the decreasing price elasticity contribute to higher investor pressure for the emission characteristic.

[15]The intuition is that a change of characteristic induces change in characteristic-based demand. A same amount of demand shift creates stronger price pressure in stocks with less price-elastic demand curves.

5.2 Investor Pressure and Future Environmental Performance

We next examine whether a firm's investor pressure is associated with its future environmental performance. Table 6 shows results from regressing future 1-year environmental performance on a stock's characteristics and investor pressures. Column (1) shows that in the cross-section, 1 standard deviation higher pressure for environmental score predicts 0.0187 standard deviation higher change of environmental score over the next year. Column (2) shows that a 1 standard deviation higher pressure for emission (more negative pressure) predicts 0.0251 standard deviation more reduction of emissions intensity over the next year. Column (3) shows similar results for green innovation. Table A5 further shows that the results are robust for 2-year and 3-year future environmental performances.

We draw two conclusions from the regression results. One one hand, the coefficients highlighted above are positive and statistically significant after controlling for a stock's current non-green and green characteristics. Therefore, higher investor pressure predicts better future environmental outcomes in the cross-section, even after controlling for current green performance. On the other hand, the relationship between investor pressure and future 1-year environmental outcome is very small in magnitude. The small magnitude might be due to both the indirect relationship between stock valuation and firm decision making and the long time needed to make environmental improvements.[16]

Taken together, our results in this section show that the average firm has experienced greater investor pressure to reduce its carbon emissions intensity, but higher investor pressure today only has weak predictive power for future sustainability performance.

6 Counterfactuals and Asset Pricing Implications

We next study the asset pricing effects of sustainable equity investing through two counterfactual scenarios related to investor preferences and measures of sustainability. Specifically, we calculate counterfactual asset prices under each scenario and examine how the valuation patterns from Section 2.2 subsequently change. The steps for computing counterfactuals closely follow the algorithm in Koijen and Yogo (2019), which we detail in Appendix D. In the first counterfactual, we explore the impact of imposing ESG-agnostic mandates on select investors. In the second, we we consider incorporating the firm's green patents, which is not demanded by investors, into the construction of the environment score, a characteristics that is heavily demanded.

[16] Stock valuation could affect firm decision making in two ways: first through expected stock return and thus the firm's cost of equity capital, and second through the incentive for firm management through stock-based compensations. Both relationships are indirect in nature, therefore a large change of valuation might be needed to generate a small change of management incentives and real investment decisions.

6.1 Impact of ESG-Agnostic Mandates

In the first counterfactual analysis, we "shut off" the demand for sustainability of select investors to examine the contribution of different investors to the valuation of sustainability characteristics. Our counterfactual exercise corresponds to "ESG-agnostic" policies that force a subset of investors to not consider sustainability in their portfolio choice decisions.

Specifically, we consider three counterfactual scenarios where we set the demand coefficients for all three sustainable characteristics to zero for: (a) active institutions, (b) all institutions, and (c) all investors including the household sector.[17] In each scenario, we regress counterfactual valuations on stock characteristics as in Section 2.2, and we focus on the coefficients ("valuation gap") on the three green characteristics. We attribute the difference between actual data and scenario (a) to active institutions, the difference between scenarios (a) and (b) to passive institutions, and the difference between scenarios (b) and (c) to households[18]. Any remaining valuation gap in counterfactual scenario (c) for green characteristics are driven by the extensive margin of asset demand.[19]

Table 7 shows the valuation regression coefficients on three green characteristics under each counterfactual scenario: panel (a) for the full sample from 2013 to 2021, and panel (b) for the subsample from 2018 to 2021. First, the coefficients for environmental score in panel (a) show that the valuation gap between high-environmental score and low-environmental score stocks are not driven by the green demand of institutional investors. In the data, stocks with 1 standard deviation higher environmental score is associated with 10.7% higher market-to-book ratio on average. This valuation gap becomes 9.51% if we shut off the green demand of all institutional investors in column (3), and it becomes 5.4% if we shut off green demand of all investors in column (4). Therefore, the positive relationship between environmental score and valuation is driven roughly in half by the households' demand for high environmental score stocks, and in another half by the extensive margin of asset demand. On the extensive margin, Table A7 provides suggestive evidence that stocks with higher environmental score appear in the investment universe of a higher fraction of institutional investors, after controlling for other characteristics. Therefore, stocks with higher environmental score would have higher valuation even without any sustainable demand on the intensive margin.

Second, the coefficients for emissions intensity in both panels show that the gradually increasing valuation gap between low- and high-emission stocks is entirely driven by the green demand of institutional investors. Column (3) of panel (a) shows that emissions intensity would become *positively* correlated with

[17]Same as Section 4.2, we define "passive" institutional investors as large investment advisors, medium- or small-passive investment advisors, and long-term investors; and we define "active" institutional investors as medium- or small-active investment advisors, hedge funds, private banking, and brokers.

[18]Note that this attribution is subject to the order in which we shut off green demand for different types of investors. Table A6 shows that our results are similar when we shut off the demand for passive institutions before active institutions.

[19]The asset demand system we estimate only models the intensive margin of asset demand as a function of stock characteristics. If a stock characteristic is correlated with the extensive margin of portfolio choice (i.e., the fraction of investors that hold the stock in their portfolios, or have the stock in their investment universes), then the stock characteristic will still be positively correlated with stock valuation even without any demand for it on the intensive margin.

valuation in the full sample if we shut off the green demand of all institutions. Column (3) of panel (b) also shows that the negative relationship between emissions intensity and valuation from 2018 to 2021 would disappear if we shut off green demand of all institutions. Together, these results show that the demand of institutional investors against high-emission stocks is the main driver of their lower valuations.

Finally, the coefficients for emissions intensity in panel (b) also show that active and passive institutions contribute equally to the valuation gap between low and high-emission stocks. In the 2018-2021 sample, 1 standard deviation higher emissions intensity is associated with a 6.45% lower market-to-book ratio. This valuation gap is reduced to 3.45% if we shut off the green demand for active institutions in column (2) and becomes a statistically insignificant at 0.31% if we shut off the green demand for all institutions in column (3). Figure 6 also provides visual evidence by plotting the time series of quarterly valuation regression coefficients for emissions intensity in the data and the counterfactual scenarios. Together, these results reinforce our previous finding that active institutional investors as a whole are contributing to sustainable investing thanks to their demand for low-emission stocks instead of "undoing" sustainable investing by buying up high-emission stocks.

6.2 Hypothetical ESG Ratings: Incorporating Green Innovation

In previous analyses, we show that our measure of green innovation—ratio of green patents to asset—is not correlated with valuation in the cross-section, and does not have positive characteristic demand from investors on average. We also showed in panel (b) of Table A1 that our green patents measure is negatively correlated with environmental score. Because investors have positive demand for the environmental score on average, we can possibly increase the valuation of top green innovators—thereby encouraging their green innovation effort—by incorporating green innovation into the construction of environmental score. For example, if MSCI adjusts its environmental score definition to make the score higher for top green innovators, investors with positive demand for environmental score will be attracted to these top innovators, which will in turn push up their valuation.

In the second counterfactual analysis, we show that this change would increase the valuation of top green innovators that produce the most green patents, but at the same time the valuation gap between low- and high-emission stocks will still persist in the counterfactual equilibrium. These results show that the proposed change could increase firms' incentive to produce green patents without jeopardizing the main effect of sustainable investing on the valuation of emission.

6.2.1 Setup and Assumption

To proceed with the counterfactual, we start by increasing the environmental score for top 20% green innovators, ranked by our green patent characteristic. Specifically, we increase the standardized environmental score by 1.0 for top 20% green innovators in each quarter, and re-standardize the modified environmental score within each quarter. In an average year, the top 20% of green innovators develop 8,163 green patents, which make up 95.5% of the annual green patents developed by the firms in our sample.

Importantly, we keep all demand coefficients unchanged in these counterfactual simulations. Thus, our analyses is based on the assumption that modifying the content of environmental score will not change investors' demand curves for the standardized environmental score. While this assumption is strong and cannot be empirically verified, we offer two supporting arguments for making this assumption. First, institutional investors' demand for high-environmental score stocks is at least partially driven by an environmental score target, which can be either required by end investors or self-imposed in order to attract flows (see, e.g., Hartzmark and Sussman (2019) for evidence of mutual fund investors chasing funds with high sustainability rating on Morningstar). This type of demand for high-environmental score stocks is likely unrelated to the specific content of environmental score and thus unlikely to change in our counterfactual scenario. Second, green innovation is more likely to be perceived by investors as a positive signal for better future environmental performance (or financial performance, if the green technology like electric vehicle can be monetized). Therefore, it is unlikely that investors will reduce their environmental score demand if they know that environmental score becomes more correlated with green innovation. Based on these two reasons, we keep the demand coefficients unchanged in these counterfactual simulations.

6.2.2 RESULTS

In Table 8, we examine the difference of log market-to-book ratios between actual data and our counterfactual simulation. Column (1) shows that in the counterfactual simulation, the average log market-to-book ratio for the top 20% green innovators will increase by 0.047, and the average log market-to-book for other stocks will decrease by 0.022. These can be interpreted as a 4.7% increase of market-to-book for the top green innovators, and a 2.2% decrease of market-to-book for other stocks[20]. Columns (2) and (3) show that the relative valuation change between green innovators and non-innovators stays roughly the same after controlling for time fixed effects and non-green characteristics. Therefore, our proposed change of environmental score construction would move stock valuations in the intended direction.

Given the positive correlation between green innovation and current emissions intensity, one might be concerned that our proposed change of environmental score would also increase the valuation for high-emission stocks. Column (4) of Table 8 shows that this concern is unnecessary: the valuation regression coefficient on emissions intensity does not change significantly in the counterfactual simulation. This result shows that our proposed change of environmental score can be implemented without attenuating the existing achievement of sustainable investing (i.e., the valuation gap between low- and high-emission stocks).

[20]These results are based on the average of log market-to-book ratios across innovator or non-innovator stocks. Alternatively, we can treat each type of stocks as one asset and computes its aggregated market-to-book (sum of market equity divided by sum of book equity). Using this method, the valuation for top 20% of green innovators will increase by 7.17% in an average quarter, and the valuation for non-green-innovators will decrease by 3.62% in an average quarter.

7 Conclusion

In this paper, we investigate the heterogeneity in investor demand for sustainability and study its implications for firm decisions and asset prices. By utilizing a comprehensive set of measures for firm sustainability as well as a structural asset demand system, we provide a more nuanced understanding of the heterogeneous demand for sustainability among investors. Our findings suggest that while investors do value third-party environment scores and low emissions intensity, they do not value firms that innovate in sustainable technologies. In addition, investor pressure generated by these demand patterns translate into only limited improvements in firm sustainability.

Overall, we contribute to the ongoing conversation about sustainable equity investing by providing a more detailed understanding of investor demand for sustainability and its implications for the effectiveness of sustainable equity investing. Our framework could be used by future research to explore how the demand for sustainability varies across different regions (e.g. U.S. vs. Europe) or asset markets (e.g. green bonds), or to study sustainable demand at a more granular level (e.g. for individual mutual funds or households). We leave these directions for future research.

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Table 1: **Summary Statistics**

(a) Distribution of Characteristics

Characteristic	Count	Mean	Std. Dev.	Min	Q10	Q50	Q90	Max	% Miss
Market Equity	64184	14.0	51.7	0.3	0.8	3.0	27.4	2324.4	0
Market / Book	64184	8.8	160.2	0.0	1.1	2.8	10.5	18596.4	0
Profit / Asset	64184	0.26	0.22	-0.50	0.04	0.23	0.55	0.98	0
Asset Growth	64184	0.10	0.20	-0.52	-0.07	0.06	0.33	1.20	0
Dividend / Book Equity	64184	0.04	0.05	0.00	0.00	0.02	0.10	0.29	0
CAPM Beta	64184	1.24	0.60	-0.34	0.52	1.18	2.02	3.34	0
Non-Green Patents (bps)	64184	315	687	0	0	11	1065	3525	0
Green Patents (bps)	64184	15	43	0	0	0	42	293	0
Environment Score	54142	-1.56	1.33	-8.55	-3.50	-1.29	-0.17	0.00	0.101
Emissions Intensity	47510	189.7	660.8	0.1	0.7	13.6	343.3	6315.6	0.039

(b) Investors by Type (Average Across Quarters)

	Count	AUM ($bil)	AUM Share	Active Share
Large IA	25	9178.2	0.307	0.301
Medium-Passive IA	42	2156.0	0.073	0.287
Medium-Active IA	43	1899.6	0.066	0.592
Small-Passive IA	854	1523.0	0.051	0.412
Small-Active IA	917	2074.4	0.072	0.659
Long Term	104	1060.6	0.037	0.344
Hedge Funds	351	975.4	0.034	0.711
Brokers	83	910.6	0.031	0.511
Private Banking	816	690.1	0.023	0.530
Household	1	9065.5	0.307	0.212

This table reports the summary statistics for select variables. Panel (a) provides the distribution of stock characteristics. Panel (b) summarizes the investor types in our sample. The provided statistics are computed for each quarter and then averaged across quarters. In panel (a), profitability is defined as revenue minus cost of goods sold; asset growth rate is computed over 1 year; dividend to book equity is computed based on rolling 1-year dividend; and CAPM beta is estimated based on rolling 60 months of data. In panel (b), active share is defined as one half of sum of the difference between the weight of each stock in the portfolio and the market weight.

Table 2: **Valuation Regressions**

	Dependent Variable: Log Market-to-Book		
	(1) Full Sample	(2) 2013-2017	(3) 2018-2021
Log Book Equity	-0.390**	-0.349**	-0.451**
	[-18.78]	[-16.80]	[-17.66]
Profit / Asset	0.198**	0.188**	0.217**
	[12.08]	[10.95]	[10.35]
Asset Growth	0.121**	0.0990**	0.147**
	[9.542]	[6.816]	[7.952]
Dividend / Book Equity	0.274**	0.261**	0.292**
	[16.68]	[13.85]	[15.54]
CAPM Beta	-0.0482**	-0.0442**	-0.0535*
	[-3.483]	[-3.218]	[-2.199]
Non-Green Patents	0.142**	0.114**	0.184**
	[7.961]	[6.517]	[8.175]
Environment Score	0.107**	0.0952**	0.115**
	[8.191]	[6.738]	[6.767]
Emissions Intensity	-0.0156	0.0133	-0.0645**
	[-1.153]	[1.056]	[-4.261]
Green Patents	0.00359	0.0121	-0.0115
	[0.237]	[0.715]	[-0.603]
Year-Quarter FE	✓	✓	✓
Within R^2	.393	.377	.425
Observations	64184	37933	26251

This table summarizes the results from the valuation regression as shown in Equation (1). Specifically, we regress the market-to-book ratio on a vector of time-varying firm characteristics and year-quarter fixed effects. As sustainability characteristics, we include environment score, emissions intensity, and green patents as described in Section 2.1. Column (1) displays the results based on the entire sample, while columns (2) and (3) display results for sub periods. Standard errors are clustered by year-quarter.

Table 3: **Demand Coefficients: Summary Statistics**

	AUM-Weighted		Equal-Weighted				
	Mean	SD	Mean	SD	Q10	Q50	Q90
Log Market to Book	0.699	0.365	0.349	0.615	-0.485	0.454	0.990
Log Book Equity	1.275	0.406	0.693	0.598	-0.053	0.674	1.498
Profitability	0.010	0.179	0.046	0.371	-0.376	0.034	0.480
Asset Growth	0.031	0.151	0.082	0.327	-0.279	0.057	0.476
Dividend / Book	0.079	0.205	0.027	0.336	-0.370	0.019	0.436
Market Beta	-0.028	0.176	-0.092	0.374	-0.556	-0.067	0.339
Non-Green Patents	0.020	0.210	-0.052	0.472	-0.562	-0.021	0.423
Environment Score	0.031	0.130	0.023	0.272	-0.287	0.013	0.343
Emissions Intensity	-0.023	0.126	-0.085	0.251	-0.394	-0.061	0.190
Green Patents	-0.003	0.168	-0.026	0.376	-0.407	0.004	0.341

This table provides summary statistics for the demand coefficients estimated from Equation (6). The three sustainability characteristics—environment score, emissions intensity, and green patents—are as described in Section 2.1. For each coefficient, we compute the summary statistics across investors in every quarter and then construct an AUM(equal)-weighted average across quarters.

Table 4: **Demand for Emissions Intensity: Time Trend Analysis**

	Dep Var: Emission Demand Coef	
	(1)	(2)
Time Trend	-0.00114**	-0.00121**
	[-4.718]	[-4.670]
Investor FE		✓
AUM-Weighted	✓	✓
Observations	113231	112942

This table summarizes the within-investor time trend of demand coefficients for emissions intensity. Data is at the investor-quarter level, and each observation is weighted by the investor's AUM share in a quarter.

Table 5: **Demand for Sustainability and Investor Characteristics**

	Dep Var: Demand Coefficient		
	(1) Environment Score	(2) Emissions Intensity	(3) Green Patents
Price Inelasticity	-0.0796**	0.155**	0.00875
	[-6.268]	[12.03]	[0.732]
Log AUM	0.0521**	-0.0109	-0.00745
	[5.236]	[-1.102]	[-0.992]
Active Share	0.0223+	-0.0671**	-0.0814**
	[1.891]	[-5.174]	[-7.298]
Turnover	-0.0184+	0.0389**	0.00395
	[-1.909]	[3.843]	[0.406]
1{Non-USA}	0.122**	-0.0581+	-0.126**
	[4.724]	[-1.764]	[-4.935]
1{Style=Value}	0.0321	0.0509	0.0231
	[1.014]	[1.607]	[0.789]
1{Style=Growth}	0.0885**	-0.165**	0.0112
	[3.201]	[-5.420]	[0.418]
1{Hedge Fund}	0.0680+	0.0981*	-0.158**
	[1.984]	[2.543]	[-4.598]
1{Priv. Banking}	0.00648	-0.0333	-0.0104
	[0.283]	[-1.386]	[-0.465]
1{Long Term}	-0.0570	-0.00978	-0.0583+
	[-1.407]	[-0.210]	[-1.864]
1{Broker/Dealer}	0.0514	0.242**	0.0246
	[1.280]	[4.470]	[0.772]
Time FE	✓	✓	✓
Within R^2	.013	.041	.013
Observations	113231	113231	113231

This table summarizes the relationship between demand for sustainability and investor characteristics via cross-sectional regressions. The three sustainability characteristics—environment score, emissions intensity, and green patents—are as described in Section 2.1. Data is at the investor-quarter level., and all variables are cross-sectionally standardized.

Table 6: **Investor Pressure and Future Environmental Performance**

	Forward 1-Year Outcome		
	(1) Environment Score	(2) Emissions Intensity	(3) Green Patents
Pressure: Environment Score	0.0187^{+}	-0.000276	-0.0147*
	[2.006]	[-0.0259]	[-2.248]
Pressure: Emission Intensity	-0.0279**	0.0251**	0.00184
	[-3.097]	[2.880]	[0.319]
Pressure: Green Patents	0.00181	0.00322	0.00983^{+}
	[0.206]	[0.342]	[1.996]
Environment Score	-0.228**	-0.0617**	-0.0103^{+}
	[-19.53]	[-2.963]	[-1.740]
Emission Intensity	-0.0323*	-0.0178	0.00130
	[-2.648]	[-1.225]	[0.268]
Green Patents	-0.00625	0.00685	0.769**
	[-0.706]	[0.703]	[37.07]
Time FE	✓	✓	✓
Non-Green Controls	✓	✓	✓
Within R^2	.053	.007	.668
Observations	51065	51065	51065

This table summarizes the cross-sectional relationship between investor pressure and future environmental performance. The dependent variables are: future one-year change in environment score, future one-year change in emissions intensity, and the future one-year green patents. The main independent variables are the investor pressure for three green characteristics. "Non-Green" control variables include log book equity, investment, profitability, market beta, and dividend to book equity. All outcome variables and regressors are cross-sectionally standardized in each quarter.

Table 7: **Counterfactual Exercise: Impact of ESG-Agnostic Mandates**

(a) Counterfactual Valuation Regressions: Full Sample (2013 - 2021)

	Data	CF: Shut off Green Demand		
	(1)	(2) Active Inst	(3) All Inst	(4) All Inst + HH
Environment Score	0.107**	0.0947**	0.0951**	0.0540**
	[8.191]	[7.463]	[7.194]	[4.103]
Emissions Intensity	-0.0156	0.0101	0.0330*	0.0387**
	[-1.153]	[0.759]	[2.634]	[3.065]
Green Patents	0.00359	0.0309+	0.0249	0.0161
	[0.237]	[1.942]	[1.518]	[0.993]
Time FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	64184	64184	64184	64184

(b) Counterfactual Valuation Regressions: Subsample (2018 - 2021)

	Data	CF: Shut off Green Demand		
	(1)	(2) Active Inst	(3) All Inst	(4) All Inst + HH
Environment Score	0.115**	0.107**	0.114**	0.0698**
	[6.767]	[6.305]	[6.529]	[4.010]
Emissions Intensity	-0.0645**	-0.0345*	0.00311	0.00803
	[-4.261]	[-2.266]	[0.199]	[0.506]
Green Patents	-0.0115	0.0241	0.0150	0.00618
	[-0.603]	[1.262]	[0.784]	[0.327]
Time FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	26251	26251	26251	26251

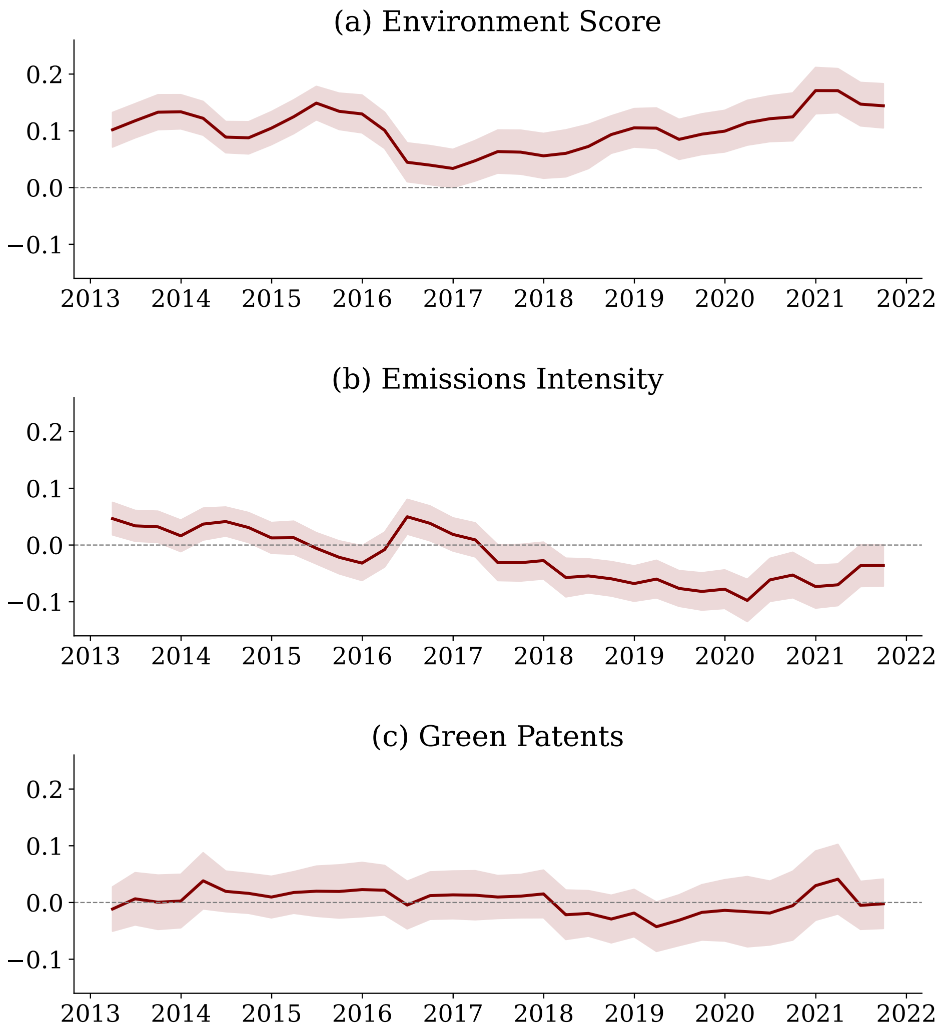
This table presents the results from valuation regressions in counterfactual scenarios where we "shut off" green demand, i.e., set the demand coefficients for all three sustainability characteristics to zero for one or more types of investors. Specifically, we consider three scenarios in which we "shut off" green demand for all active institutions (column (2)), all institutions (column (3)), and all investors including the household sector (column (4)). After obtaining counterfactual valuations, we re-estimate the valuation regression as shown in Equation (1). We present results for both the full sample as well as the 2018-2021 subsample.

Table 8: **Counterfactual Exercise: Hypothetical ESG Ratings with Green Patents**

	Dep Var: Log M/B, Counterfactual − Actual			
	(1)	(2)	(3)	(4)
1{Top 20% Green Innovator}	0.0470**	0.0692**	0.0684**	
	[15.15]	[18.79]	[17.80]	
1{Not Top Green Innovator}	-0.0222**			
	[-26.40]			
Emissions Intensity				0.000495
				[0.870]
Time FE		✓	✓	✓
Controls			✓	✓
Observations	64184	64184	64184	64184

This table presents the results from the counterfactual exercise that explores the consequences of adjusting the environmental score definition to reward companies with high green innovation. Specifically, we increase the environmental score by 1.0 for the top 20% green innovators as ranked by our green patent characteristic in each quarter. We then re-standardize the modified environmental score within each quarter. We keep the demand coefficients unchanged in these counterfactual simulations. After obtaining the counterfactual valuations, we compute the difference of log market-to-book ratios between the actual data and the counterfactual.

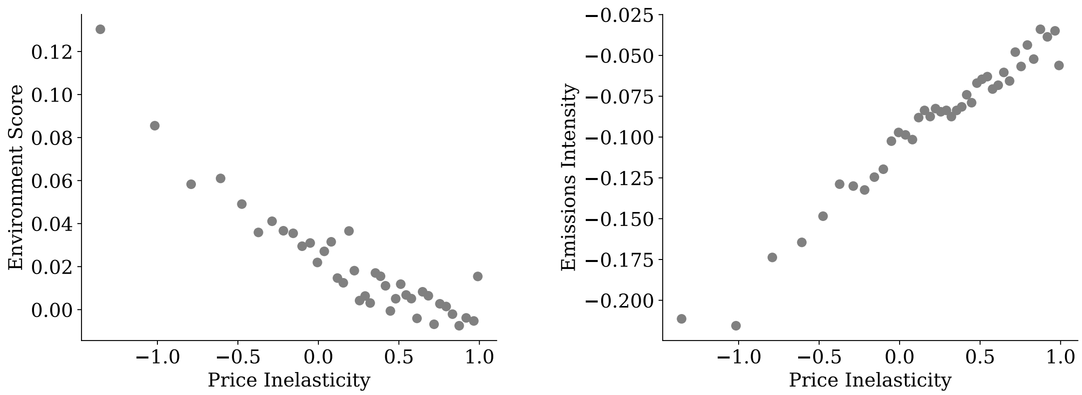
Figure 1: **Valuation Regressions: Time-Series of Coefficients**



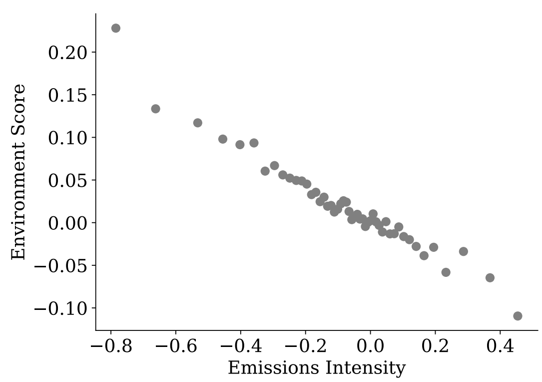
This figure plots the time-series of the coefficients obtained from the valuation regression as shown in Equation (1). We first estimate Equation (1) cross-sectionally for each quarter. The shaded area represents the 95% confidence interval around the mean.

Figure 2: **Binned Scatterplots of Coefficients across Investors**

(a) Price Elasticity vs. Demand for Sustainability

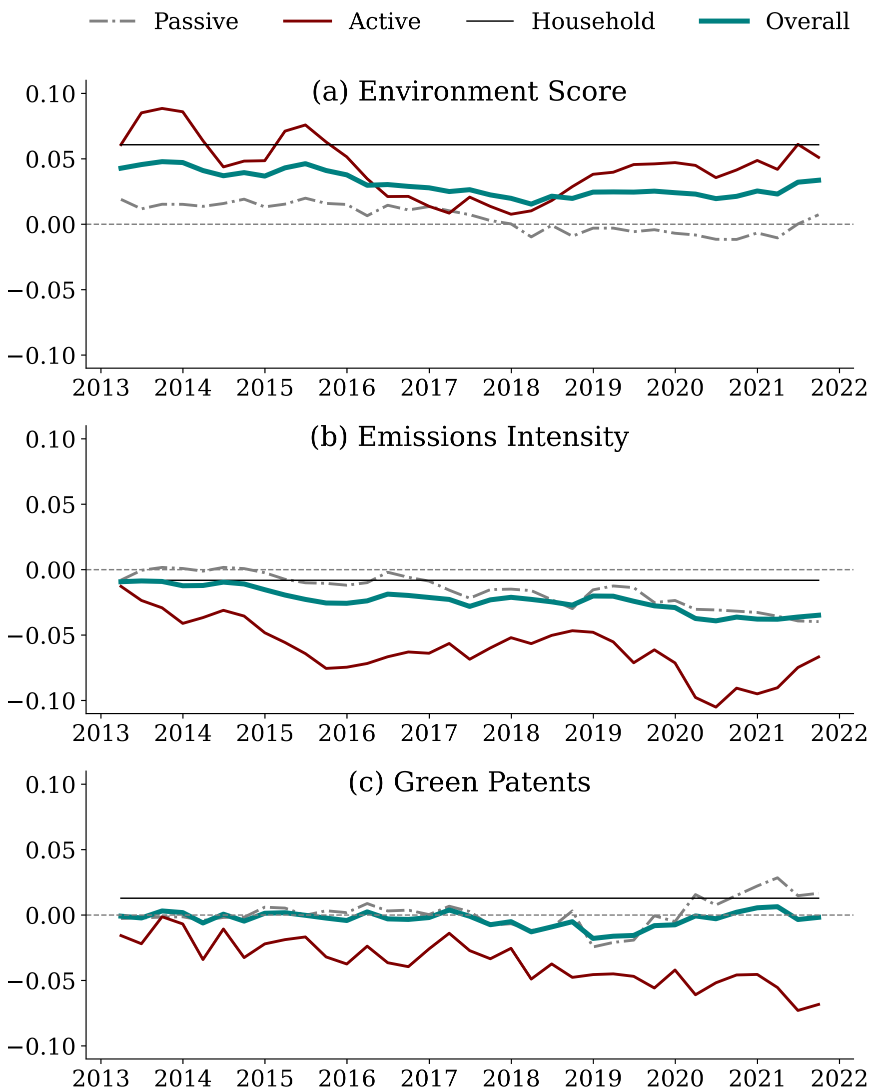


(b) Demand across Sustainability



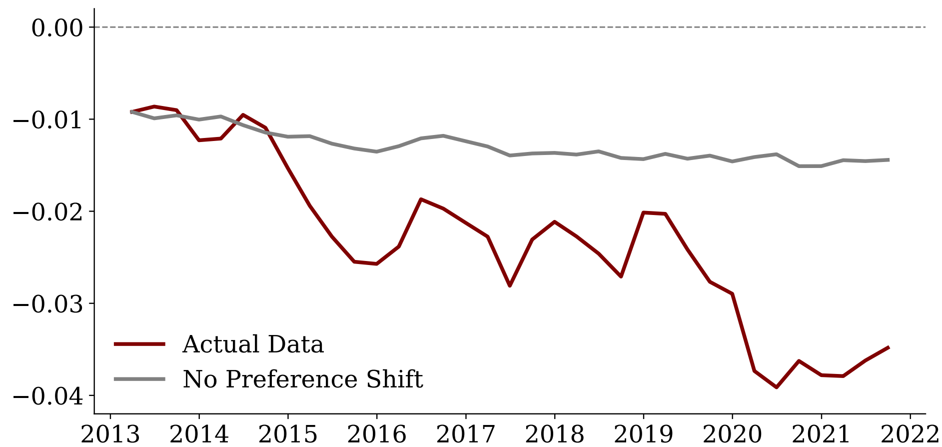
This figure summarizes the relationship between pairs of demand coefficients across investors. In panel (a), we plot the binscatter of coefficient on environment score against price inelasticity (left) as well as the coefficient on emissions intensity on price inelasticity (right). In panel (b), we plot the coefficient on environment score against the coefficient on emissions intensity.

Figure 3: **Trends in Average Coefficients**



This figure summarizes the time trends in the AUM-weighted average coefficient of investors. We define "passive" institutional investors as large investment advisors, medium- or small-passive investment advisors, and long-term investors; and we define "active" institutional investors as medium- or small-active investment advisors, hedge funds, private banking, and brokers.

Figure 4: **Demand Coefficient for Emission: Role of Within-Investor Preference Shift**



This figure plots the AUM-weighted average demand efficient on emissions intensity across time both in the actual data and in the counterfactual where there is no within-investor shift in preference. Specifically, let $T_{0,i}$ be the first quarter when investor i appears in our sample and let $\beta_{i,GHG,t}$ be investor i's demand coefficient for Log GHG1 intensity in quarter t. For each quarter, we compute the average of demand coefficients in the data $\left(\bar{\beta}_{GHG,t}\right)$:

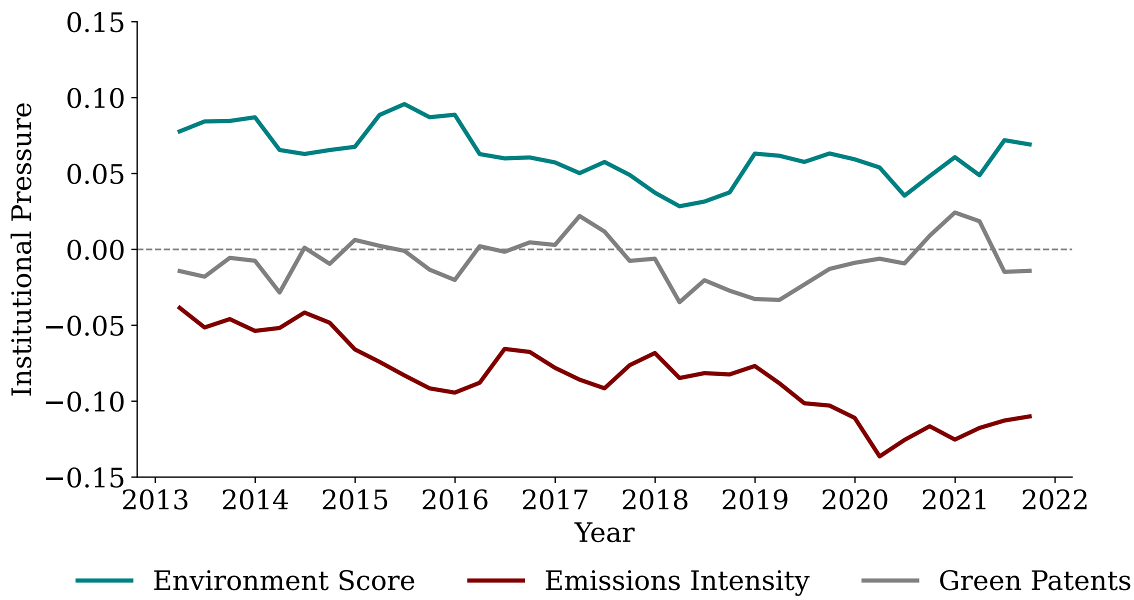
$$\bar{\beta}_{GHG,t} \coloneqq \frac{\sum_i A_{i,t}\beta_{i,GHG,t}}{\sum_i A_{i,t}}$$

as well as the average of the counterfactual coefficients if there is no shift in preferences $\left(\bar{\beta}^*_{GHG,t}\right)$:

$$\bar{\beta}^*_{GHG,t} \coloneqq \frac{\sum_i A_{i,t}\beta_{i,GHG,T_{0,i}}}{\sum_i A_{i,t}}$$

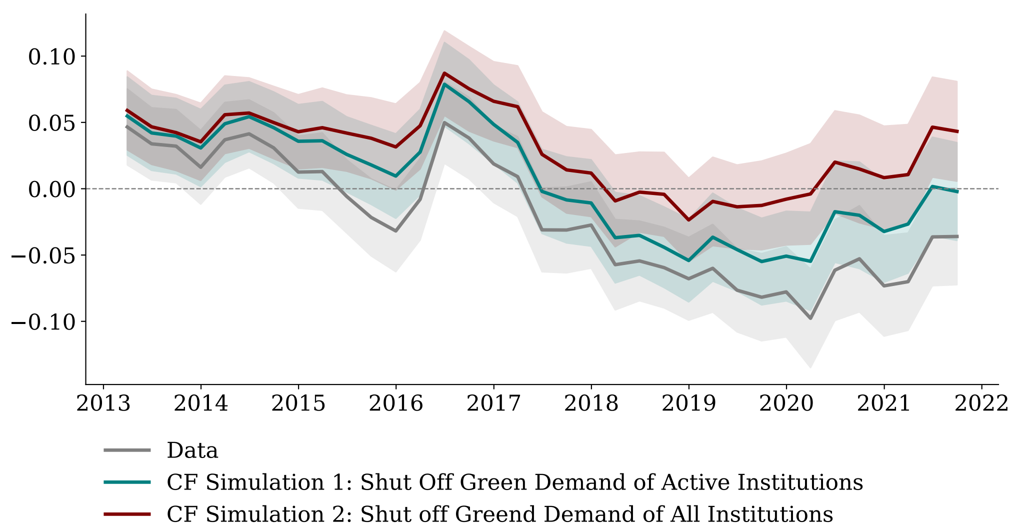
We then plot the time-series of both $\bar{\beta}_{GHG,t}$ and $\bar{\beta}^*_{GHG,t}$.

Figure 5: **Time Series of Average Investor Pressure across Stocks**



This figure plots the average investor pressure across stocks for each quarter and each green characteristic. We compute the investor pressure for sustainability for each stock using the procedure described in Section 5.

Figure 6: **Counterfactual: Impact of ESG-Agnostic Mandates**



This figure plots the time-series of the quarterly valuation regression coefficients on emissions intensity in the data and in the counterfactual where we shut off green demand of select investors.

Online Appendix

A Data

A.1 MSCI Data

As discussed in Section 2.1, we define the *raw environment score* as:

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

where $E_t(n)$ is the environmental pillar score provided by MSCI, and $w_t^E(n)$ is the environmental pillar weight provided by MSCI. $E_t(n)$ measures a firm's environmental performance relative to peers, and $w_t^E(n)$ measures the importance of environmental issue for the firm. $E_t(n)$ ranges from 0 (worst) to 10 (best) and represents the weighted average score across various dimensions related to environmental issues.

Figure A2 illustrates the distribution of $E_t(n)$, $w_t^E(n)$, and $g_t(n)$ for stocks in the Oil & Gas and Banking industries. The distribution of MSCI environmental pillar score $E_t(n)$ is similar across the two industries, which indicates that $E_t(n)$ is constructed based on peer-to-peer comparisons. However, the MSCI pillar weights $w_t^E(n)$ for oil & gas stocks are significantly higher than those for banking stocks. Therefore, the pillar weights are necessary for measuring the absolute (rather than peer-adjusted) level of companies' environmental performance. Figure A2 confirms that our raw environmental score $g_t(n)$ is significantly higher for banking stocks compared to oil & gas stocks.

A.2 PatentsView Data

We obtain data of granted U.S. patents from the PatentsView database provided by the U.S. Patents and Trademark Office.[21] For each patent granted from 1975 to 2021, we have the name of patent assignee (the company that applied for the patent) and two patent classification codes (Cooperative Patent Classification and International Patent Classification codes—CPC and IPC).

We first match assignee names in the patent data to companies in CRSP. We start from the mappings from individual patents to Compustat firm identifiers (GVKEY) provided by Autor et al. (2020) from 1975 to 2012 and by the WRDS US Patents database from 2011 to 2019. Based on these two mappings, we construct a mapping from the PatentsView assignee names to Compustat GVKEY, and extrapolate these mappings to patents from 2020 to 2021[22]. Based on these mappings, we match 2,319,184 out of 3,642,855 patents from 2008 to 2021 to Compustat firms.

We then classify each patent as "green" or "non-green" based on a modified list of environment-related CPC or IPC codes provided by Haščič and Migotto (2015)[23]. Compared with the original list of Haščič

[21] https://patentsview.org/download/data-download-tables

[22] Because the WRDS data covers fewer patents than the Autor et al. (2020) data between 2011 to 2012, we also extrapolate the patent assignee to Compustat mapping from Autor et al. (2020) to patents from 2013 to 2019 that are not covered by the WRDS data.

[23] Cohen et al. (2020) uses the exact list provided by Haščič and Migotto (2015) to define "green" patents.

and Migotto (2015), we add three more CPC sub-classes related to climate change mitigation[24]. Among the 2,319,184 patents matched to Compustat firms from 2008 to 2021, 210,716 (9.1%) are classified as green based on our criteria.

A.3 Portfolio Holdings, Asset Prices, and Characteristics

The FactSet database provides an "Entity Sub-type" for each reporting institution. We first follow Koijen et al. (2022) to classsify the type codes into five categories:

- Investment Advisors: IA, MF, IC
- Long-term Investors: FO, IN, PF, SV
- Hedge Funds: HF, FF, FH, FS
- Private Banking: PB, FY, CP, VC
- Brokers: BM, BR

Because "investment advisors" constitute 80% of total AUM of all institutional investors, we break down this category further based on AUM and active share. We classify the largest 25 investment advisors (who constitute 50% of total AUM of all investment advisors) as "large". We then divide all other investment advisors into 4 groups of equal total AUM (medium-passive, medium-active, small-passive, small-active) based on AUM and active share.

We also aggregate all non-institutional holdings of stocks in our universe into a household sector. In cases where total institutional holdings exceeds shares outstanding due to missing short positions or misreporting, we scale back the holdings of each institution to ensure total institutional holdings equals shares outstanding. The demand estimation procedure also requires the investment universe for each institution-quarter. Following Koijen and Yogo (2019), we define the investment universe for each institution as all stocks the institution has held in the previous three years.

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) 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.

To mitigate the impact of missing data and make sure our results are not driven by micro-caps, we only use the largest stocks that collectively constitute 99% of total market cap in each quarter for analysis. There are 64,184 stock-quarter observations from 2013Q1 to 2021Q3 in our sample, averaging to 1,834 stocks per quarter.

[24]The CPC sub-classes added are: Y02D (climate change mitigation technologies in information and communication), Y02P (climate change mitigation technologies in the production or processing of goods), and Y02W (climate change mitigation technologies related to wastewater treatment or waste management).

B Additional Empirical Results

B.1 Relationship among Measures of Firm Sustainability

Table A1 summarizes the relationship between our three measures of firm sustainability. In Panel (a), we examine the relationship between green patents and other dimensions of sustainability based on cross-sectional regressions. Column (1) of the panel shows that in the cross-section, firms with higher emissions intensity and lower environmental score tend to have more green patents, after controlling for non-green patents. In the cross-section, 1 standard deviation higher environmental score (emissions intensity) is associated with 0.08 standard deviation lower (0.04 standard deviation lower) green innovation. Column (2) shows that the negative relationship between environmental score and green innovation is entirely across-industry, while the positive relationship between emission and green innovation still holds within-industry.

Panel (b) examines whether our three green characteristics could predict future change of emissions intensity in the cross-section. In column (1) of the panel, we regress future 1-year change in emissions intensity on all stock characteristics, controlling for year-quarter fixed effects. The regression show that 1 standard deviation higher environmental score is associated with 4.14% lower emissions intensity over the next year, with t-statistic of 2.5 based on clustered standard errors. Columns (2) and (3) of the panel also show that this predictive relationship is robust to adding industry fixed effects or using industry-time fixed effects. These result show that the environmental score has real information content as it has predictive power for future emissions reduction.[25]

B.2 Robustness to Alternative Environmental Scores

In the paper, we construct environmental score as $g_t(n) = \frac{-(10-E_t(n))w_t^E(n)}{100}$, where $E_t(n)$ is the MSCI environmental pillar score and $w_t^E(n)$ is the MSCI environmental pillar weight; we then residualize $g_t(n)$ against emission intensity in each quarter to arrive at the environmental score we use for valuation regressions and demand estimations. $g_t(n)$ will be high for stocks that have superior environmental performance compared to their peers (high $E_t(n)$), or for stocks in industries where environmental issues are not important (low $w_t^E(n)$).

In this appendix, we show that our results are robust to two alternative constructions for $g_t(n)$:

- Alternative Environment Score (1): $g_t^{(1)}(n) = E_t(n)$: use MSCI environmental pillar score directly without adjusting for environmental pillar weights. $g_t^{(1)}(n)$ will only be high for stocks with good peer-adjusted environmental performance.
- Alternative Environment Score (2): $g_t^{(2)}(n) = \frac{(E(n)-5)w_t^E(n)}{100}$. In this construction, we use the environmental pillar weight $w_t^E(n)$ (which ranges from 0 to 100) to scale the peer-adjusted environmental

[25] Igan et al. (2021) find that higher ESG scores do not predict larger decrease in carbon emissions. It should be noted that the independent variable in their work is the firm-level ESG score from Refinitiv (Thomson Reuters), while it is the residualized environment score in our case.

performance $E_t(n) - 5$ (which ranges from -5 to 5). $g_t^{(2)}(n)$ will be high for stocks in environmentally-important industries that have better environmental performance relative to its peers.

Importantly, compared to $g_t(n)$, neither the two alternative scores will be high for stocks in environmentally-unimportant industries such as banking.

VALUATION REGRESSION Table A8 shows the valuation regression results based on the alternative scores defined above. The alternative scores $g_t^{(1)}(n)$ and $g_t^{(2)}(n)$ are both residuzlied against log scope-1 emission intensity in each quarter to maintain consistency with our main specification in the paper. Table A8 first shows that both alternative scores are consistently positively priced in the cross-section of valuations. Columns (2-3) also show that the MSCI environmental pillar score has a significantly higher valuation coefficient in the 2018-2021 subsample compared to the 2013-2017 subsample. Comparing Table A8 with the valuation regression results in the main paper (Table 2), we find that the coefficients for emission intensity and green patents are almost the same.

DEMAND COEFFICIENTS Figure A3 shows the AUM-weighted average demand coefficient for environmental score by broad investor types under different environmental score definitions. The figure confirms that there is consistently positive demand for stocks with high third-party environmental score throughout our sample period.

Figure A4 shows the demand coefficients for emission intensity under different environmental score definitions. The figure shows that the demand coefficients for emission intensity are not affected by how we construct the environmental scores.

B.3 COUNTERFACTUAL: WITHIN-INVESTOR DEMAND SHIFT OR ACROSS-INVESTOR AUM SHIFT

In this counterfactual analysis, we undo the within-investor changes in demand for sustainability as well as the changes in AUM to quantify the relative importance of within-investor demand shift versus across-investor AUM shift. We find that the increasing valuation difference between low- and high-emission stocks is almost entirely driven by within-investor demand shifts. This result highlights that the growth of sustainable investing is primarily driven by institutional investors rebalancing their portfolios from high-emission to low-emission stocks.

In the first counterfactual simulation, we shut off within-investor change of all three green demand coefficients as in Section 4.2 by setting each investor's green demand coefficients to their values in the first quarter when the investor appears in our sample. In the second counterfactual simulation, we first shut off within-investor demand change in the same way as above, and then further shut off AUM shift across investors by reallocating AUM across investors based on their AUM in 2013Q1 (we set counterfactual AUM to zero for investors not in our data in 2013Q1). We attribute the difference between actual data and the first counterfactual simulation to within-investor shift of green demand, and we attribute the difference between the first and second counterfactual simulation to the shift of AUM between green and brown investors.

Figure A5 plots the quarterly valuation regression coefficients for the emission characteristic, based on the data or the two counterfactual simulations. In the data, the valuation gap per 1 standard deviation higher emissions intensity is 4.65% in 2013Q1, which flips in sign to -3.60% in 2021Q3 and subsequently reaches as low as -9.77% in 2020Q1 with t-statistic greater than 5. If we shut off within-investor demand shift (the line labelled "Simulation 1" in the figure), this valuation gap is still a positive 2.83% in 2021Q3, and is never statistically significantly negative in any quarter. Columns (1) and (2) of Table A9 further supports this results based on a pooled valuation regression on the 2018-2021 data, showing that the valuation gap between low- and high-emission stocks mostly disappear if there had been no within-investor demand change since 2013Q1. Moreover, the comparison between two counterfactual simulations show that the shift of AUM across investors has little impact on the green-brown valuation gap.

In sum, these results reinforce our finding that the increasing valuation difference between low-emission and high-emission stocks is almost entirely driven by a preference shift towards low-emission stocks within institutional investors.

C Theory

C.1 Including Sustainability as a Characteristic

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

If sustainability is informative about the expected returns, it immediately follows from the same line of argument as in Koijen and Yogo (2019) that it should enter the characteristics-based demand. Suppose on the other hand that sustainability is not informative about the expected returns, but investors face a minimum sustainability constraint instead, similar to Pástor et al. (2021). More concretely, suppose for some $c > 0$ investor i faces, on top of short-sale constraints, an extra constraint[26]

$$\mathbf{b}_{it}'\mathbf{w}_{it} = (d_i\mathbf{g}_t)'\mathbf{w}_{it} > c \tag{A1}$$

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

Proposition 2. *If an investor faces a sustainability constraint, the optimal portfolio weight on asset n for which the short-sale constraint is not binding is*

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

[26]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.

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

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

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

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

Proposition 2 is identical to Proposition 1 in Koijen and Yogo (2019) but with a slight modification to the constant terms to account for the shadow benefit of sustainability, $\nu_{it}\mathbf{b}_{it}$. This addition comes from the fact that green assets are valuable beyond their expected returns because they relax the sustainability constraint. Even with the new constraint, the key content remains: variation in characteristics $\mathbf{y}_{it}(n)$ is the only source of variation in the portfolio weights. Furthermore, the expression for $\tilde{\Phi}_{it}$ reveals that even if investors do not believe sustainability is informative about expected returns (the factor loading on sustainability is zero in Φ_{it}), the optimal portfolio weights will still be positively related to sustainability.

C.2 Derivation of Investor Pressure in Proposition 1

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

$$\mathbf{p} = \log\left(\sum_i A_i \mathbf{w}_i\right) - \mathbf{s} \tag{A2}$$

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

$$\mathrm{I} = \begin{pmatrix} \left(\frac{1}{\sum_i A_i w_i(1)}\right)\left(\frac{\partial}{\partial \mathbf{p}(1)}\sum_i A_i w_i\,(1)\right) & \cdots & \left(\frac{1}{\sum_i A_i w_i(1)}\right)\left(\frac{\partial}{\partial \mathbf{p}(n)}\sum_i A_i w_i\,(1)\right) \\ \\ \left(\frac{1}{\sum_i A_i w_i(n)}\right)\left(\frac{\partial}{\partial \mathbf{p}(1)}\sum_i A_i w_i\,(n)\right) & \cdots & \left(\frac{1}{\sum_i A_i w_i(n)}\right)\left(\frac{\partial}{\partial \mathbf{p}(n)}\sum_i A_i w_i\,(n)\right) \end{pmatrix}$$
$$= \begin{pmatrix} \frac{1}{\sum_i A_i w_i(1)} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \frac{1}{\sum_i A_i w_i(n)} \end{pmatrix} \begin{pmatrix} \frac{\partial(\sum_i A_i w_i(1))}{\partial \mathbf{p}(1)} & \cdots & \frac{\partial(\sum_i A_i w_i(1))}{\partial \mathbf{p}(n)} \\ \vdots & & \vdots \\ \frac{\partial(\sum_i A_i w_i(n))}{\partial \mathbf{p}(1)} & \cdots & \frac{\partial(\sum_i A_i w_i(n))}{\partial \mathbf{p}(n)} \end{pmatrix}$$
$$\equiv \mathbf{H}^{-1}\frac{\partial}{\partial \mathbf{p}}\left(\sum_i A_i \mathbf{w}_i\right) \tag{A3}$$

where

$$\mathbf{H} := \mathrm{diag}\left(\sum_i A_i \mathbf{w}_i\right) = \sum_i A_i \mathrm{diag}\left(\mathbf{w}_i\right) \tag{A4}$$

Furthermore, it can be shown that:

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

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

which can be rewritten as

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

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

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

Now going back to the market clearing condition (A2) and differentiating both sides by $\mathbf{x}_k$:

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

Rearranging yields the desired expression:

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

$\square$

D Computing Counterfactuals

We summarize the steps for computing counterfactual which closely follows the algorithm in Koijen and Yogo (2019). For each quarter t, given AUM $\{A_{i,t}\}$ and demand coefficients $\{\boldsymbol{\beta}_{i,t}\}$ for all investors i, non-price stock characteristics $\{\boldsymbol{x}_t(n), g_t(n)\}$ for all stocks n, and latent demand $\{\varepsilon_{i,t}(n)\}$, we compute the equilibrium log market capitalization $\widetilde{me}_t(n)$ as follows:

1. Start from an initial guess $\widetilde{me}_t(n;0)$.

2. Plug $\widetilde{me}_t(n;0)$ and $\{\boldsymbol{\beta}_{i,t}, \boldsymbol{x}_t(n), g_t(n), \varepsilon_{i,t}(n)\}$ into Equation 5 for quarter t to compute portfolio weights $w_{i,t}(n)$.

3. Use the market-clearing condition to compute the prices corresponding to portfolio weights: $\widetilde{me}^*_t(n) = \log \sum_i A_{i,t} w_{i,t}(n) - \log BE_t(n)$.

4. Update the guess for prices: $\widetilde{me}_t(n;1) = \widetilde{me}_t(n;0) + k_t(n) \cdot \left[\widetilde{me}^*_t(n) - \widetilde{me}_t(n;0)\right]$.

   (a) $k_t(n)$ is the stock- and time-specific speed of update. Koijen and Yogo (2019) uses the optimal $k^*_t(n) = \left[1 - \frac{\sum_i \beta_{0,i,t} A_{i,t} w_{i,t}(n)[1-w_{i,t}(n)]}{\sum_i A_{i,t} w_{i,t}(n)}\right]^{-1}$ derived based on Newton's Method.

   (b) To improve numerical stability, we use a smaller update speed $k_t(n) = 0.25 \cdot k^*_t(n)$. If the procedure fails to converge, we try $k_t(n) = 0.1 \cdot k^*_t(n)$ and $k_t(n) = 0.05 \cdot k^*_t(n)$.

   (c) If the procedure still fails to converge, we then try fixed update speeds $k_t(n)$= 0.8 / 0.5 / 0.2.

5. Iterate back to step (1) until the price vector converges: min $|\widetilde{me}_t(n;1) - \widetilde{me}_t(n;0)| < 10^{-4}$.

For each set of primary inputs, we can compute the counterfactual portfolio holdings and investor pressures after computing the prices.

Table A1: **Relationship Between Green Characteristics**

(a) Green Patent and Other Green Characteristics

	Dep Var: Green Patents	
	(1)	(2)
Non-Green Patent / Asset	0.545**	0.476**
	[16.53]	[14.49]
E-Score Residual	-0.0782**	-0.00300
	[-5.653]	[-0.200]
Log GHG1 Intensity	0.0439**	0.0444*
	[4.570]	[2.282]
Time FE	✓	✓
FF-48 Industry FE		✓
Within R^2		
Observations	64184	64184

(b) Green Characteristics and Future Change in Emissions Intensity

	Dep Var: Future 4Q Change in Emissions Intensity		
	(1)	(2)	(3)
E-Score Residual	-0.0414*	-0.0386*	-0.0436*
	[-2.511]	[-2.603]	[-2.670]
Log GHG1 Intensity	-0.00867	-0.0686*	-0.0268*
	[-1.667]	[-2.503]	[-2.173]
Green Patent / Asset	0.00239	0.00187	0.00289
	[0.782]	[0.537]	[0.903]
Non-Green Controls	✓	✓	✓
Time FE	✓	✓	
FF-48 Industry FE		✓	
FF-12 Industry × Time FE			✓
Within R^2	.021	.032	.022
Observations	51065	51065	51065

This table summarizes the relationships between the different measures of sustainability. Panel (a) examines the relationship between the measure of green innovation and other characteristics in the cross-section. Panel (b) examines the predictability of each characteristic for future one-year ahead change in emissions intensity in the cross-section.

Table A2: **Sustainable Demand and UNPRI Signatory Status: Cross-Sectional**

	E-Score Resid		Emission		Green Patent	
	(1)	(2)	(3)	(4)	(5)	(6)
1{UNPRI Signatory}	0.0578*	-0.0000795	-0.0252	-0.0225	-0.0275	-0.0108
	[2.268]	[-0.00309]	[-0.801]	[-0.749]	[-1.058]	[-0.414]
Time FE	✓	✓	✓	✓	✓	✓
Investor Controls		✓		✓		✓
Within R^2	0	.013	0	.041	0	.013
Observations	113231	113231	113231	113231	113231	113231

This table summarizes the relationship between green demand and investor characteristics via cross-sectional regressions. Data is at the investor-quarter level, and all continuous variables are cross-sectionally standardized. Controls include all investor charcteristics in Table 5.

Table A3: **Sustainable Demand and UNPRI Signatory Status: Time-Series**

	Demand Coefficients		
	(1) E-Score Resid	(2) Emission	(3) Green Patent
1{UNPRI Signatory}	-0.00135	-0.00916	-0.00391
	[-0.123]	[-0.945]	[-0.244]
Time Trend	-0.000883**	-0.00144**	-0.00157**
	[-3.052]	[-4.682]	[-4.286]
Investor FE	✓	✓	✓
Within R^2	.001	.004	.002
Observations	112942	112942	112942

This table summarizes the within-investor change in demand for sustainability after an investor becomes a UNPRI signatory via time-series regressions.

Table A4: **Investor Pressure: Summary Statistics**

	Mean	SD	Q10	Median	Q90
E-Score Residual	0.063	0.084	-0.033	0.056	0.162
Emission	-0.084	0.085	-0.192	-0.071	0.004
Green Patent	-0.008	0.092	-0.118	0.008	0.082

This table summarizes the investor pressure. Statistics are computed in each quarter, and then averaged across quarters.

Table A5: **Investor Pressure and Future Environmental Performance: Longer Horizons**

	Forward 2-Year Outcome			Forward 3-Year Outcome		
	(1) E-Score Resid	(2) GHG	(3) Green Patent	(4) E-Score Resid	(5) GHG	(6) Green Patent
Pressure: E-Score Residual	0.0236^{+}	-0.0145	-0.0137^{+}	0.0131	-0.0453**	-0.0155
	[1.923]	[-1.074]	[-1.792]	[0.929]	[-3.245]	[-1.689]
Pressure: GHG	-0.0437**	0.0339**	0.00289	-0.0629**	0.0305*	0.00243
	[-3.566]	[2.788]	[0.420]	[-4.176]	[2.164]	[0.321]
Pressure: Green Patent	-0.000842	0.0113	0.0152*	0.00769	0.0109	0.0200**
	[-0.0653]	[1.064]	[2.680]	[0.490]	[0.855]	[2.983]
E-Score Residual	-0.300**	-0.123**	-0.0138^{+}	-0.349**	-0.178**	-0.0174^{+}
	[-20.03]	[-4.839]	[-1.916]	[-19.25]	[-6.342]	[-2.007]
Log GHG1 Intensity	-0.0414*	-0.0429**	0.00233	-0.0438*	-0.0530**	0.00291
	[-2.620]	[-2.816]	[0.364]	[-2.332]	[-3.067]	[0.380]
Green Patent / Asset	0.00293	0.00564	0.784**	-0.000242	0.00360	0.781**
	[0.216]	[0.469]	[29.65]	[-0.0144]	[0.220]	[24.48]
Time FE	✓	✓	✓	✓	✓	✓
Non-Green Controls	✓	✓	✓	✓	✓	✓
Within R^2	.094	.029	.71	.134	.067	.722
Observations	41486	41486	40754	33182	33182	32099

This table summarizes the cross-sectional relationship between investor pressure and future environmental performance. The dependent variables are: future 2/3-year change in environmental score, future 2/3-year change in emissions intensity, and the future 2/3-year number of green patents divided by total assets. The main independent variables are the investor pressure for three green characteristics. "Non-Green" control variables include log book equity, investment, profitability, market beta, and dividend to book equity. All outcome variables and regressors are cross-sectionally standardized in each quarter.

Table A6: **Counterfactual Exercise: Impact of ESG-Agnostic Mandates, Alternative Order**

(a) Counterfactual Valuation Regressions: Full Sample (2013 - 2021)

	Data	CF: Shut off Green Demand		
	(1)	(2) Passive Inst	(3) All Inst	(4) All Inst + HH
E-Score Residual	0.107**	0.107**	0.0951**	0.0540**
	[8.191]	[7.927]	[7.194]	[4.103]
Log GHG1 Intensity	-0.0156	0.00697	0.0330*	0.0387**
	[-1.153]	[0.552]	[2.634]	[3.065]
Green Patent / Asset	0.00359	-0.00211	0.0249	0.0161
	[0.237]	[-0.136]	[1.518]	[0.993]
Time FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	64184	64184	64184	64184

(b) Counterfactual Valuation Regressions: Subsample (2018 - 2021)

	Data	CF: Shut off Green Demand		
	(1)	(2) Passive Inst	(3) All Inst	(4) All Inst + HH
E-Score Residual	0.115**	0.123**	0.114**	0.0698**
	[6.767]	[7.005]	[6.529]	[4.010]
Log GHG1 Intensity	-0.0645**	-0.0275+	0.00311	0.00803
	[-4.261]	[-1.789]	[0.199]	[0.506]
Green Patent / Asset	-0.0115	-0.0209	0.0150	0.00618
	[-0.603]	[-1.107]	[0.784]	[0.327]
Time FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	26251	26251	26251	26251

This table presents the results from valuation regressions in counterfactual scenarios where we “shut off” green demand, i.e., set the demand coefficients for all three sustainability characteristics to zero for one or more types of investors. Importantly, we shut off the demand for passive institutions before active institutions, which is in contrast to the baseline procedure as described in Section 6.1. Specifically, we consider three scenarios in which we “shut off” green demand for all passive institutions (column (2)), all institutions (column (3)), and all investors including the household sector (column (4)). After obtaining counterfactual valuations, we re-estimate the valuation regression as shown in Equation (1). We present results for both the full sample as well as the 2018-2021 subsample.

Table A7: **Stock Characteristics and Investment Universe Coverage**

	Investment Universe Coverage	
	(1) Equal-Weighted	(2) AUM-Weighted
E-Score Residual	0.00971**	0.00331
	[6.164]	[1.687]
Log GHG1 Intensity	-0.000324	-0.00155
	[-0.187]	[-0.788]
Green Patent / Asset	0.000919	-0.000244
	[0.522]	[-0.136]
Log Book Equity	0.109**	0.0794**
	[38.18]	[33.82]
Profit / Asset	0.0258**	0.0263**
	[16.28]	[17.32]
Asset Growth	0.00556**	0.00499**
	[5.262]	[5.440]
Dividend / Book Equity	0.0319**	0.0146**
	[12.99]	[6.570]
CAPM Beta	0.00131	0.00212
	[1.001]	[1.204]
Non-Green Patent / Asset	0.0150**	0.0108**
	[8.604]	[6.097]
Time FE	✓	✓
Dep. Var. Mean	.196	.679
Within R^2	.659	.412
Observations	64184	64184

This table summarizes the results from regressing investment universe coverage on stock characteristics. For column (1), the equal-weighted investment universe coverage for a stock is the fraction of investors by number that have the stock in their investment universes. For column (2), the AUM-weighted investment universe coverage for a stock is the fraction of investors by AUM that have the stock in their investment universes.

Table A8: **Valuation Regression with Alternative Environment Scores**

	Dependent Variable: Log Market-to-Book					
	(1) Full Sample	(2) Full Sample	(3) 2013-2017	(4) 2013-2017	(5) 2018-2021	(6) 2018-2021
Alternative E-Score (1)	0.170**	0.141**	0.212**			
	[11.94]	[10.79]	[11.43]			
Alternative E-Score (2)				0.124**	0.114**	0.139**
				[9.308]	[8.236]	[7.452]
Emission Intensity	-0.0133	0.0159	-0.0646**	-0.0138	0.0152	-0.0641**
	[-1.005]	[1.279]	[-4.458]	[-1.016]	[1.202]	[-4.303]
Green Patent	-0.00608	0.0000154	-0.0156	-0.0113	-0.00230	-0.0262
	[-0.420]	[0.000947]	[-0.851]	[-0.782]	[-0.142]	[-1.428]
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Within R^2	.411	.39	.452	.397	.382	.431
Observations	64184	37933	26251	64184	37933	26251

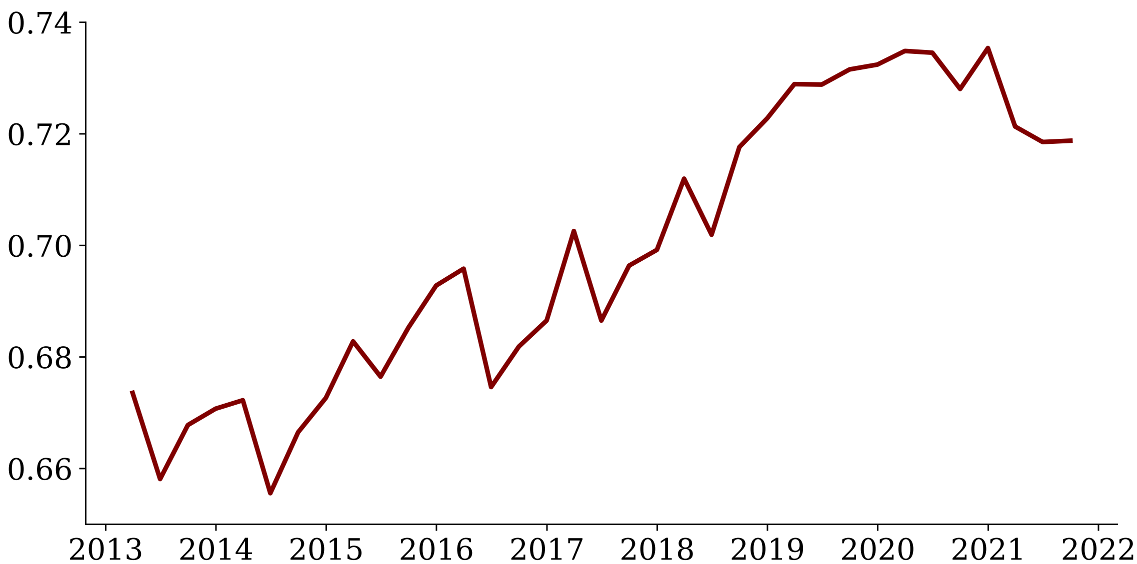
This table presents the valuation regression results based on two alternative measures of environmental scores defined in Appendix B.2. Both non-sustainable and sustainable characteristics are included in the regression, but the coefficients for sustainable characteristics are presented to save space.

Table A9: **Counterfactual Exercise: Demand vs. AUM Shifts**

	Data	CF Simulations	
	(1)	(2)	(3)
		Simulation 1	Simulation 2
Environment Score	0.115**	0.119**	0.118**
	[6.767]	[6.725]	[7.164]
Emissions Intensity	-0.0645**	-0.0124	0.00715
	[-4.261]	[-0.793]	[0.476]
Green Patents	-0.0115	0.0706**	0.0607**
	[-0.603]	[3.584]	[3.059]
Time FE	✓	✓	✓
Controls	✓	✓	✓
Observations	26251	26251	26251

This table presents the results from valuation regressions in counterfactual described in Appendix B.3, which is designed to juxtapose the relative importance of demand shifts *within* investors against the AUM shift *across* investors. In the first scenario, we shut off the within-investor change of all green demand coefficients by setting each investor's green demand coefficients to their values in the investor's first quarter. In the second scenario, we first shut off the within-investor demand change in the same way as above and then further shut off the AUM shift across investors by reallocating AUM across investors based on their AUM in 2013Q1. After obtaining counterfactual valuations, we re-estimate the valuation regression as shown in Equation (1).

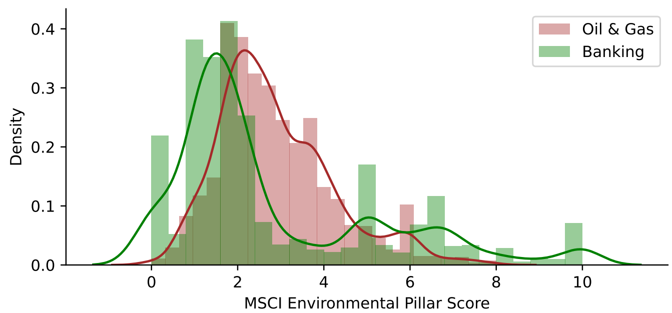
Figure A1: **Average Price Inelasticity Over Time**



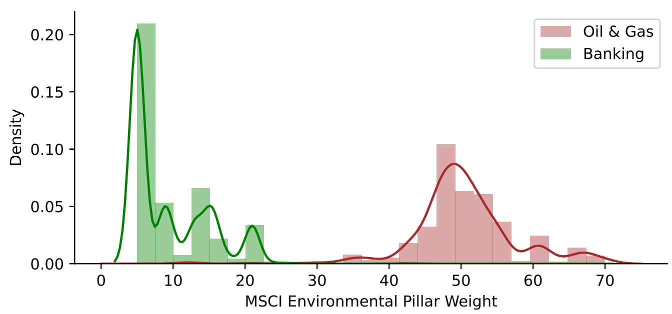
This figure summarizes the time trends in the AUM-weighted average price inelasticity coefficient ($\beta_{0,i,t}$) across all investors.

Figure A2: **Distribution of Environmental Scores for Oil & Gas and Banking Stocks**

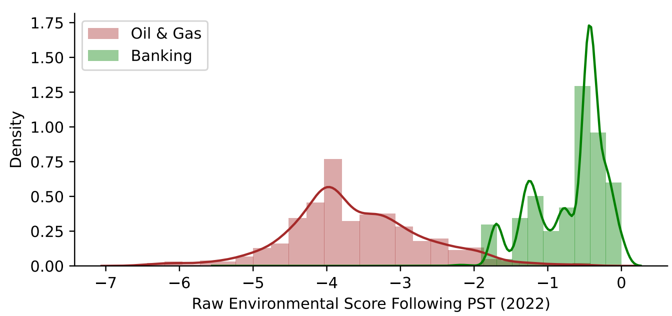
(a) MSCI Environmental Pillar Score: $E_t(n)$



(b) MSCI Environmental Pillar Weight: $w_t^E(n)$

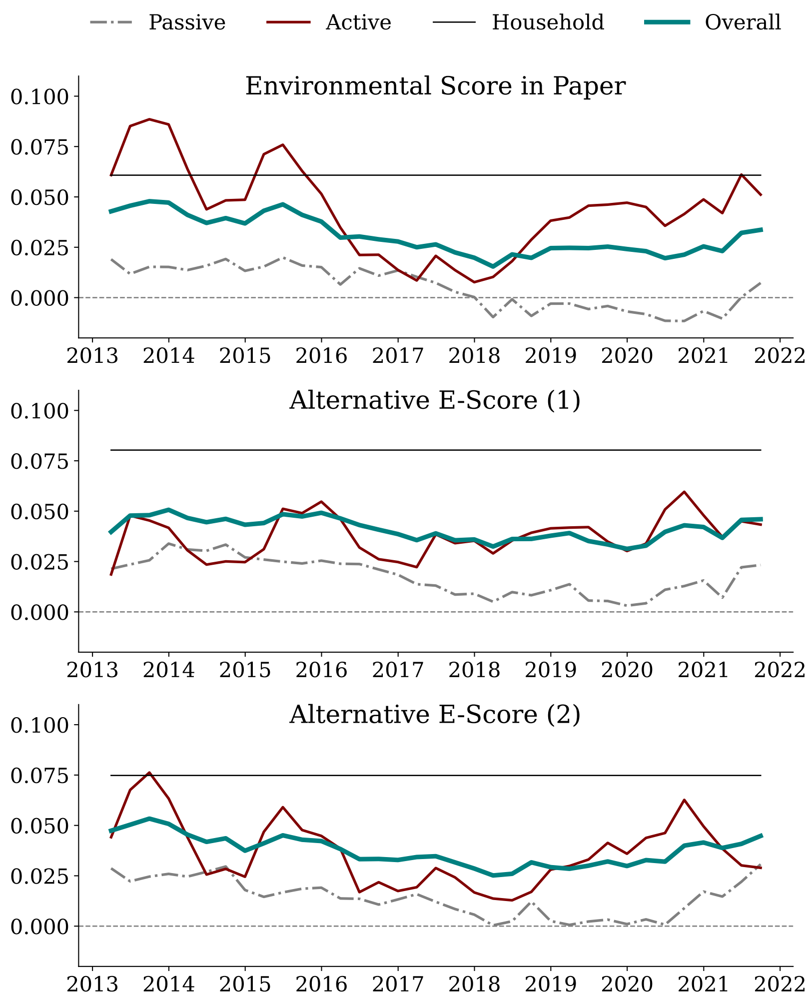


(c) Raw Environmental Score Following Pástor et al. (2022): $g_t(n)$



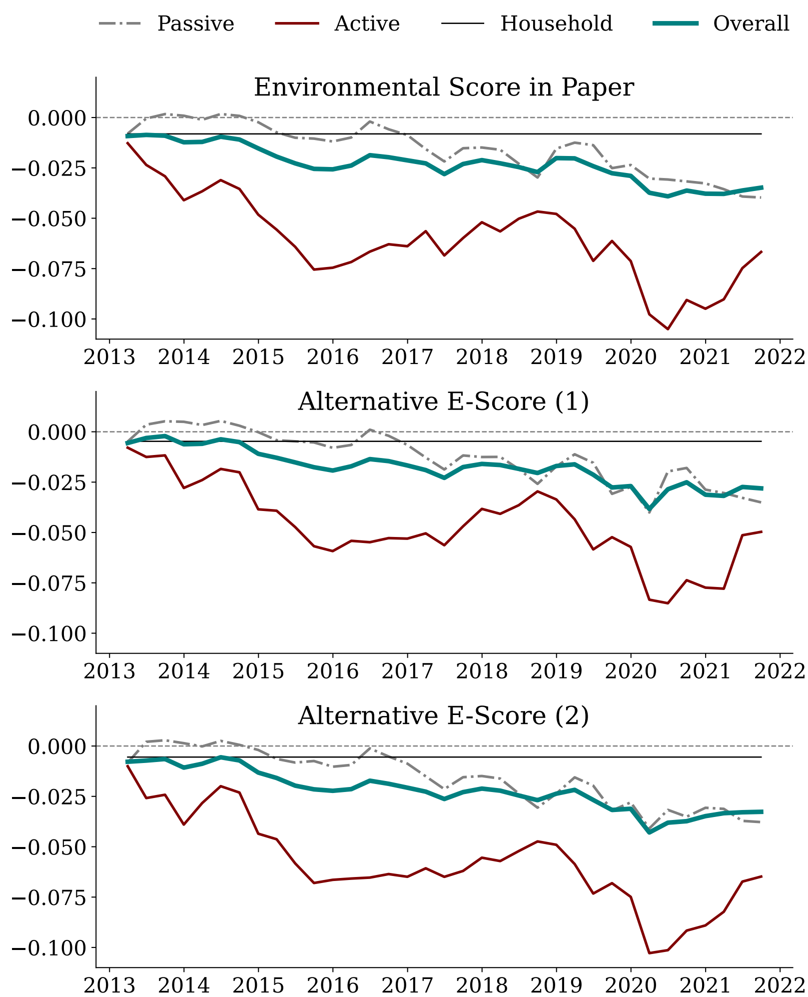
This figure illustrates the distribution of MSCI environmental pillar scores, MSCI environmental pillar weights, and the raw environmental scores across stock-quarters from oil & gas and banking industries. We use the 48-industry classifications from Ken French's website to select observations for each industry.

Figure A3: **Demand Coefficients for Environmental Score: Alternative Environment Score Constructions**



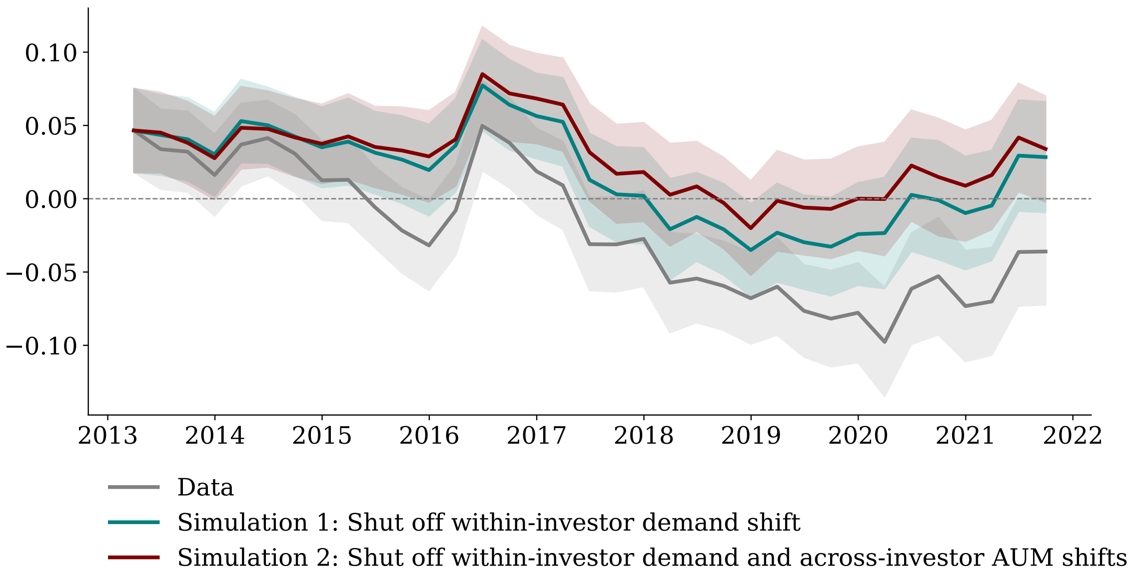
This figure plots the average demand coefficient for environmental score by broad investor types (passive institutions, active institutions, and the household sector) based on different definitions of environmental score. The alternative scores are defined in Appendix B.2. The investor classifications are the same as in the main paper.

Figure A4: **Demand Coefficients for Emission Intensity: Alternative Environment Score Constructions**



This figure plots the average demand coefficient for emission intensity by broad investor types (passive institutions, active institutions, and the household sector) based on different definitions of environmental score. The alternative scores are defined in Appendix B.2. The investor classifications are the same as in the main paper.

Figure A5: **Counterfactual: Demand vs. AUM Shifts**



This figure plots the time-series of the quarterly valuation regression coefficients on emissions intensity in the data in the counterfactual described in Appendix B.3, which is designed to juxtapose the relative importance of demand shifts *within* investors against the AUM shift *across* investors..