The Informational Role of Sustainable Investors *

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Abstract

Recent evidence suggests that sustainable investors may weaken information transmission into asset prices while being simultaneously classified as active traders. Using a demand-based asset pricing approach, we examine the behavior of sustainable investors and their impact on price informativeness. We find that sustainable investors are price elastic, enhancing informativeness by trading on both sustainable characteristics and long-term fundamentals. Stocks with strong sustainable demand exhibit greater price elasticity and responsiveness to idiosyncratic news, though this effect is weaker for green stocks, where sustainable investors trade less actively. Importantly, identifying sustainable investors outside a demand system misattributes passive demand as sustainable, distorting the estimated impact of sustainable investors. Overall, sustainable investors play a dual role: acting as active traders across their portfolios while behaving as preference-driven holders of sustainable stocks. We have no financial sources that would constitute any conflict of interest.

JEL Classifications: G11, G12, G32

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1 Introduction

Financial markets are incomplete with respect to carbon emissions. Emissions are not fully tradeable and imperfect information limits investors' ability to identify firms that remain productive in a net-zero economy. Consequently, sustainable investors need to trade based on beliefs which companies will or should make the transition. An important question is whether sustainable investors produce information that identifies stocks with long-run value.

To answer this question, we analyze how sustainable investors trade and impact aggregate informational efficiency in the stock market. Our approach is motivated by unresolved challenges in the literature. First, at an aggregate level, it is not clear whether *value*-driven or *values*-driven preferences dominate. Starks (2023) distinguishes between values (e.g., warm glow effect, ethical concerns) and value (i.e., related to future financial performance) motives underlying investors' preferences for sustainable stocks, and many investors are likely to act on a combination of these. The impact of sustainable investing on prices depends on the distribution of these motives across investors.[1] The evidence on how these preferences affect aggregate informational efficiency is not conclusive. For example, Goldstein et al. (2022) theoretically show that investor heterogeneity in valuation motives leads to lower price informativeness as long as sustainable performance is not perfectly correlated with financial performance.[2] Yet, in the model of Avramov et al. (2022b) heterogeneous sustainable preferences increase information gathering and result in higher price informativeness about firms' fundamental values. Empirically, recent evidence shows that stocks with high sustainable ownership incorporate fundamental news less effectively (Starks et al., 2017; Hitzemann et al., 2024; Qu, 2023), however, Agarwal et al. (2024) provide evidence that the information environment at the stock level improves with the presence of sustainable investors. Existing causal estimates of how sustainable demand affects price informativeness tend to be at the stock-level. Understanding this relationship at the market level considering the entire distribution of investors however remains a challenge.

Second, sustainable investing can be both active and passive in nature. For example, investors can buy a sustainable ETF, where portfolio weights are determined by market equity under a sustainability constraint (Andersson et al., 2016). Starks et al. (2017) find that long-term investors tilt their portfolios towards sustainable stocks and are less likely to sell their holdings in response to

[1] See, for example, (Heinkel et al., 2001; Pedersen et al., 2021; Pástor et al., 2021; Oehmke and Opp, 2024; Goldstein et al., 2022; Qu, 2023; Hut, 2024; Avramov et al., 2022b).

[2] Note that there is no consensus in the literature on how sustainable performance is related to financial performance, and investors may differ in how they perceive it (e.g., Liang and Renneboog (2021)).

negative earnings news, reflecting a more passive investment approach. Noh et al. (2023) find that sustainable investors on average exhibit higher price elasticities than other investors and Pastor et al. (2023) show that ESG tilts are more pronounced for institutions with a greater active share, reflecting active sustainability preferences. Furtheremore, Pastor et al. (2023) highlight that active ESG trading can enhance price efficiency, while passive ESG investing can contribute to pricing distortions if it grows too large. Koijen et al. (2024) however find little impact on price informativeness by index investors. Overall, not distinguishing between active and passive sustainable demand could lead to a possible weak information transmission channel from sustainable investors to be confounded with a passive investment style.

Third, the impact on prices is also dependent on the substitution across sustainable and non-sustainable stocks. For example, Van der Beck (2021) finds a low willingness to substitute between green and brown stocks *within* investors, resulting in price impact of flows into representative sustainable portfolios, while Berk and Van Binsbergen (2025) and Edmans et al. (2022) argue that the price impact is negligible because of high substitutability *across* investors. Not distinguishing between within and across investor effects on aggregate price informativeness masks the underlying channels.

These challenges underscore the importance of understanding the heterogeneity both between and within sustainable investors when analyzing the aggregate effects of sustainable demand on price informativeness. To address these challenges, we employ a demand-based asset pricing system of Koijen and Yogo (2019), which is an equilibrium framework that links investor demand functions to asset prices. We use the system to estimate individual investor demand for sustainability, which we measure by emission intensity. We estimate investors' price elasticity and sustainable demand jointly, separating active from passive sustainable demand. Hence, any effects of sustainable demand on price informativeness are unlikely directly confounded by passive investing (Sammon, 2024). Similarly, to identify sustainable investor while correcting for common tilts, we also estimate an investor's demand for other characteristics.[3] The system allows for computing counterfactual valuations when shifts in sustainable investor demand, both across different investors and within individual investors, affect price informativeness. In these analyses, we consider the entire wealth distribution of investors and allow for substitution effects. Finally, we go beyond the demand system and examine how sustainable investors influence the incorporation of information into stock prices, for which separating active from passive sustainable demand is

[3]Pastor et al. (2023) similarly develops an approach to correct sustainability demand for common tilts by estimating a conditional probability model.

important.

Our analysis yields several novel insights. First, we find that on average institutional investors have a negative demand coefficient for emission intensity, although significant heterogeneity exists. We define sustainable investors as investors with strong demand for low-emission intensity stocks after correcting for common tilts. On average, investors lower demand by 12% if stocks increase emission intensity by one standard deviation. Moreover, we find that the weights of the market portfolio correlate negatively with emission intensity. Hence, prior estimates of how sustainable investors—when defined based on portfolio emission intensity—influence prices may be confounded by passive investing.

Second, around one third of the time-series variation in sustainable demand can be attributed to active re-balancing towards more sustainable stocks and remaining part is due to passively holding stocks that become more sustainable over time. At the same time, we find that sustainable investors are more price elastic than non-sustainable investors on average, which suggests they tend to trade relatively actively.

Third, we find that across- but not within-sustainable investor demand shifts improve aggregate price informativeness. This finding is consistent with sustainable investors not trading merely based on sustainability characteristics but also incorporate broader long-term fundamental information. Consistently, we find that sustainable investors change prices in a way that improve real investment-to-price sensitivity at longer horizons. When analyzing their role in information transmission, we find that stocks with a higher value-weighted demand for sustainability are price elastic and more sensitive to idiosyncratic rather than systematic news. Furthermore, within the stocks with high value-weighted demand for sustainability, price elasticity and sensitivity to news is lower in green compared to brown stocks. These findings suggest that sustainable investors are active traders but relatively inactive in stocks to which they tilt.

Our analysis provides a deeper understanding of the complex behavior of sustainable investors. Our findings suggest a dual role of sustainable investors as active traders over their entire portfolio holdings and preference-driven holders for sustainable stocks to which they tilt their portfolios. At the aggregate level, sustainable investors are informed not merely by trading on sustainability characteristics but by incorporating broader, long-term fundamental information, hence they facilitate improvements in informational efficiency.

Our research relates to the demand-based asset pricing literature. Koijen and Yogo (2019) develop an asset demand system linking institutional and household holdings to stock prices and

characteristics. Koijen et al. (2024) create a new estimator for the demand system and examines the impact of market trends and regulatory changes on asset prices, price informativeness, and the wealth distribution. Van der Beck (2021) studies the price impact of flows towards ESG funds. Noh et al. (2023) incorporates sustainability into the demand equation and investigates the price pressure of sustainable investors. We contribute to this literature by studying empirically how sustainable demand interacts with price elasticity and informational efficiency.

We contribute to the literature on the effects of sustainable investing on price formation. Hwang et al. (2022) finds that higher SRI ownership is linked to negative stock returns. Cao et al. (2023) find that abnormal returns are more pronounced for stocks predominantly held by SR institutions. Pástor et al. (2021) analyze the asset pricing implications of ESG investing, differentiating between expected and realized returns. Pedersen et al. (2021) introduce an equilibrium asset pricing model incorporating ESG into portfolio choices based on risk and preferences. Goldstein et al. (2022) theoretically show that green and traditional investors react differently to similar ESG signals, which could reduce price informativeness. Qu (2023) and Hut (2024) find negative relation between sustainable ownership and short-term price informativeness. Hitzemann et al. (2024) explores whether sustainable investors delay the incorporation of fundamental information into asset prices and attribute this to sustainable investors paying less attention to fundamental cash flow news and discount rates. In contrast, Noh et al. (2023) and Pastor et al. (2023) find that sustainable investors have high price elasticities and high active shares, suggesting they react strongly to price signals. The literature thus far has focused on the price elasticity of sustainable investors based on all stocks they hold (Noh et al., 2023) or the price elasticity of stocks based on all investors that hold the stock (Van der Beck, 2021), but lacks a within-investor analysis that shows investors' conditional price elasticity. We show that overall sustainable investors are active compared to non-sustainable investors, though underreact in stocks with preferential characteristics. In addition, we argue that our analysis complements research connecting passive investing and price informativeness as it is unclear whether inelastic sustainable behavior results from preferences or a genuine passive investment strategy. A preference-driven trade that is orthogonal to future earnings in inelastic markets likely reduces information quality whereas a passive investment strategy does not necessarily (Koijen et al., 2024).

Finally, we contribute to the literature on the real effects of financial markets. Chen et al. (2007) and Foucault and Fresard (2014) show that stock prices influence capital investment decisions in public firms. Bai et al. (2016) derive a welfare-based measure of price informativeness and show

that prices have become stronger predictors of real investment. Theoretical advancements that connect prices to real investment come from Bond et al. (2010), Goldstein et al. (2013), Edmans et al. (2015). Berk and Van Binsbergen (2025) shows that divestment has a minimal effect on polluting firms' cost of capital, which is unlikely to affect real investment. We show that sustainable demand shifts improved price informativeness and investment-to-price sensitivity. The increased connection between equity prices and real economic decisions suggests that sustainable demand shifts have been important for firm investment decisions that affect future cash flows.

2 Estimation of the sustainability-based demand system

The core of our approach requires defining sustainable investors empirically. We use a recently growing literature following Koijen and Yogo (2019) and estimate demand systems that links portfolio holdings to equilibrium prices using characteristics-based demand, where stock characteristics proxy for exposure to systematic factors. We follow the framework of Koijen et al. (2024) and incorporate the idea of Pástor et al. (2021) that apart from financial reasons to invest sustainable, such as to hedge against transition risk, some sustainable demand is non-fundamental that is, demand not exclusively based on expected financial earnings. Part of these demand effects arise because some investors are willing to pay a premium to hold environmentally friendly assets.[4]

2.1 Characteristics-based demand

We derive investor demand as a function of stock characteristics in the two-period model.[5] There are N stocks, indexed by $n = 1, \ldots, N$, each with a normalized supply of one unit. Stock n's characteristics are captured by the vector $\mathbf{x}(\mathbf{n})$. The vector $\mathbf{x}(n)$ is a set of k stock characteristics that have been shown to be important drivers of investors demand, such as for example, dividend-to-book ratio, profitability or investments ratios. For each stock n, we define the market-to-book equity in period 0 and denote it as $MB(n) = \frac{P(n)}{B(n)}$. We define $x(n)^s$ as an element of the vector of stock characteristics $\mathbf{x}(\mathbf{n})$ that captures sustainable characteristics, such as for example emission intensity or green patents.

[4]Although widely debated, the (implicit) willingness to pay for ESG has been documented among retail investors (Hartzmark and Sussman, 2019; Riedl and Smeets, 2017), pension fund participants (Bauer et al., 2021) and somewhat more indirectly among institutional investors (Starks et al., 2017; Avramov et al., 2022a; Goldstein et al., 2022; Van der Beck, 2021).Whether institutional investors have non-pecuniary preferences is less clear, as a willingness to sacrifice returns conflicts with their fiduciary duty to act in the best interest of shareholders.

[5]See Appendix B for the details on the derivations.

The economy consists of I investors indexed by $i = 1, \ldots, I$ with exponential utility of the form:

$$U(A_{i1}, Q_i) = -\exp\left(-\gamma_i A_{i,1} - \mathbf{b}_i' \mathbf{Q}_i\right). \tag{1}$$

where A_i measures investors assets under management, Q_i denotes the investor's holdings of stock n in units of book equity $B(n)$ as $Q_i(n) = B(n)q_i(n)$ with $q_i(n)$ being the number of shares of stock n that investor holds in period 0. Investors have heterogeneous coefficients of absolute risk aversion, parameterized by $\gamma_i = \frac{1}{\tau_i A_i}$, where τ_i denotes risk tolerance.

In the spirit of Pástor et al. (2021), the vector $\mathbf{b}_i$ captures non-pecuniary benefits of investor i:

$$\mathbf{b}_i = d_i \mathbf{x}^s, \tag{2}$$

where x^s is an $N \times 1$ vector whose nth element is $x^s(n)$, and $d_i \geq 0$ is a scalar measuring the degree of agent i's sustainability taste. Investor i hence derives a non-financial benefit of $\mathbf{b}_i$ from holding stock n. Agents with higher values of d_i have stronger tastes for the sustainability characteristics of their holdings.

For simplicity, all stocks have constant idiosyncratic risk σ^2. For the investors with exponential utility in Equation 1, one can express the demand of investor i for stock n, $Q_i(n)$, as a function of stock n's characteristics:

$$Q_i(n) = \frac{1}{\gamma_i \sigma^2}\left(- \text{MB}(n) + \frac{1}{\gamma_i} b_i(n) + \underbrace{(\Phi_i^\mu - c_i \Phi_i^\rho)}_{\beta_i} \mathbf{x}(n) + \underbrace{(\phi_i^\mu - c_i \phi_i^\rho)}_{\epsilon_i(n)} \right). \tag{3}$$

The characteristics thus capture demand shifters. Demand is decreasing in price (market-to-book), risk σ^2 and risk aversion γ_i. Correcting for demand shifters, investors thus prefer stocks that are cheap. The vectors Φ_i^μ and Φ^ρ are loadings on firm characteristics that capture investor views on how characteristics proxy for expected return and risk (factor exposure), respectively. The loadings are constant across assets so that the only variation of portfolio weights stems from asset characteristics. Together, they form β_i, which captures investors' demand elasticities with respect to these characteristics.

Sustainability characteristic $x^s(n)$ enters in vector $\mathbf{x}(n)$ as it contains information on expected return and risk. Thus sensitivity of demand to the sustainable characteristics being a proxy for expected return or risk is captured with β_i^s (a component of the vector β_i). In addition, sustainability characteristic enters via $b_i(n) = d_i x^s(n)$, where d_i measures investor i's sustainability taste for

sustainable characteristic. This sustainability demand component is unrelated to expected returns or systematic risk. Thus, the total demand sensitivity to changes in sustainability characteristics is captured with $\widetilde{\beta}_i^s = \beta_i^s + \frac{1}{\gamma_i} d_i$. The estimated demand coefficients for sustainable characteristics do not allow us to separate investors' belief that sustainable characteristics proxies for stronger risk-return prospects not captured with other characteristics, investor disagreement, sentiment, and/or non-pecuniary preferences for sustainable stocks.

2.2 Estimation of the demand system

While the theoretical outline shows how characteristics enter investors' demand function in closed-form, we follow Koijen and Yogo (2019) and Koijen et al. (2024) by using a logit demand system to estimate investors' sensitivity towards characteristics.[6]

Consider that there are N inside assets indexed by $n = 1, \ldots, N$. Inside assets are the largest 90% stocks by market equity with non-missing observations on the characteristics included in the demand system. The outside asset consists of the remaining stocks (micro-cap), such that the demand system is based on the largest and most liquid stocks. Each investor i allocates their wealth $A_{i,t}$ in period t across its investment universe $\mathcal{N}_{i,t} \subseteq \{1, \ldots, N\}$ and the outside asset. Investment mandates or constraints determine each investor's investment universe. Investor i's portfolio weight on stock $n \in \mathcal{N}_{i,t}$ in period t is denoted by $w_{i,t}(n)$. The portfolio weight on the outside asset is denoted by $w_{i,t}(0)$. Dividing the portfolio weight on inside asset n by that on outside assets yields a non-linear demand equation for investor i at time t:

$$\frac{w_{it}(n)}{w_{it}(0)} = \exp\left(b_{0,it} + \beta_{0,it}\text{mb}_t(n) + \beta_{1,it}\mathbf{x}_t(n)')\epsilon_{it}(n)\right). \tag{4}$$

Equation 4 implies a cross-sectional relation between investors' portfolio weights and stock prices, characteristics $\mathbf{x}_t(n)$, as well as latent demand $\epsilon_{it}(n)$. $\mathbf{x}_t(n)$ is a set of k variables that capture demand shifters that include both financial, $x^f(n)$, and sustainable, $x^s(n)$, characteristics. $\beta_{1,it}$ measures the vector of investor i demand coefficients for the set of characteristics included in $\mathbf{x}_t(n)$. While $\beta_{0,it}$ measures sensitivity of investor's demand to price, with investors with a high demand coefficient on $\beta_{0,it}$ having inelastic demand.

Equation 3 shows that sustainability characteristics, $x^s(n)$, can enter investor demand through non-pecuniary preferences (i.e., $b_i(n) = d_i x^s(n)$) and through its impact on expected return and risk. Empirically, sustainability tilts aggregate into the estimated demand coefficient on sustain-

[6]The motivation for a logit demand system is that holdings are close to a lognormal distribution.

ability, hence one is unable to distinguish non-pecuniary preferences from risk-based, sentiment or disagreement views. To understand whether the estimated demand for sustainability stems from pecuniary or non-pecuniary motives, in our subsequent analysis we study how sustainable investors trade in response to fundamental news.

Since demand and prices are jointly determined in equilibrium, we use the instrument of Koijen and Yogo (2019) to identify price elasticity. The instrument relaxes the assumption that investors are atomistic and that demand shocks are uncorrelated. The instrument exploits an exogenous demand component that arises from investment mandates. Since investment mandates are not observable for all investors, we construct an investor's investment universe as the set of stocks held by in the current and past 11 quarters. Investment universes are stable over time such that for a given investor the investment mandates of other investors can be regarded exogenous. Let $\mathcal{N}_{i,t}$ be investor i's investment universe in period t, and $|\mathcal{N}_{i,t}|$ be the number of stocks in it. The instrument for log market equity of stock n is:

$$\widehat{\text{mb}}_{i,t}(n) = \log\left(\sum_{j \notin \{i,1\}} A_{j,t} \frac{\mathbb{1}_j(n)}{1 + |\mathcal{N}_{j,t}|}\right). \tag{5}$$

The instrument represents log market equity for stock n in a hypothetical market where investors hold an equal-weighted portfolio within their investment universe. The instrument is investor-specific, excluding own holdings and the household sector. The intuition of the instrument is that if an asset is included in a large number of investor's investment universes, the exogenous component for a given investor is relatively large. If demand is downward-sloping, a larger exogenous component of demand results in higher prices unrelated to latent demand. The instrument thus serves as a counterfactual market price and is investor specific. The identifying assumption is that investment universes as well as all characteristics other than market-to-book are exogenous.

We estimate equation 4 using non-linear GMM and the following moment condition:

$$E_t\left[\epsilon_{i,t}(n) \mid \widehat{\text{mb}}_{it}(n), \mathbf{x}_{it}(n)\right] = 1.^{7} \tag{6}$$

[7]The mean of latent demand is normalized to one for each investor such that the intercept in equation 4 is identified.

3 Data

Sustainability data We use two characteristics that measure firm-level sustainability. First, we use emission intensity from Trucost's Environmental Database. Emission intensity is defined as the sum of scope 1 and 2 emissions divided by sales. Scope 1 emissions capture direct emissions from production and scope 2 capture indirect emissions from consumption of purchased electricity, heat, or steam. Including both allows for a more comprehensive and comparable metric across firms and industry given the variation in whether the carbon emissions are realized directly by the firm or indirectly via the supply chain. Green (brown) firms are those that create economic value while minimizing climate damage.[8]

In our inside assets sample, about 40% of emission intensity observations are missing. We estimate the missing observations for firms with at least one non-missing observation using a simple extrapolation model. As firm emission intensity is rather constant over time, our approach yields an 85% out-of-sample R-squared. For firms without emission data, we use the average emission intensity of their industry (based on the 2-digit SIC code), which yields a 65% out-of-sample R-squared. Panel A in Figure A1 shows that the share of predicted emission observations declines over time as Trucost expands its sample.

Second, we use the data on green patents from the Google Patent database. We download cleaned data from Kogan et al. (2017). We classify patents as green based on Cooperative Patent Classification (CPC) codes from the OECD green patent methodology, following the steps of Haščič and Migotto (2015). Green patents cover patents related to waste management, air pollution abatement and nuclear energy, among others. Our green patent measure is the number of green patents issued in the past five years divided by current assets.

We lag all sustainability data by 12 months to mitigate the concern that data is not available for investors at the moment of reporting portfolio holdings.

Accounting and return data We source accounting data from Compustat and daily and monthly stock return data from CRSP. We compute book equity as stockholders' equity plus deferred taxes and investment tax credit (if available) minus the value of preferred stock. We calculate the logarithm of market-to-book, dividend-to-book ratio as annual dividends payments divided by book equity, profitability as revenues minus cost of goods sold, investment as annual asset growth and

[8]There is an ongoing debate on whether emissions intensity or emission levels most appropriately captures climate damage. One argument to use emission intensity is that emission levels correlate with size, which is captured by book-equity in the demand estimation.

earnings per share.

In addition, we source factor return data from the Kenneth R. French Library. We calculate monthly stock betas with the capital asset pricing model (CAPM) using a 60-month moving window, with at least 24 months of non-missing returns, by regressing monthly excess returns over the 1-month Treasury-bill rate against excess market returns.

We winsorize the dividend-to-book ratio, investment, market beta, emission intensity and profit-to-assets at the 2.5% level, and winsorize all return-related variables at the 1% level.

Holdings data We gather institutional holdings data from 2005 to 2022 through SEC $13F$ filings from Thomson's Institutional Holdings Database ($s34$ file).[9] Institutions are labeled by index i. The number of shares held by investor i in stock n is denoted by $q_{it}(n) = \frac{A_{i,t} w_{i,t}(n)}{P_t(n)}$, where $w_{i,t}(n)$ is the portfolio weight and $A_{i,t}$ are assets under management (AUM).

Following Koijen and Yogo (2019), we assume that shares not held by 13F institutions are held by households. When shares held by all institutional investors exceeds shares outstanding, e.g. due to missing short positions or misreporting, we scale each institution's holdings such that total institutional holdings equals shares outstanding. We lag all accounting variables by at least 6 months, with a maximum of 18 months prior to linking accounting data to holdings data to ensure that all accounting information was public.[10]

Analyst forecast data Lastly, we obtain analyst earnings forecast information I/B/E/S from 2000 to 2022[11] We use annual earnings forecasts to analyze forecast informativeness by stock type and horizon. In addition, we use quarterly earnings forecasts to assess stock price reactions to news. Following Hirshleifer and Sheng (2022), we define standardized unexpected earnings (SUE) for stock i as the difference between actual earnings reported by I/B/E/S and the median analyst earnings forecast made within 90 days of the earnings announcement scaled by price at the end of the quarter:

$$SUE_t(n) = \frac{X_t(n) - E_{t-1}[X_t(n)]}{P_t(n)}, \tag{7}$$

where $X_t(n)$ denotes realized earnings, $E_{t-1}[X_t(n)]$ the median analyst forecast made prior to the realization and $P_t(n)$ the price per share. Correcting for ex-ante analyst expectation ensures that $SUE_t(n)$ can be regarded as a shock to the market.

[9] In the US, institutional investment managers with portfolios exceeding 100 million in designated $13F$ securities must report their holdings quarterly.

[10] We give preference to annual data.

[11] To precisely construct the measure, we borrow parts of the code generously shared by Koijen et al. (2024).

Sample Our overall sample includes ordinary common shares (i.e., share codes 10, 11 and 12) traded on the NYSE, AMEX and Nasdaq (i.e., exchange codes 1, 2 and 3). We further restrict the sample to include stocks with non-missing price and non-missing shares outstanding only and drop all equities with negative market equity. Our main sample period is from 2005 to 2020 and it is dictated by the availability of the emission data.

Summary statistics Table A1 shows the summary statistics of inside assets. The median firm emits 42.2 tons of CO2-equivalent for each million dollar in revenue. The distribution is highly skewed. Panel B in Figure A1 shows the trend in the average and median emission intensity over time including all stocks. The average emission intensity is 150 tons of CO2e for each million $ in revenue in 2022 and has decreased by about 30% since 2005.

Table A2 shows summary statistics of the institutional investors included in the sample. The number of investors included in the sample ranges from 2,195 in 2005 to 4,500 in 2022. The median investor in 2022 has 217$m assets under management and 103 stocks in its portfolio. Figure 1 shows that, in line with lowering stock emission intensities, portfolio emission intensities decreased.

4 Sustainable demand

In this section, we identify the demand for sustainable stocks via the characteristic-based demand system and show how sustainable demand and active trading interact.

4.1 Demand for emission intensity

To identify sustainable investors we estimate a characteristic-based demand system in Equation 4. We include two characteristics that aim to measure sustainable demand, namely firms' emission intensity (over scope 1 and 2 emissions) and the number of green patents issued. We control for other well-known characteristics that have been shown to be important drivers of investors demand: log market-to-book, log book equity, market beta, dividend-to-book ratio, profit-to-assets, investment, and lerner ratio. By controlling for other characteristics commonly associated with expectations about firm's fundamentals, we estimate investors' sustainable demand net of these demand drivers.

We estimate demand coefficients for 119,217 investor-quarter pairs. Table 1 summarizes the coefficients. We first compute the equal- and asset-under-management-weighted (AUM-weighted) mean of demand coefficients in each quarter across all investors. We report in the table the time-

series averages of these cross-sectional means, denoted by $Mean$ and the time-series standard deviations of these cross-sectional means, denoted by $SD(time)$. Next, we compute in each quarter the cross-sectional standard deviation of demand coefficients and report the time-series averages of these cross-sectional standard deviations as $SD(cross)$. Panel A reports demand coefficients for all characteristics based on all investors. Panel B reports the emission intensity demand coefficient across investor types.

Panel A of Table 1 shows that the equal-weighted average of demand coefficients on emissions intensity is -0.12, indicating that on average investors lower their demand by 12% if stock emission intensity increases by one standard deviation. This negative coefficient implies that on average investors prefer more sustainable stocks (i.e., stocks with lower emission intensity). The cross-sectional standard deviation of sustainable demand is 0.5, indicating large heterogeneity in sustainable demand across investors. The AUM-weighted emission intensity demand coefficient equals -0.04, suggesting that larger investors tend to be less sustainable as they have stronger tilts towards high-emission intensity stocks. Panel B shows the heterogeneity in sustainable demand across types of investors. Mutual funds and investment advisors have the lowest emission intensity demand coefficient, but are most dispersed in their preference for sustainable investments.

In contrast, the demand coefficient on green patents is around zero and therefore we find no strong evidence that green patents are a strong predictor of institutional investor demand. The demand coefficients for the remaining characteristics are similar to the ones reported in previous studies (Koijen and Yogo, 2019; Koijen et al., 2024; Noh et al., 2023). We also find large heterogeneity across investors with respect to their demand coefficients on these financial characteristics, with the largest dispersion in their price elasticity (as captured by 1 minus the demand coefficient for log market-to-book ratio).

Figure 2 plots the time trend in AUM-weighted emission intensity demand coefficients by investor type. Sustainable demand does not vary substantially over time, which is consistent with small $SD(time)$ in Table 1. The demand coefficient is negative for all investor types across most quarters. Sustainable demand coefficients for households and banks have increased in our sample period, which indicates that these institutions increasingly tilt their portfolio towards browner stocks, consistent with Pastor et al. (2023). Pension funds decreased their emission intensity demand coefficient from 0 to -0.05 during 2015-2021, indicating tilts towards greener stocks.

To gain more intuition for the size of the estimated demand coefficients, we create a hypothetical investor that solely cares about sustainability. We replace the weights of fund 'Vanguard' with

hypothetical weights that are inversely proportional to the stocks' emission intensities. Each quarter, we re-scale emission intensity to be between 1 and 2 before computing the weights to avoid indivisibility by zero. We estimate the demand for this investor using all characteristics. Panel A in Figure A2 shows that the resulting demand coefficient equals -0.7 across the sample period and, as expected, on all other characteristics, we recover a demand coefficient of roughly zero. This provides a useful benchmark to compare how sustainable investors with a well-diversified portfolio are.

To understand how polluting the entire market is, we replace the weight of fund 'Vanguard' with weights proportional to stock market equity. Such a hypothetical fund, therefore, mimics a passive market fund.[12] To estimate how sensitive such a passive fund's holdings are to emission intensity, we estimate for it Equation 4 removing all characteristics except the constant and emission intensity. Panel B in Figure A2 shows that the market on average has a negative association of ≈ -0.15 with emission intensity. Hence, the weights of the market portfolio on average decreases by 15% if a stock increases its emission intensity by one standard deviation. Similarly, since the market portfolio's weights are proportional to market equity, this implies that market equity on average increase by 1% for every one fifteenth standard deviation decrease in emission intensity. This challenges the finding of Pástor et al. (2021) that the market is ESG-neutral.

Overall, we find that, on average, investors demand more sustainable stocks with lower emission intensity. However, there is significant heterogeneity among investors in their demand for sustainable stocks. This illustrates the importance of identifying sustainable investors using a demand system that accounts for investor heterogeneity.

4.2 Relation between price elasticity and sustainability demand

We are interested in understanding how sustainable demand and active trading interact. We investigate this relationship by estimating investor sustainable demand and price elasticity jointly, which allows us to separate the demand for emission intensity from passive investing. Investor price elasticity is captured by the demand coefficient for the market-to-book. We define investor's price elasticity as one minus the demand coefficient on log market-to-book, denoted by $\beta_{0,it}$ in Equation 4. Passive investors are perfectly price inelastic, i.e. such investors will not change their holdings if the price of a stock changes. For example, an index fund with portfolios weights proportional to market equity, has zero demand coefficients for all characteristics except for $\beta_{0,it} = 1$, which

[12] If we re-estimate the demand system for that fund, we obtain a coefficient of 1 on log market-to-book, a coefficient of $\approx$1.3 on log book-equity and 0 on all other characteristics as in Koijen and Yogo (2019), which illustrates the demand system's ability to identify such passive investor.

translates to fully inelastic demand.

Figure 3 plots the relation between investor's price elasticity and investor's demand coefficient for emission intensity. To remove noise, each quarter, we sort investors into 3,000 percentiles by their emission intensity demand. For each percentile, we calculate the equal-weighted average coefficient on price elasticity and average emission intensity demand coefficient. We fit a linear function to estimate the slope of this relationship. The figure shows that investors with strong tilts towards low emission intensity stocks (i.e., more sustainable investors) are on average relatively price elastic, i.e, the correlation based on the binned data is -0.42. However, this relation is non-monotonic. Compared to sustainable investors, investors whose portfolio has no association with emission intensity are inelastic. This is consistent with passive investors having demand coefficients of close to zero on non-price related characteristics Koijen and Yogo (2019). Yet, compared to index investors, investors with positive tilts towards high-emission intensity stocks are also elastic.

Figure A3 in the Appendix shows how the results change if we change the binning approach. Panel A shows that the pattern is robust to performing an AUM-weight summary per bin, although the correlation lowers to -0.23. Furthermore, the slope is less steep, which suggests that larger sustainable investors are passive relative to smaller sustainable investors. Panel B shows that the unbinned data is noisy with a weak correlation of -0.15. The fact that we are primarily interested in comparing price elasticity averages across groups of investors justifies binning observations to remove noise.

In Figure A4, we show the relationship between sustainable demand and the active share measure of Cremers and Petajisto (2009)—an alternative measure of price elasticity. Investor i's active share in period t is $AS_{i,t} = \frac{1}{2}\sum_{n\in\mathcal{N}_{i,t}}\left|w^I_{i,t}(n) - w^M_{i,t}(n)\right|$, where $w^I_{i,t}$ is the portfolio weight and $w^M_{i,t}(n)$ the market equity weighted portfolio among investor i's inside assets. The active share quantifies the share of an investor's portfolio that deviates from market weights. Each quarter, we sort investors in 3,000 percentiles based on their emission intensity demand coefficient and calculate the equal-weight average of investors' active share for each bin. We calculate also the equal-weight emission intensity demand for each bin. The figure confirms the non-monotonic relationship between active share and emission intensity demand.

The fact that the weights of the market portfolio correlate negatively with emission intensity while sustainable investors are classified as price elastic suggests that the demand system filters out parts of sustainable demand that are inherently passive. To highlight the importance of using a demand system to identify sustainable investors, we examine how the classification of sustainable

investors changes if we identify sustainable investors only based on portfolio emission intensity. Figure 4 plots portfolio emission intensity against the emission intensity demand coefficient. The observations labeled with 'mismatch' cover investors characterized as sustainable based on portfolio emission intensity but not based on the emission intensity demand coefficient, that is investors with lowest portfolio emission intensity but positive demand coefficient for emission intensity (i.e., bottom right corner in the plot). We decompose this group into price elastic investors, who have price elasticity higher than the median investor in a given quarter. The remainder comprises price inelastic investors. A high proportion of investors classified as price inelastic would suggest that the demand system indeed filters out passive sustainable demand. We find that 61% of investors in the mismatch group are price inelastic. This suggests that after accounting for the fact that a part of sustainable demand is inherently passive, sustainable investors are active traders. In addition, not accounting for passive sustainable demand could incorrectly classify passive investors as sustainable when only based on portfolio emission intensity.

Overall, we show that sustainable investors are heterogeneous in how price elastic they are. On average, sustainable investors are relatively price elastic, however this relationship is less strong among larger sustainable investors, indicating presence of both active and passive sustainable demand. Our results furthermore emphasize the importance of measuring sustainable demand using a demand system that controls for financial and price-related characteristics, as opposed to solely using the sustainable characteristics of portfolio holdings.

4.3 Active and passive sustainable demand

Having established that sustainable investors are both active and passive investors, we investigate the role of active sustainable demand in lowering portfolio emissions as documented in Figure 1.

A change in portfolio's emission intensity can be the result of investors tilting their portfolio towards stocks with different characteristics or passively holding stocks that change characteristics themselves. If the entire market becomes greener, while investors keep their relative allocation between green and brown assets constant over time, the association with emission intensity is expected to remain stable as in Figure 2, while portfolio emission intensity decreases as in Figure 1. To investigate this possibility, we decompose changes in investors' sustainability demand into active and passive changes. Thus, changes in investor demand for a given stock can be expressed as changes in demand coefficients beta given lagged characteristics (active) and changes in characteristics given demand coefficients (passive). Taking the first-difference of the log-linearized version

of Equation 4 and adding and subtracting redundant terms gives:

$$\Delta \log\left(\frac{w_{it}(n)}{w_{it}(0)}\right) = \Delta b_{0,it} + \underbrace{\Delta\beta_{0,it} mb_{t-1}(n) + \Delta\beta_{1,it}\mathbf{x}_{t-1}(n)'}_{\text{Active change}} + \underbrace{\beta_{0,it}\Delta mb_t(n) + \beta_{1,it}\Delta\mathbf{x}_t(n)'}_{\text{Passive change}} + \Delta\epsilon_{it}(n). \tag{8}$$

We re-run the demand estimation with non-standardized characteristics to be able to compare firm emission intensity across quarters. For each portfolio holding, we compute the active change and passive change on emission intensity, denoted by $\Delta\beta_{it}x_t^s(n)$ and $\beta_{it-1}\Delta x_t^s(n)$, respectively. We compute active and passive demand changes annually as emission intensity similarly is an annual variable. For each investor-stock-quarter pair, we sum active and passive changes, which we denote as the total change in emission intensity demand. Subsequently, for each investor in each quarter, we regress the total change on the active change across her portfolio holdings and compute the R-squared of this regression. Figure 5 plots over time the equal-weighted average across investors of the R-squares.[13] Across investors, the average R-squared is 32%. This implies that investors actively changing their demand for sustainable stocks explains only 32% of the time-series variation in sustainability demand, although they have been growing over time to reach around 50% at the end of our sample period. Thus, primarily firm emission reductions rather than large active tilts have contributed to portfolios with lower portfolio emission intensities.

5 Sustainable investing and information transmission

In this section we analyze how sustainable demand impacts prices. We assess how shifts in sustainable investor demand, both across different investors and within individual investors, affect price informativeness. In addition, we go beyond the demand system and examine how sustainable investors influence the incorporation of information into stock prices, for which separating active from passive demand is important.

5.1 Implications for aggregate information quality

To understand the causal impact of sustainable demand on the quality of the information, we model counterfactual shifts in the sustainable demand and analyze their impact on price informativeness. We adopt the price informativeness measure from Bai et al. (2016), who estimate price informativeness through a cross-sectional regression of future profitability on the ratio of market

[13] The value-weight average across investors of shows a qualitatively similar time-trend.

equity to book assets:

$$\frac{E_{t+h}(n)}{A_t(n)} = \alpha_t + \pi_t \log\left(\frac{P_t(n)}{A_t(n)}\right) + \rho_t \frac{E_t(n)}{A_t(n)} + \nu_t(n), \tag{9}$$

where $E_t(n)$ are earnings before interest and taxes for stock n and $A_t(n)$ book assets for stock n. Subscript h denotes the number of years in the future and t the current year. The coefficient π measures how equity prices predict future earnings. Price informativeness in quarter t at horizon h is the forecasting coefficient π_t multiplied by $\sigma_t(\log(P_t(n)/A_t(n)))$, the cross-sectional standard deviation of the forecasting variable $\log(P_t(n)/A_t(n))$ in year t. Price informativeness, thus, measures the extent to which current market prices predict future cash flows.

If information provided by financial markets is relatively informative, the feedback from current prices to future real investment is expected to be stronger. The idea is that managers can derive more information from prices about firm prospects if prices precisely signal future earnings. If sustainable investors improve the information content in prices, we expect the predictability of investment from prices to be higher. This can be tested through the following regression:

$$\frac{I_{t+h}}{A_t(n)} = a_t + \pi_t \log\left(\frac{P_t(n)}{A_t(n)}\right) + \kappa_t \frac{I_t(n)}{A_t(n)} + \rho_t \frac{E_t(n)}{A_t(n)} + \nu_t(n), \tag{10}$$

where $A_t(n)$ denotes assets in place, $P_t(n)$ market equity and $E_t(n)$ earnings. As investment indicators $I_t(n)$, we use capital expenditures, $CapEx_{t+h}(n)$, Research and Development, $R\&D_{t+h}(n)$, and assets, $A_{t+h}(n)$. In the latter case, the dependent variable corresponds to asset growth as a measure of total investment. Investment-to-price sensitivity is given by the forecasting coefficient π_t multiplied by $\sigma_t(\log(P_t(n)/A_t(n)))$, the cross-sectional standard deviation of the forecasting variable, analogously to price informativeness.

We analyze two types of counterfactual demand shifts. First, we analyze the shift of demand across investors from sustainable to non-sustainable ones. Second, we analyze within investors demand shifts, from green stocks to brown stocks. In both cases, we use the demand system to construct market prices under the counterfactual scenario that mutes the effects of sustainable investors. If prices become less informative about future earnings or investments under counterfactual market prices, this suggests that sustainable investors improved aggregate information quality.

5.1.1 Across investor demand shifts

One way through which sustainable investors could have affected information quality is through across-investor shifts in assets under management. Indeed, ESG-labelled funds received significant inflows as sustainable investing grew in popularity (Van der Beck, 2021). These flows have created significant price impact, which could have changed the informational content in prices.

We quantify the relative importance of a sustainable investors (group S) by modeling a counterfactual flow from this group to non-sustainable investors (group B). Group S comprises of investors whose emission intensity demand coefficient is below zero. Group B comprises of investors whose emission intensity demand coefficient is larger than zero. We set $A_{k,t} = 0$ for all investors $k \in S$. We do not modify the wealth of households (hh). Investors part of group B receive an inflow $F_{i,t}$ proportional to their wealth:

$$F_{i,t} = \frac{A_{i,t}}{\sum_{j \notin \{S,hh\}} A_{j,t}} \sum_{k \in S} A_{k,t}. \tag{11}$$

We do not modify demand coefficients or the weight on the outside assets. Investor i's wealth in the counterfactual market is:

$$A_{i,t}^{C}\left(P_t^C\right) = A_{i,t}\left(w_{i,t}(0) + \sum_{n \in N_{i,t}} \frac{P_t^C(n)}{P_t(n)} w_{i,t}(n)\right) + F_{i,t}. \tag{12}$$

Superscript C denotes the counterfactual. The new wealth is the sum of the investor's initial portfolio under counterfactual prices P_t^C and the inflow $F_{i,t}$. Counterfactual prices P_t^C are computed using the algorithm in Koijen et al. (2024) by iterating on the market clearing condition:

$$P_t^C(n) = \sum_{i=1}^{I} A_{i,t}^{C}\left(P_t^C\right) w_{i,t}^{C}\left(n; P_t^C\right). \tag{13}$$

We run price informativeness regressions in Equations 9 and 10 for $h = 1, 3$ using counterfactual market prices P_t^C and the original market prices P_t. In each regression we control for industry fixed effects (1-digit sic-code). We focus on the period 2015-2019. This is the period in which ESG investing grew in popularity, but before the ESG backlash took place. We perform this regression in the entire sample of stocks, and also separately for low- and high-emission intensity stocks to understand in which stocks sustainable investors changed price informativeness. In these regressions, we define green stocks as stocks below the median emission intensity in a given quarter and brown stocks as the remainder.

Figure 6 shows that after the flows from sustainable to non-sustainable investors, price informativeness decreased at longer horizons ($h = 3$), but not at shorter horizon ($h = 1$). At longer horizons, counterfactual price informativeness is visibly lower than actual price informativeness. This suggests that sustainable investors improved price informativeness at longer horizons. Their demand shifters were informative to the extent that without sustainable investors aggregate price informativeness would be lower. Furthermore, sustainable demand has improved price informativeness in both brown and green stocks, at longer horizon.

Figure 8 shows the impact of the same across-investor demand shifts but on the three measures of the investment-to-price sensitivity. Across-investor sustainable demand shifts changed prices in a way that increased investment-to-price sensitivity due to its impact on total investment and R&D expenditures, but not on capital expenditures.

5.1.2 Within-investor sustainable demand shifts

A second counterfactual analysis looks at the impact of within investor demand shifts to low-emission stocks. This counterfactual focuses on the impact of changing only the sustainable demand shifter (i.e., the coefficient for emission intensity). Holding other demand shifters constant, we set the demand coefficient on emission intensity to zero for all investors who have negative demand for emission intensity. Thus, we eliminate investors' tilts towards stocks with low emission intensity. We then compute counterfactual market prices.

Next, we again run the price informativeness regressions in Equations 9 and 10 for $h = 1, 3$ using counterfactual market prices and the original market prices. Figure 7 shows no visual difference between counterfactual and realized price informativeness in the entire sample of stocks and also among the green and brown stocks.

Figure 9 shows the impact of within-investor demand shifts on investment-to-price sensitivity. We find no meaningful difference between investment-to-price sensitivity under counterfactual and actual market prices. This shows that tilts towards low-emission stocks, as a standalone decision within an investor, did not affect investment-to-price sensitivity. Rather, it has been the entire set of demand shifters of sustainable investors that have contributed to a stronger connection between prices and investment documented above.

To formally test a change in price informativeness, we run regression in Equation 9 for the period 2015-2019. Columns 1, 4 and 7 in Table 2 provide the baseline price informativeness results. Columns 2, 5 and 8 provide the results under counterfactual market equity when assets flows from

sustainable to non-sustainable investors. Price informativeness in the scenario where we mute the effects of sustainable investors is significantly lower as indicated by the coefficient on log market equity to assets. Columns 2, 5 and 8 provide the results under counterfactual market equity when we set the demand coefficient on emission intensity to zero for all investors who have negative demand for emission intensity. We find that such within-investor demand shifts did not significantly alter price informativeness.

Overall, we find that across-investor demand shifters but not within-investor sustainable demand shifts improve price informativeness and investment-to-price sensitivity, primarily at longer horizons. Since the across-investor demand shifts affect market equity through the entire set of demand shifters, we conclude that sustainable investors are informed about future earnings through their entire demand function and not just based their views on emissions.

5.2 Implications for the incorporation of news

The analysis in the previous section relies on assumptions about how counterfactual market equity is constructed. To analyze the impact of sustainable investors on actual prices, we study its impact on stock price reactions to cash flow news.

We have so far shown that sustainable investors can be both passive or active, but on average are price elastic compared to non-sustainable investors. Sustainable investors being price elastic implies they quickly adjust their holdings to price changes compared to non-sustainable investors. Consequently, we expect them to react more aggressively to fundamental price news. Stocks with high active sustainable ownership should thus experience larger price reactions to news. However, stocks are held by a mixture of investors being sustainable and non-sustainable, as well as active and passive. Therefore, it is important to control for the heterogeneity of the investors base when analyzing stock price reactions.

5.2.1 Sustainable stock ownership

We measure sustainable stock ownership as the holding-weighted average emission intensity demand coefficient of the underlying investors. We similarly compute stock-level price elasticity as the holding-weighted price elasticity of the underlying investors. We exclude households from the calculation it comprises multiple unidentified investors for which we don't know how they allocate wealth across stocks.[14] We calculate sustainable ownership based on the shares held by investors

[14]For example, the household sector could in theory consist of 50% sustainable investors and 50% non-sustainable investors, holding different stocks. In this case, the household will be classified as a neutral investor, missing important heterogeneity. The household sector accounts for a sizeable portion of the market and including it in the calculation distorts a significant portion of sustainable ownership estimates.

with available demand coefficients. While the estimation of demand is based on inside assets, we link investors' demand coefficients to the broader sample of stocks and not just inside assets (as included in the demand system) to enhance the validity of our results. We also remove penny stocks, i.e. stocks with market equity in the bottom 10% percentile.

Each quarter, we sort stocks into quintiles based on emission intensity and the holding-weighted emission intensity demand coefficient of the underlying investors. Next, we compute an value-weight average of stock-level price elasticity in each sort. Table 3 shows that stocks held by sustainable investors are, on average, more elastic than those held by non-sustainable investors (as shown in the last row) and across all levels of emission intensity (rows 1 to 5). In contrast, the last column shows that average price elasticity does not vary with emission intensity, as green and brown stocks are equally price elastic. Column 1 furthermore shows that green stocks with high sustainable ownership have lower price elasticity compared to brown stocks with high sustainable ownership. This suggests that sustainable investors are less willing to give up their green stocks in response to price changes, consistent with a non-pecuniary preference for green stocks. Given that the elasticity of stocks held by non-sustainable investors is constant across emission intensity sorts, suggests that non-sustainable investors respond similarly to price changes for both green and brown stocks.

We next investigate whether the relatively low elasticity on green stocks with high sustainable ownership is driven by passive investors. If passive investor have relatively high ownership shares in these stocks, the low elasticity may be due to passive ownership and not inelastic sustainable demand. We again compute price elasticity across sorts based on stock emission intensity and underlying demand for emission intensity, but compute averages separately for different groups of investors. Specifically, within a given stock, we compute the holding-weighted price elasticity for: i) green-active, ii) other active and iii) passive investors. Passive investors are investors who in a given quarter have an active share below the median. Among the remaining investors, green-active investors have a negative demand coefficient on emission intensity and other-active investors have a positive demand coefficient on emission intensity. Finally, we compute an equal-weight average of stock-level price elasticity across stocks per group of investors. We keep sorts for which we have at least 30 observations.

Columns 1 and 2 in Panel A of Table 4 show that green active investors have price elasticities that vary by emission intensity. In contrast, passive investors have constant price elasticity. This suggests that the relatively low elasticity in green stocks with high sustainable ownership is driven

by sustainable investors and not passive ownership. In Panel B, we show the ownership shares of the different investor groups within stocks sorted on emission intensity and underlying demand for emission intensity. Passive investors have high ownership shares compared to green active investors. Overall, this reveals that while average stock-level price elasticity is driven by both green active and passive investors, how stock-level elasticity varies across emission intensity conditional on sustainable demand is driven by green active investors.

We show that sustainable investors are indeed more price elastic overall; however, green stocks with high sustainable ownership have lower price elasticity compared to brown stocks with high sustainable ownership. This indicates that, although sustainable investors are more active traders, they are nevertheless less willing to give up their green stocks in response to price changes, which is consistent with the presence of a non-pecuniary preference for green stocks. We confirm that this pattern is driven by sustainable investors and not passive ownership.

5.2.2 Stock price reactions to cash flow news

As a source of firm-specific news, we use quarterly earnings announcements that release information on realized earnings in the past quarter to the market. Each quarter, we independently sort stocks based on their sustainable ownership into quintiles and based on $SUE_t(n)$ into 11 quantiles. Stocks with positive surprises are assigned to 1 to 5. Similarly, stocks with negative surprises are assigned to 7 to 11. Portfolio 6 contains stocks with no earnings surprises. We define stocks experiencing good news as stocks in the 10th and 11th news quantile. Similarly, bad news stocks are stocks in the 1st and 2nd news quantile. As an alternative news measure, we compare all positive news incidents (quantiles 7 to 11) to all negative news incidents (quantiles 1 to 5).[15]

Following DellaVigna and Pollet (2009), for each earnings announcement date τ in quarter t, we construct buy-and-hold abnormal return for stock n over the period $(\tau + h, \tau + H)$ as:

$$R_t^{h,H}(n) = \left[\prod_{j=\tau+h}^{\tau+H}(1 + R_j(n))\right] - \hat{\beta}_t(n)\left[\prod_{j=\tau+h}^{\tau+H}(1 + R_j^m) - 1\right], \tag{14}$$

where $R_j(n)$ stands for the return on day j for stock n, R_j^m stands for the market return and $\hat{\beta}_t(n)$ is the market beta obtained from $R_j(n) = \alpha_j(n) + \beta_j(n)R_{j,m} + \epsilon_j(n)$ for days $j \in [\tau - 300, \tau - 46]$.

We compute the announcement day return over the first 2 trading days $R_t^{(0,1)}(n)$ as a measure of immediate stock-price response. After removing stocks with missing underlying sustainable de-

[15] Overall, the literature uses earnings surprises categories instead of raw earnings surprises as the latter do not result in a well-specified linear regression (Bernard and Thomas, 1989; Hirshleifer and Sheng, 2022).

mand, our sample consists of 144,753 observations. We provide summary statistics on announcement returns in Table A3.

Given 11 news sorts and 5 sustainable demand sorts, we obtain 55 double-sorted portfolios for which we compute equal-weighted portfolio returns.[16] Figure 10 shows the average announcement return for the 1st, 3rd and 5th emission intensity demand quintiles across the 11 news sorts. We observe that stocks with high sustainable ownership experience stronger price reactions to both positive and negative earnings information than stocks with low sustainable ownership. This is consistent with sustainable investors being more price elastic than non-sustainable investors. To formally test how sustainable ownership affects the price reaction to news, we compare abnormal stock returns following the earnings announcement for stocks held by sustainable and non-sustainable investors. Specifically, we perform the following regression:

$$R_t^{0,1}(n) = \beta_1 \, Top\, SUE_t(n) \times Sust.Inv + \beta_2 \, Sust.Inv_t(n) + \beta_3 \, Top\, SUE_t(n) + \gamma' \mathbf{x} + \theta_t + \mu(n) + \epsilon_t(n), \tag{15}$$

where $Top\, SUE$ takes value 1 if the stock is in the 10th and 11th SUE quantile and zero if the stock is in the 1st and 2nd SUE quantile. The variable $Sust.Inv_t(n)$ takes value one if stock n is held by investors whose holding-weighted emission intensity demand is in the bottom quintile, and zero if the stock is held by investors whose holding-weighted emission intensity demand is in the top quintile, which are non-sustainable investors. The vector $\mathbf{x}$ with controls includes log market equity, log market-to-book, the number of analysts covering the stock and the number of earnings announcements made by other firms on the same day, emission intensity, idiosyncratic volatility and an indicator whether the stock is part of the S&P500. In addition, we control for Ardia et al. (2023)'s measure of climate news that occurs on the same day.[17] The variable θ_t captures quarter-fixed effects and $\mu(n)$ captures stock fixed effects. We adjust standard errors for heteroskedasticity and cluster by the day of the earnings announcement.

Table 5 presents the results. Stocks with high sustainable ownership overreacting to news requires the coefficient on $Top\, SUE \times Sust.Inv$, namely β_1 to be positive. The first row shows the estimate for this coefficient which is 1.2% in both the baseline specification (column 1) and the strictest specification (column 4). The effect is robust across specifications and significant at the 1% level. This implies that a stock experiencing a strong earnings surprise has a 1.2% higher

[16] Computing value-weighted portfolios yields qualitatively similar results.

[17] Hirshleifer and Sheng (2022) show that firm-specific news and macro-economics news act as complements rather than substitutes. If climate news on average favors low-emission intensity stocks in our sample, coefficient estimates would inflate.

announcement-day return if it is held by a sustainable investor compared to a stock held by a non-sustainable investor. Economically, stock market reactions to news are greater by 21% (1.2/5.6) when the stock is held by a sustainable investor compared to an non-sustainable investor. The coefficient on $Sust.Inv$ ranges between -0.34 and -0.51 and significant at the 5% level. This implies that stocks held by sustainable investors also react stronger to negative news.

We adjust regression 15 by replacing Top SUE by Positive SUE, where Positive SUE takes on value 1 if the stock has $SUE > 0$ and zero if $SUE < 0$. Columns 5-8 in Table 5 similarly reveal significant overreaction to good and bad news. The economic magnitude is column 8 is 32% (1.2/3.8), suggesting that stocks overreact also for smaller amounts of positive news.

Sustainable investors (by definition) hold relatively many sustainable stocks and possibly overreact only to stocks with certain preferential characteristics. Informally, if an investor's demand for sustainable assets is less dependent on financial stimuli, she may trade less aggressively on financial news on these assets. We run the following regression to test this intuition:

$$R_t^{h,H}(n) = \beta_1 \, Top\, SUE_t(n) \times Sust.Inv_t(n) \times Green\, stock_t(n) + \gamma' \mathbf{x} + \theta_t + \mu(n) + \epsilon_t(n), \tag{16}$$

where $\mathbf{x}$ contains the same set of controls and all lower-order interaction terms. In a given quarter, the variable $Green\, stock$ takes value 1 if emission intensity is in quintile 1 and 0 in quintile 5. Table 6 provides the results. The coefficient on $Top\, SUE \times Sust.Inv$ remains positive and significant, indicating that stocks held by sustainable investor experience stronger earning surprises than stocks held by non-sustainable investors. However, the coefficient on $Top\, SUE_t(n) \times Sust.Inv_t(n) \times Green\, stock_t(n)$ is negative indicating that the abnormal returns for stocks held by sustainable investors is weaker for green stocks as opposed to brown stocks. This effect is robust to all specifications. Thus, we conclude that the overreaction by sustainable investors is less strong in green stocks, which is consistent with the finding that sustainable investors are relatively inelastic on green stocks. The coefficient on $Sust.Inv \times Top\, SUE$ remains significant at the 1% level after controlling for $Sust.Inv \times Green\, stock$, implying that overreaction cannot be explained by stock characteristics only.

The coefficient on $Sust.Inv \times Green\, stock$ is positive, indicating that sustainable investors trade less aggressively on negative earnings shocks in green stocks. This echoes the finding of Starks et al. (2017) that sustainable investors sell less after negative earnings news. Our analysis is complementary as it shows that such underreaction only takes place in stocks with preferential characteristics.

In addition, it suggests that while inelastic behavior on green stocks results in significant price pressure upon demand shocks as in Van der Beck (2021), it also results in dampened reaction to earnings information in green stocks held by sustainable investors.

Overall, we find that stocks with high sustainable ownership react more strongly to earnings announcements news than similar stocks held by non-sustainable investors. However, green stocks held by sustainable investors underreact to news, which is consistent with the findings that sustainable investors are relatively inelastic on green stocks. These results highlight a dual role of sustainable investors as active traders over their entire portfolio holdings and preference-driven holders for sustainable stocks to which they tilt their portfolios.

6 Alternative explanations and robustness

We analyze a number of alternative explanations that ask whether the different reaction to news can be explained by variations (i) in the way we identify sustainable demand, (ii) in information collected before the announcement, (iii) the differences in the predictability of future earnings, and (iv) different reactions to systematic versus idiosyncratic news.

6.1 Identifying sustainable demand outside demand system

Since the weights of the market portfolio correlate negatively with emission intensity, we have argued that identifying sustainable investors based on portfolio emission intensity could incorrectly classify some passive demand as sustainable demand. Such passive sustainable demand could explain a relatively low sensitivity to fundamental news as documented in for example Hitzemann et al. (2024). We test whether defining sustainable investors solely based on portfolio emission intensity lowers the heightened reaction to news as documented in Table 5. For each stock, we calculate sustainable ownership as the holding-weighted portfolio emission intensity of the underlying investors. Next, each quarter, we sort stocks into quintiles based on sustainable ownership and perform regression 15. Column 1-4 in Table 7 shows that the heightened reaction to news lowers by 35-55% compared to the results in Table 5. This finding suggests that part of the lower sensitivity to fundamental news in high-sustainability ownership stocks, as documented in existing studies, can be attributed to confounding effects of passive ownership.

6.2 Pre-earnings announcement price informativeness

Sammon (2024) argues that if less information was incorporated into prices ahead of earnings releases, the earnings day return should be larger. The intuition is that if investors generate less

information, they lower pre-earnings announcement price informativeness. When news arrives, they update their beliefs more significantly, leading to higher average price reactions.

We follow Sammon (2024) by measuring pre-earnings announcement price informativeness as

$$jump_t^{(a,b)}(n) = \frac{R_t^{0,b}(n)}{R_t^{-a,b}(n)}. \tag{17}$$

We set $a = 21$ and $b = 1$ such that the numerator is the cumulative abnormal return during the first 2 trading days starting at the earnings announcement date τ. The denominator captures the cumulative abnormal return in the 21 days prior and 2 days after the earnings announcement. $jump$ thus captures the fraction of the total abnormal return from date $\tau - a$ to $\tau + b$ that occurs after the earnings release. Higher values of $jump_t^{(a,b)}(n)$ mean that more information was incorporated into the price before the release, implying higher pre-earnings announcement price informativeness.

To measure the relation between pre-earnings announcement price informativeness and sustainable demand, we run the following regression:

$$jump_t^{(a,b)}(n) = \alpha + \beta\ Sust.Inv + \gamma'\mathbf{x} + \theta_t + \mu(n) + \epsilon_t(n). \tag{18}$$

As controls $\mathbf{x}$, we include log market equity, returns from month t$-$12 to t$-$2, log market-to-book, number of analysts that cover the firm, number of announcements on the same day and whether the stock is part of S&P500. In addition, we include CAPM beta, total volatility and idiosyncratic volatility computed over the previous 252 trading days.

Columns 1-3 in Table 8 show that stocks with the highest sustainable ownership on average have 6% higher $jump$ than stocks with the lowest sustainable ownership. However, this result does not survive in the specification with stock fixed effects reported in Column 4. Thus, after accounting for differences in fixed characteristics between stocks with high and low sustainable ownership, stocks held by sustainable investors have similar pre-earnings announcement price informativeness as the ones held by non-sustainable investors. Overall, the possibility that sustainable investors generate less information pre-announcement, which leads to larger surprises, cannot explain the heightened reaction to news in stocks with high sustainable ownership.

6.3 Predictability of future earnings based on news

Potentially, earnings news is differently informative for low- and high sustainable ownership stocks. If earnings in high-sustainable ownership firms have high persistence, the heightened reac-

tion could reflect expected changes in future earnings. We compute the future percentage change in firm earnings 1, 2, 3 and 4 quarters ahead. We run regression 15 separately for firms whose future earnings percentage change is below and above the median in a given quarter. We replace the variable $Top\,SUE$ by $Positive\,SUE$ to mitigate small sample size issues.

Table 9 shows that in columns 1-4 the heightened reaction to news in stocks with high sustainable ownership is relatively high in stocks whose future earnings percentage change is above the median. This suggests that stocks whose earnings correlate positively over time experience larger price reactions to the same amount of news, which is as expected. Conversely, the heightened reaction to news in stocks with high sustainable ownership is relatively low in stocks whose future earnings percentage change is below the median, though remains significant. This indicates that while differences in the informativeness of earnings news for high- and low sustainable ownership firms partially explains the heightened reaction to news, it does not explain the entire effect.

6.4 Systematic versus idiosyncratic earnings news

We have documented so far that sustainable investors have high active shares and thus deviate from the market. Such deviations from the market portfolio could lead to sustainable investors facing higher idiosyncratic risk exposure compared to non-sustainable investors. If idiosyncratic risk is more important to sustainable investors, they may have incentives to collect relatively little information on the systematic components of earnings news. Hence, part of the heightened reaction to news may be due to lower informational efficiency of systematic news in stocks held by sustainable investors.

To investigate this possibility, we follow Glosten et al. (2021) and decompose earnings news into systematic and idiosyncratic news by running the following regression:

$$SUE_t(n) = \beta_0 + \beta_1 SUE_t^{mkt} + \beta_2 SUE_t^{ind} + \epsilon_t(n), \tag{19}$$

where SUE_t^{mkt} is the market equity-weighted earning surprise of all firms and SUE_t^{ind} is the market equity-weighted earning surprise of all firms with the same two-digit SIC code as firm i. Systematic earnings news $SUE_t^{sys}(n)$ is the fitted value from regression 19. Firm-specific earnings news $SUE_t^{idio}(n)$ is obtained as the residuals of regression 19. We run the following regression

each quarter:

$$\begin{aligned} R_t^{0,1}(n) =& \beta_1 \widehat{SUE_t^{idio}}(n) \times \mathbb{1}_{\widehat{SUE^{idio}}>0} \times Sust.Inv_t(n) + \\ & \beta_2 \left|\widehat{SUE_t^{idio}}(n)\right| \times \mathbb{1}_{\widehat{SUE^{idio}}\leq 0} \times Sust.Inv_t(n) + \\ & \beta_3 \widehat{SUE_t^{sys}}(n) \times \mathbb{1}_{\widehat{SUE^{sys}}>0} \times Sust.Inv_t(n) + \\ & \beta_4 \left|\widehat{SUE_t^{sys}}(n)\right| \times \mathbb{1}_{\widehat{SUE^{sys}}\leq 0} \times Sust.Inv_t(n) + \\ & \gamma' \mathbf{x} + \theta_t + \mu(n) + \epsilon_t(n). \end{aligned} \tag{20}$$

We cross-sectionally standardize $\widehat{SUE_t^{sys}}$ and $\widehat{SUE_t^{idio}}(n)$ to interpret the coefficients in terms of standard deviation changes.[18] We use the same set of controls and fixed effects as in the previous regressions.

Table 10 shows that stocks held by sustainable investors overreact to idiosyncratic news, but not to systematic news. Columns 1 to 4 show that stocks held by sustainable investors react $1.7-2.4\%$ stronger to a one-standard deviation increase in positive idiosyncratic earnings news than stocks held by non-sustainable investors. We find no overreaction for systematic news. Our results, thus, indicate that lower informational efficiency about the systematic components of earnings news cannot explain the heightened reaction to news. The overreaction to idiosyncratic news is best explained by sustainable investors paying more attention to idiosyncratic news as this is more important to them.

We next investigate how sustainable investors react to climate news as a second source of systematic news. Whether sustainable investors would under- or overreact to climate news is conceptually ambiguous. One possibility is that sustainable investors view climate change as a first order concern, could be well and timely informed about innovations in climate concerns and consequently trade stronger in response to climate news. A second possibility is that sustainable investors are relatively insensitive to climate news as their incentive to invest sustainably is less dependent on fundamental news. Informally, sustainable investor hold green stocks in good and bad times. To test the effect of systematic climate news, we run the following regression with daily excess returns as the dependent variable:

$$\begin{aligned} R_t(n) = \beta_1 \, Climate\, news_t \times Sust.Inv_t(n) \times Greenstock_t(n) + \\ \gamma' \mathbf{x} + \theta_t + \mu(n) + \epsilon_t(n). \end{aligned} \tag{21}$$

[18] We do not sort stocks into news quintiles given the fact that we have two news measures and the need to evaluate them jointly.

The variable $Climate\,news$ is Ardia et al. (2023)'s daily climate news indicator, which captures unexpected innovations in climate news based on textual analysis applied to newspaper. Larger values on this climate news measure imply good news to green stocks. We use the same controls as in Ardia et al. (2023), which include the Fama and French 5-factors and indices on the price of crude oil, natural gas, propane. In addition, we include the VIX index, the TED spread and the U.S. Climate Policy Index. The regression warrants a triple interaction as climate news is relevant only for stocks with either sustainable or non-sustainable characteristics. Column 1 in Table 11 confirms the result of Ardia et al. (2023) that stocks with low-emission intensity benefit from increases in climate concerns. The coefficient on $Climate\,news \times Green\,stock \times Sust.Inv$ in column 2, 3 and 4 reveals that after controlling for the direct effect of climate news on returns through a stock's emission intensity, green stocks held by sustainable investor underreact to climate news. Specifically, conditional on a stock being classified in green, its daily return increases by 0.09-0.11% less to one unit increase in climate news if it is held by a sustainable investor. Hence, while sustainable investors are sensitive to idiosyncratic news, they underreact to systematic news.

Overall, we show that differences in reactions to news cannot be explained by variations in information collected before the announcement or the predictability of future earnings. Instead, our results point towards sustainable investors being more informed about idiosyncratic news and less about systematic news.

7 Conclusion

We investigate how actively sustainable investors trade and study implications for aggregate informational efficiency. We find that sustainable investors have high price elasticity, but are relatively inelastic on stocks with characteristics to which they tilt. Using counterfactual analyses, we find that across-investor demand shifts but not within-investor sustainable demand shifts improve price informativeness and investment-to-price sensitivity, primarily at longer horizons. Sustainable investors are thus informed about future earnings based on their entire set of demand shifters and not just their views on emissions. Stocks held by sustainable investors experience larger price reactions to news, yet this overreaction weakens on green stocks. This differential price reaction is driven by sustainable investors being more sensitive to idiosyncratic over systematic news and not by differences in pre-earnings announcement price informativeness or the predictability of future earnings based on news.

Previous studies have shown that while sustainable investors underreact to fundamental news,

they have high price elasticity, which implies aggressive trading in response to price changes. We reconcile these seemingly puzzling results by showing that sustainable investors only underreact in stocks with preferential characteristics. In addition, our results emphasize the need to jointly estimate sustainable demand and price elasticity, as identifying sustainable investors based on sustainable characteristics of portfolio holdings could erroneously classify passive demand as sustainable demand. This suggests that estimates in prior studies classifying sustainable based on holding-weighted portfolio characteristics may be confounded with passive demand.

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Figure 1: AUM-weighted average portfolio emission intensities by type. In each quarter, we first compute the holdings-weighted portfolio emission intensity for each investor. We then calculate the AUM-weighted average portfolio emission intensity for each investor type.

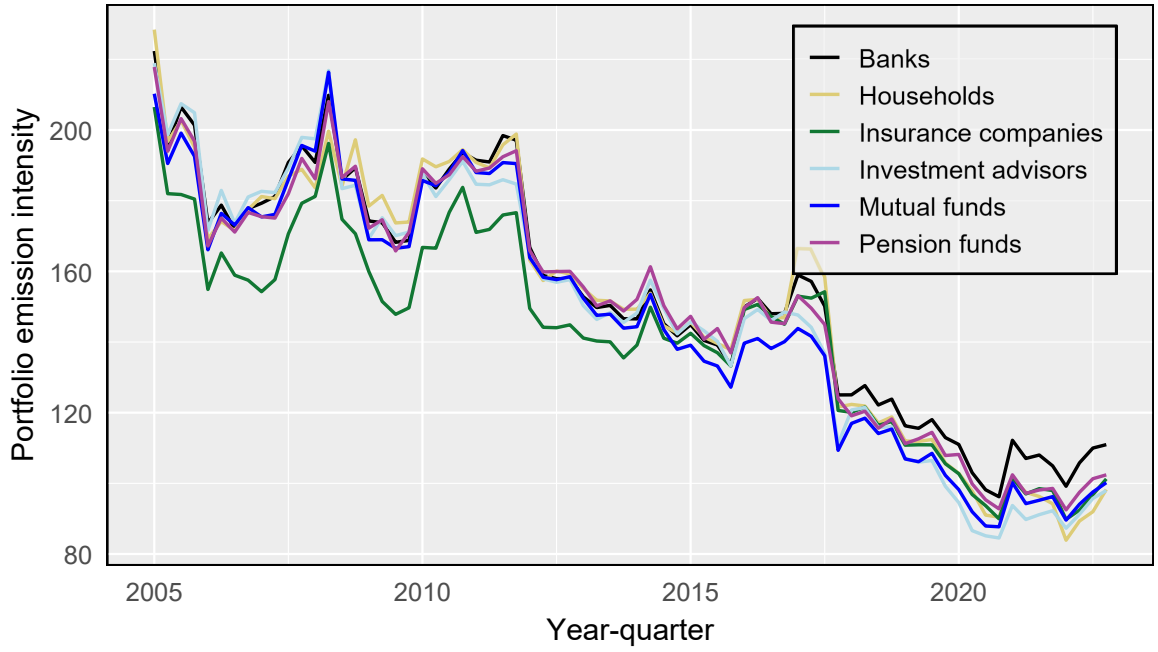


Figure 2: Demand coefficient of scope 1 and 2 emissions intensity over time. The plot shows the asset under management weighted demand coefficient by investor type over time.

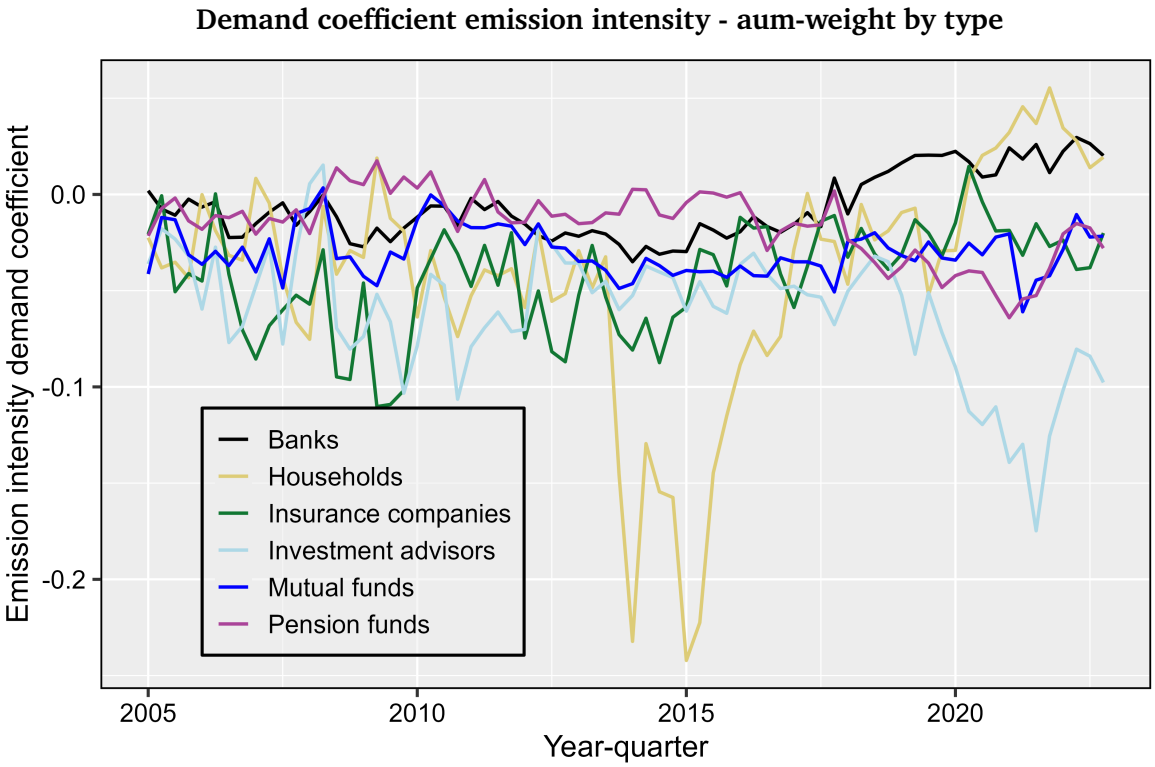


Figure 3: Relation between investor-level price elasticity and demand coefficient for emission intensity. Each quarter, we sort investors into 3,000 percentiles by their emission intensity demand. For each percentile, we calculate the equal-weighted average coefficient on price elasticity and average emission intensity demand coefficient. Investor price elasticity is defined as 1 minus the demand coefficient on market-to-book, denoted by $\beta_{0,it}$ in equation 4.

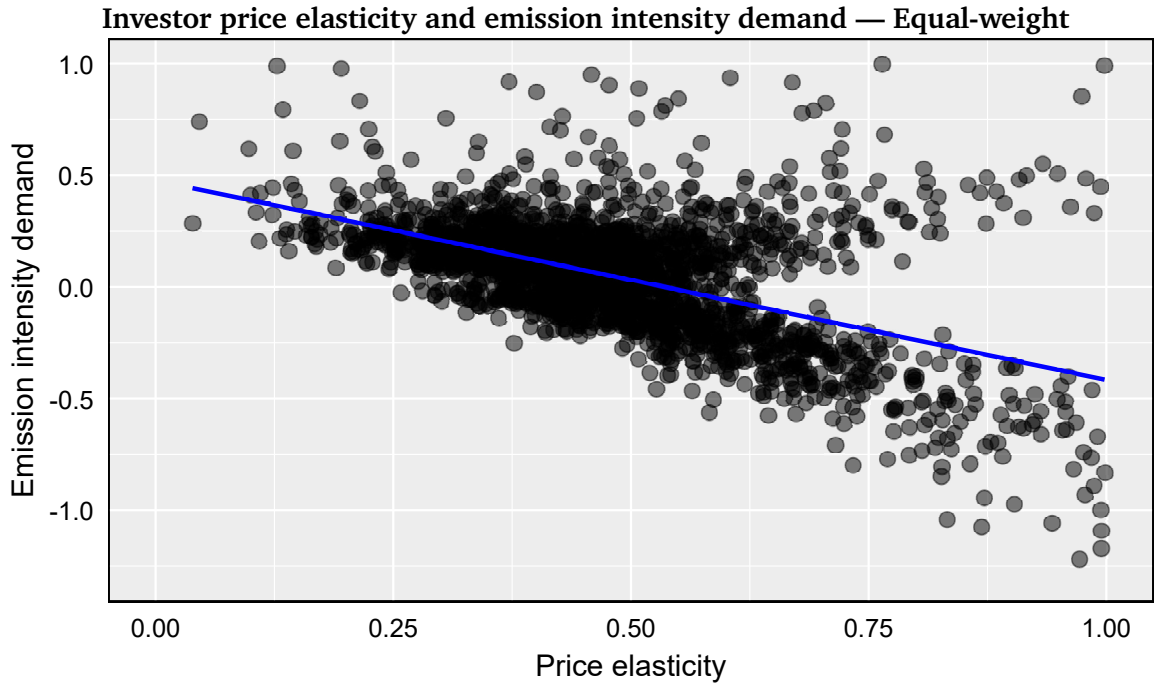


Figure 4: The relationship between investor portfolio emission intensity and investor emission intensity demand coefficients. The observations labeled with 'mismatch' cover investors characterized as sustainable based on portfolio emission intensity but not based on the demand system. We decompose this group into price elastic investors, who have price elasticity larger than the median investor in a given quarter. The remainder comprises price inelastic investors.

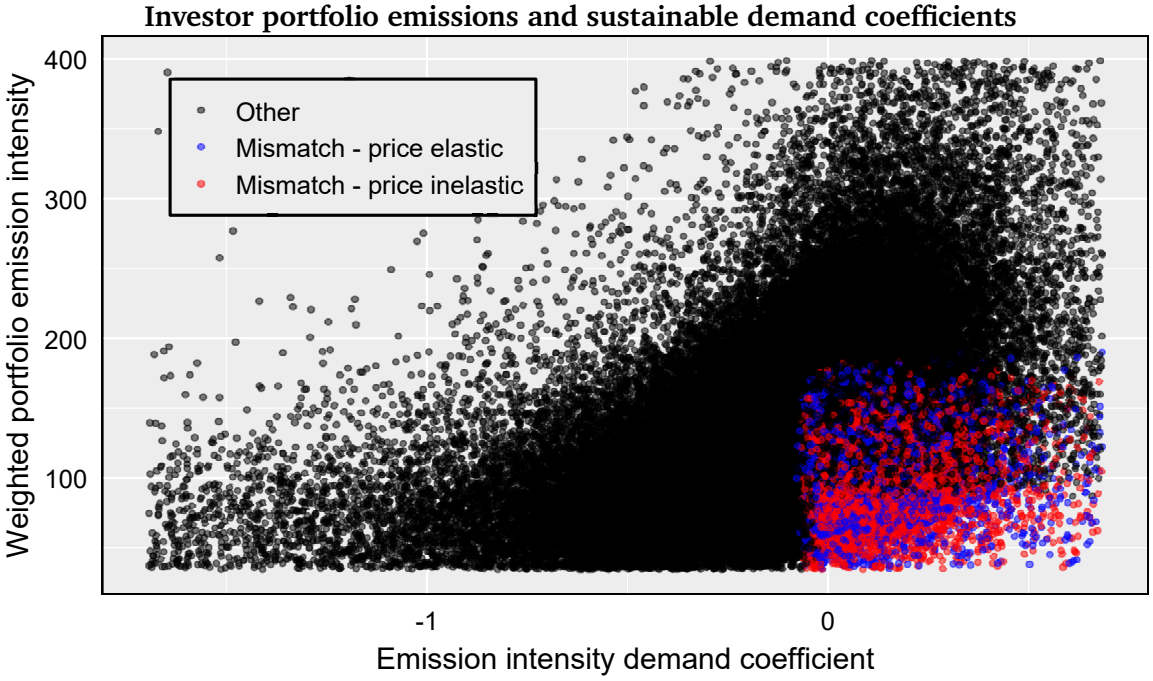


Figure 5: R-squared of a quarterly regression of total emission intensity demand changes on active emission intensity demand changes.

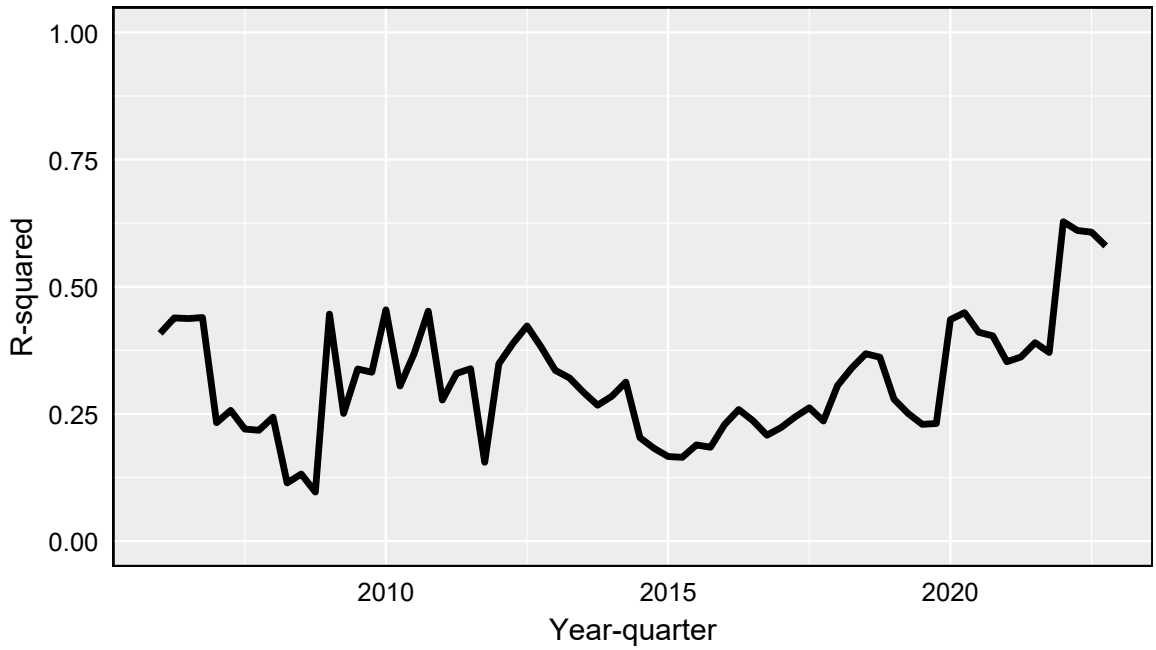


Figure 6: Impact of across-investor demand shifts on price informativeness. Each quarter, we model that assets under management of investors whose emission intensity demand coefficient is negative flow to investors whose emission intensity demand coefficient is positive. We compute counterfactual market prices using the algorithm of Koijen et al. (2024). Green (Brown) stocks are stocks whose emission intensity is above (below) the median in a given quarter.

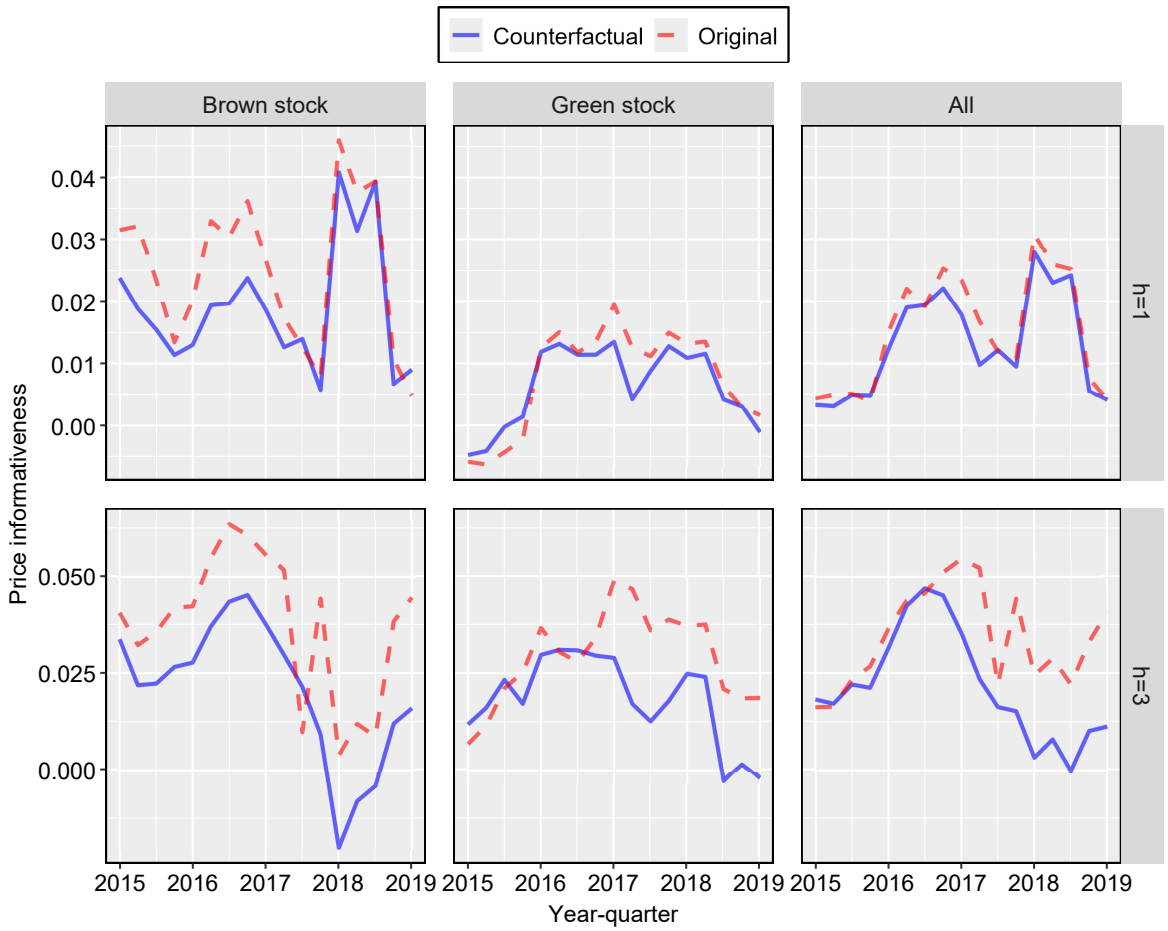


Figure 7: Impact of within-investor demand shifts on price informativeness. Each quarter, we set the emission demand coefficient to zero of investors whose emission intensity demand coefficient is negative. We compute counterfactual market prices using the algorithm of Koijen et al. (2024). Green (Brown) stocks are stocks whose emission intensity is above (below) the median in a given quarter.

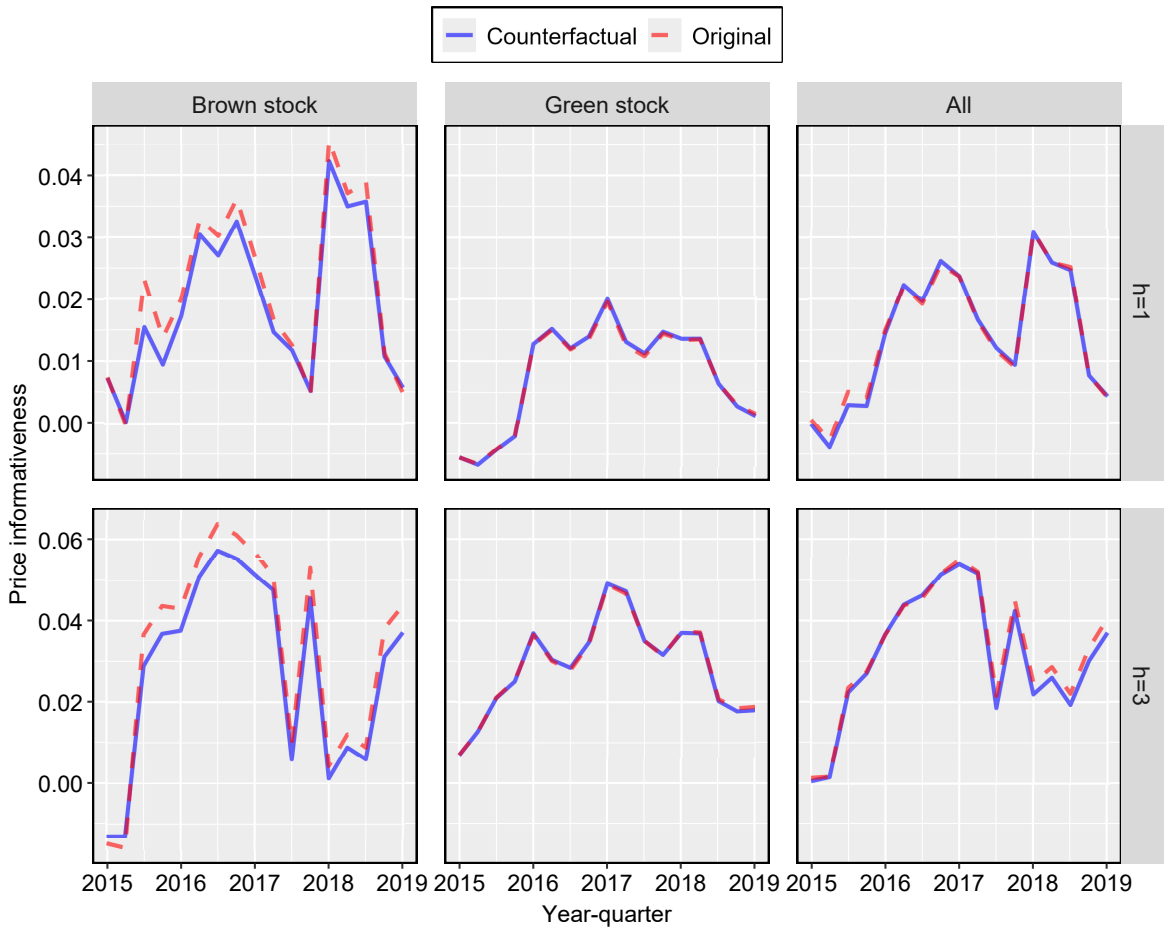


Figure 8: Impact of across-investor demand shifts on investment-to-price sensitivity. Each quarter, we model that assets under management of investors whose emission intensity demand coefficient is negative flow to investors whose emission intensity demand coefficient is positive. We compute counterfactual market prices using the algorithm of Koijen et al. (2024). Green (Brown) stocks are stocks whose emission intensity is above (below) the median in a given quarter.

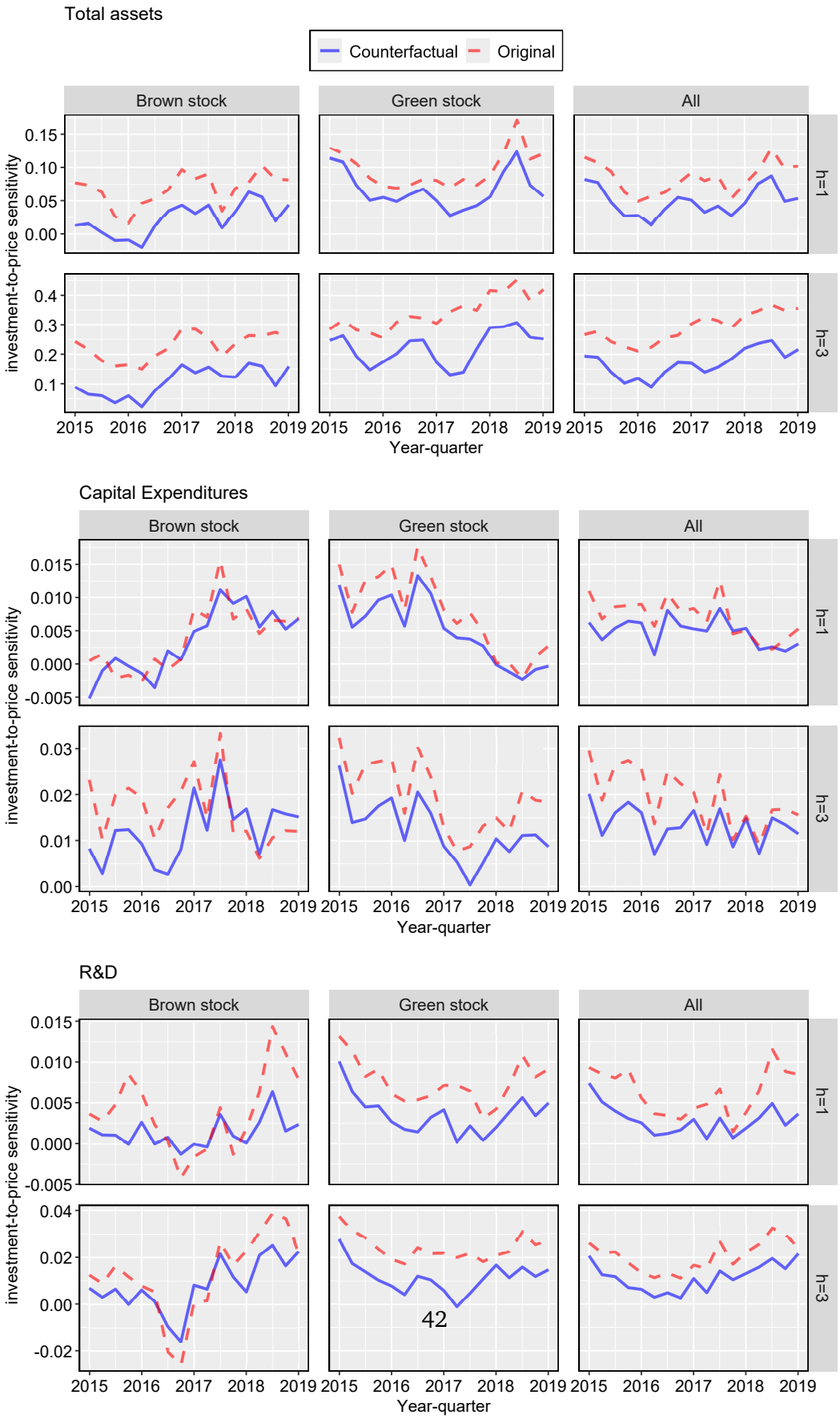


Figure 9: Impact of within-investor demand shifts on investment-to-price sensitivity. Each quarter, we set the emission demand coefficient to zero of investors whose emission intensity demand coefficient is negative. We compute counterfactual market prices using the algorithm of Koijen et al. (2024). Green (Brown) stocks are stocks whose emission intensity is above (below) the median in a given quarter.

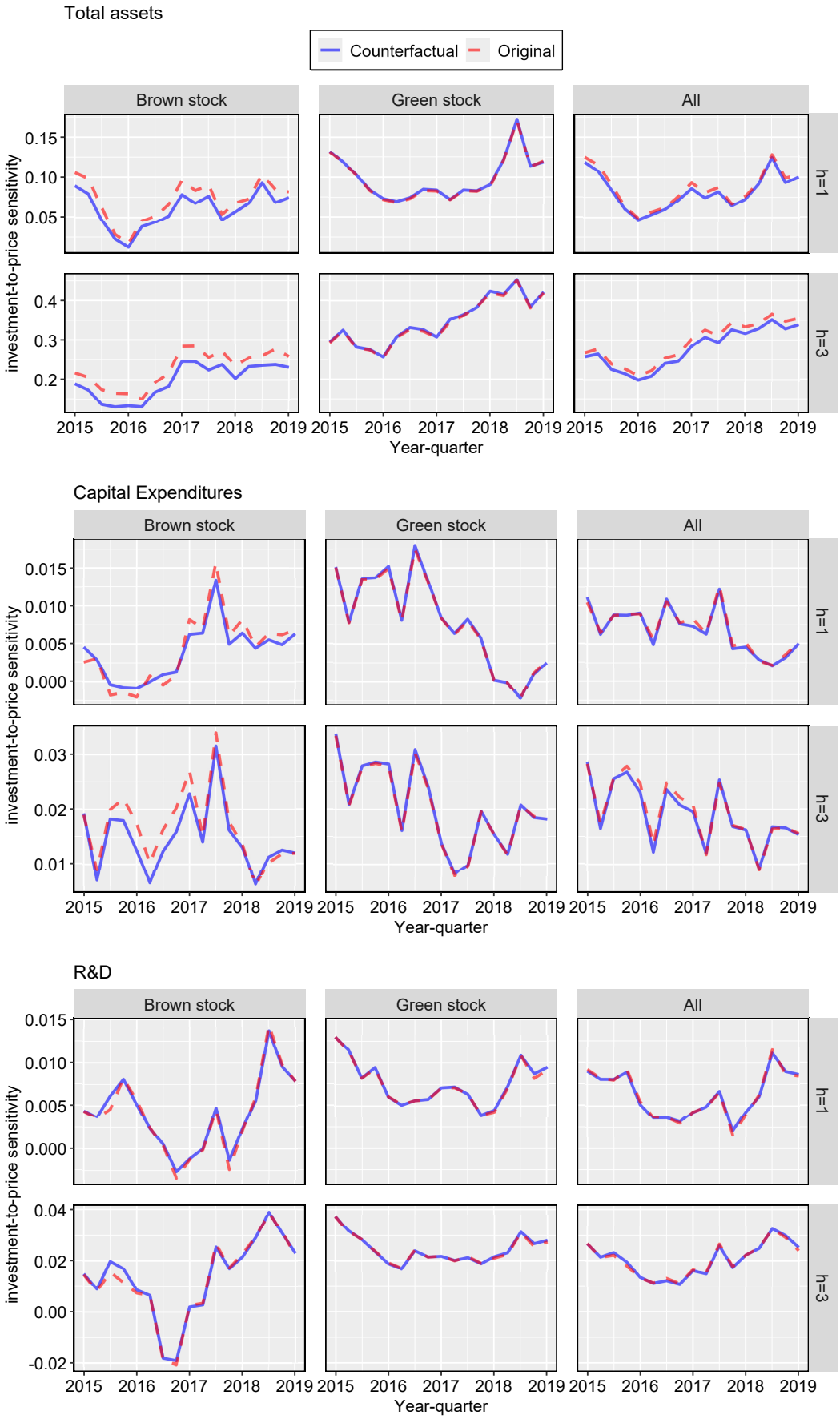


Figure 10: Earnings day abnormal return (AR) across stocks with different levels of sustainable ownership. Each quarter, stocks are independently sorted into quintiles based the holding-weighted emission intensity demand coefficient of the underlying investors and their earnings surprise. Stocks held by investors whose holding-weighted emission intensity demand coefficient is in the bottom (top) quintile are classified as sustainable (unsustainable). Announcement day abnormal return is the cumulative abnormal return in the 2 trading days following the announcement.

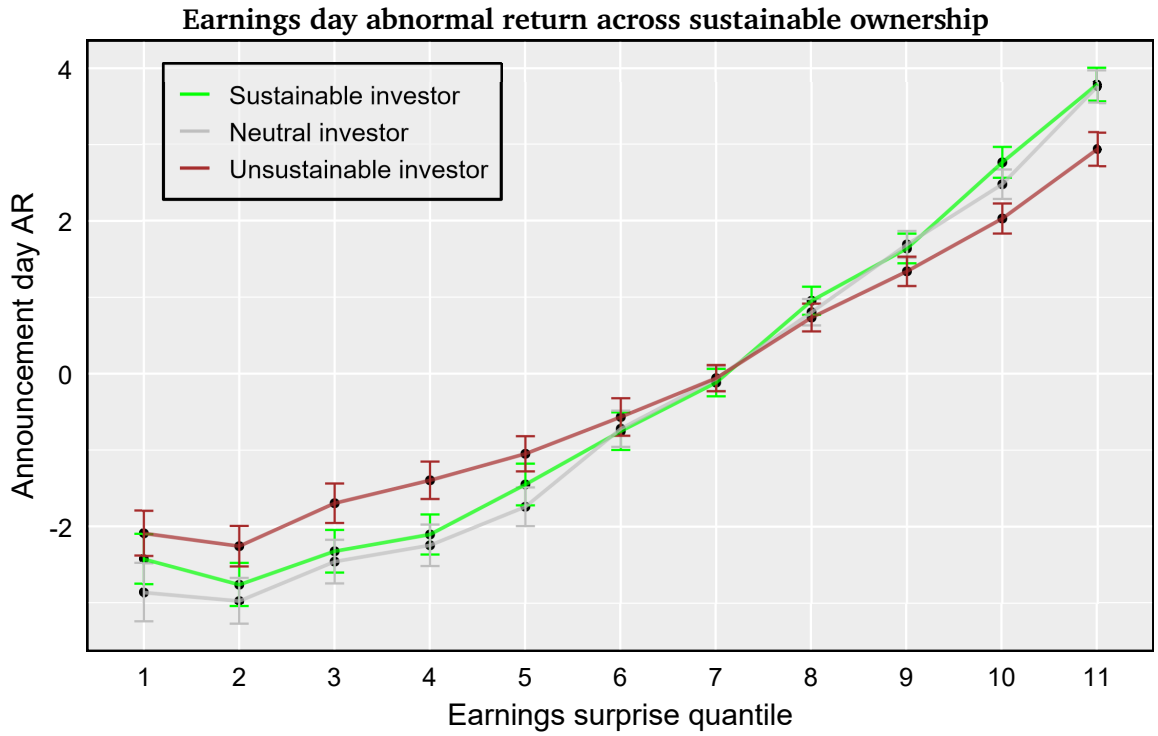


Table 1: Estimated demand coefficients. For each investor i in each quarter t, we estimate the following regression: $\frac{w_{it}(n)}{w_{it}(0)} = \exp\left(b_{0,it} + \beta_{0,it}\text{mb}_t(n) + \beta_{1,it}\mathbf{x}_t(n)'\right)\epsilon_{it}(n)$. We first compute the equal- or value-weight mean and standard deviation of investor demand coefficients in each quarter, after which we calculate the time-series average, denoted by $Mean$ and the standard deviation of the time-series, denoted by $SD(time)$. $SD(cross)$ is the time-series average of the cross-sectional standard deviation of investor demand coefficients. Panel A reports demand coefficients for all characteristics based on all investors. Panel B reports the emission intensity demand coefficient across investor types. Households are considered a single investor in the demand system and thus have no information on cross-sectional standard deviations.

	Equal-Weight			**Value-Weight**		
	Mean	SD (time)	SD (cross)	Mean	SD (time)	SD (cross)
Panel A: all characteristics						
Log market-to-book	0.44	0.12	0.69	0.72	0.11	0.42
Log book equity	0.77	0.15	0.62	1.20	0.12	0.38
Market beta	-0.06	0.06	0.39	-0.00	0.02	0.16
Dividends-to-book	0.03	0.04	0.41	0.07	0.02	0.24
Scope 1+2 emission intensity	-0.12	0.03	0.50	-0.04	0.02	0.20
Profit-to-assets	0.05	0.04	0.37	0.05	0.02	0.16
Investment	0.05	0.05	0.35	0.03	0.02	0.15
Green patents (5y) to assets	-0.03	0.03	0.41	0.01	0.01	0.17
Panel B: emission intensity						
Banks	-0.08	0.03	0.23	-0.01	0.02	0.08
Insurance companies	-0.08	0.04	0.21	-0.04	0.03	0.13
Investment advisors	-0.12	0.03	0.52	-0.06	0.03	0.36
Mutual funds	-0.13	0.05	0.49	-0.03	0.01	0.21
Pension funds	-0.03	0.03	0.14	-0.02	0.02	0.07
Households	-0.04	0.06	-	-	-	-
Other	-0.15	0.07	0.48	-0.09	0.05	0.25

Table 2: Results of regression 9 with h-years earnings to assets ahead as the dependent variable. CF-across captures market equity in a scenario where all assets from investors with a negative demand coefficient on emission intensity flow to investors with a positive coefficient on emission intensity. CF-within captures market equity when we set the demand coefficient on emission intensity to zero for all investors who have negative demand for emission intensity. The p-value corresponds to a test of whether the coefficient on 'Log market equity to assets' differs significantly from that on 'Log market equity to assets$^{\text{CF}}$'. Standard errors are reported in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	h-year ahead earnings								
	$h=1$			$h=3$			$h=5$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log market equity to assets	0.02***			0.03***			0.08***		
	(0.001)			(0.001)			(0.003)		
Log market equity to assets$^{\text{CF-across}}$		0.01***			0.02***			0.05***	
		(0.001)			(0.001)			(0.002)	
Log market equity to assets$^{\text{CF-within}}$			0.02***			0.03***			0.07***
			(0.001)			(0.001)			(0.003)
Earnings to assets	0.90***	0.91***	0.90***	0.83***	0.87***	0.84***	0.66***	0.75***	0.68***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)
Constant	0.12***	−0.07***	−0.10***	0.29***	−0.09***	−0.16***	0.61***	−0.29***	−0.44***
	(0.01)	(0.005)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
P-value difference in coefficients		0.00	0.89		0.00	0.61		0.00	0.77
Observations	8,342	8,342	8,342	8,000	8,000	8,000	5,428	5,428	5,428
R^2	0.75	0.74	0.75	0.53	0.52	0.53	0.38	0.35	0.38
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Average stock-level price elasticity across of stock emissions intensity and underlying investor demand for emission intensity. Each quarter, we sort stocks into quintiles based on emission intensity and the holding-weighted demand for emissions intensity of the underlying investors. In each, we compute an value-weighted average of price elasticity. A value of 1 represents highly elastic and close to zero represents inelastic. Households are excluded from the calculation of stock-level measures. Standard deviations are in brackets and absolute t-statistics in parentheses.

	Demand for emission intensity						
Stock emission intensity	**1**	**2**	**3**	**4**	**5**	**[5-1]**	**Single sort**
1	0.24	0.14	0.14	0.15	0.18	-0.07	0.16
	[0.50]	[0.09]	[0.08]	[0.08]	[0.18]	(16.11)	[0.20]
2	0.18	0.15	0.15	0.14	0.17	-0.02	0.15
	[0.16]	[0.09]	[0.08]	[0.07]	[0.11]	(13.39)	[0.10]
3	0.22	0.15	0.16	0.16	0.18	-0.04	0.16
	[0.18]	[0.10]	[0.10]	[0.09]	[0.11]	(27.58)	[0.11]
4	0.29	0.17	0.16	0.16	0.17	-0.11	0.17
	[0.26]	[0.12]	[0.09]	[0.07]	[0.11]	(35.60)	[0.12]
5	0.47	0.22	0.17	0.16	0.17	-0.30	0.18
	[0.68]	[0.15]	[0.09]	[0.08]	[0.09]	(24.97)	[0.16]
[5-1]	0.22	0.08	0.03	0.01	-0.01		
T-statistic	(19.38)	(35.22)	(22.47)	(6.15)	(1.93)		
Single sort	0.24	0.15	0.16	0.16	0.17		
	[0.35]	[0.10]	[0.09]	[0.08]	[0.11]		

Table 4: Panel A shows the average stock-level price elasticity across of stock emissions intensity and underlying investor demand for emission intensity. Within a given stock, we compute the holding-weighted price elasticity for: i) green-active, ii) other active and iii) passive investors. Next, each quarter, we sort stocks into quintiles based on emission intensity and the holding-weighted demand for emissions intensity of the underlying investors. In each quintile, we compute a value-weighted average of price elasticity for each investor group separately. Panel B shows the ownership shares by investor-stock type combination. For each, we compute the ownership share of the different investors. Next, each quarter, we sort stocks into quintiles based on emission intensity and the holding-weighted demand for emissions intensity of the underlying investors. In each quintile, we compute a value-weighted average of ownership shares for each investor group separately.

Panel A: Stock-level price elasticity

	Demand for emission intensity				
	1	**2**	**3**	**4**	**5**
Green active					
1	0.49	0.62	-	-	-
2	0.53	0.61	-	-	-
3	0.49	0.62	-	-	-
4	0.52	0.59	-	-	-
5	0.68	0.65	-	-	-
Other active					
1	-	-	-	0.42	0.40
2	-	-	-	0.44	0.44
3	-	-	-	0.46	0.44
4	-	-	-	0.46	0.47
5	-	-	-	0.52	0.55
Passive					
1	-	0.08	0.07	0.08	-
2	-	0.08	0.07	0.07	-
3	-	0.07	0.07	0.08	-
4	-	0.08	0.07	0.08	-
5	-	0.09	0.08	0.08	-

Panel B: Ownership shares

	Demand for emission intensity				
	1	**2**	**3**	**4**	**5**
Green active					
1	0.07	0.08	-	-	-
2	0.06	0.07	-	-	-
3	0.06	0.06	-	-	-
4	0.05	0.06	-	-	-
5	0.05	0.05	-	-	-
Other active					
1	-	-	-	0.04	0.03
2	-	-	-	0.04	0.03
3	-	-	-	0.04	0.03
4	-	-	-	0.04	0.03
5	-	-	-	0.04	0.04
Passive					
1	-	0.63	0.56	0.54	-
2	-	0.62	0.57	0.55	-
3	-	0.62	0.57	0.57	-
4	-	0.60	0.54	0.49	-
5	-	0.58	0.56	0.57	-

Table 5: Regression results of regression 15 using $R_{nt}^{0,1}$ as the dependent variable. Sust.Inv takes value 1 if the stock is held by investors whose holding-weighted demand coefficient on emission intensity is in quintile 1 and 0 if in quintile 5. In columns 1-4 Top SUE takes value 1 for earnings surprises in the 10th and 11th quintile and 0 for earnings surprises in the 1st and 2nd quintile. In columns 4-6, Positive SUE takes value 1 for SUE>0 and 0 for SUE<0. No. analysts measures the number of analysts tracking the stock, No. announcements is the number of announcement happening on the same day, S&P500 is an indicator for whether the stock is part of the S&P500, emission intensity the sum of scope 1 and 2 emissions divided by sales and climate news is the shock indicator by Ardia et al. (2023). Standard errors are clustered by stock and day of the announcement and are reported in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	2-day announcement AR							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top SUE × Sust.Inv	1.19***	1.12***	1.15***	1.16***				
	(0.19)	(0.26)	(0.26)	(0.31)				
Top SUE	5.18***	5.56***	5.49***	5.58***				
	(0.13)	(0.19)	(0.19)	(0.23)				
Positive SUE × Sust.Inv					0.76***	1.03***	1.02***	1.20***
					(0.11)	(0.14)	(0.14)	(0.16)
Positive SUE					3.62***	3.77***	3.77***	3.80***
					(0.08)	(0.10)	(0.10)	(0.11)
Sust.Inv	−0.34**	−0.15	−0.20	−0.51*	−0.40***	−0.48***	−0.50***	−0.62***
	(0.16)	(0.21)	(0.22)	(0.29)	(0.09)	(0.12)	(0.12)	(0.15)
Constant	−2.78***	−1.01	2.21		−2.14***	1.77***	1.05	
	(0.10)	(1.08)	(3.49)		(0.06)	(0.65)	(1.86)	
Observations	19,297	10,702	10,702	10,702	47,777	27,887	27,887	27,887
R^2	0.15	0.19	0.20	0.20	0.08	0.11	0.11	0.13
Stock FE	No	No	No	Yes	No	No	No	Yes
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Quarter FE	No	No	Yes	Yes	No	No	Yes	Yes

Table 6: Regression results of regression 15 using $R_{nt}^{0,1}$ as the dependent variable. Sust.Inv takes value 1 if the stock is held by investors whose holding-weighted demand coefficient on emission intensity is in quintile 1 and 0 if in quintile 5. In columns 1-4 Top SUE takes value 1 for earnings surprises in the 10th and 11th quintile and 0 for earnings surprises in the 1st and 2nd quintile. In columns 4-6, Positive SUE takes value 1 for SUE>0 and 0 for SUE<0. The variable Green stock takes value 1 if emission intensity is in quintile 1 and 0 in quintile 5. As controls, the include the number of analysts tracking the stock, the number of announcement happening on the same day, an indicator for whether the stock is part of the S&P500 and climate news is the shock indicator by Ardia et al. (2023). Standard errors are clustered by stock and day of the announcement and are reported in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	2-day announcement AR							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top SUE × Sust.Inv × Green	−1.693**	−2.244***	−2.355***	−2.044**				
	(0.708)	(0.816)	(0.824)	(0.881)				
Positive SUE × Sust.Inv × Green					−1.605***	−2.169***	−2.177***	−2.134***
					(0.372)	(0.438)	(0.438)	(0.458)
Top SUE × Sust.Inv	1.683***	1.951***	2.016***	1.423**				
	(0.481)	(0.544)	(0.550)	(0.591)				
Top SUE × Green	0.817*	0.795	0.979*	0.809				
	(0.486)	(0.579)	(0.581)	(0.655)				
Positive SUE × Sust.Inv					1.577***	1.872***	1.862***	1.998***
					(0.264)	(0.300)	(0.300)	(0.307)
Positive SUE × Green					0.854***	1.109***	1.132***	1.043***
					(0.237)	(0.287)	(0.287)	(0.320)
Sust.Inv× Green	1.272**	2.119***	2.210***	3.065***	0.877***	1.754***	1.763***	2.067***
	(0.587)	(0.671)	(0.679)	(0.886)	(0.297)	(0.349)	(0.350)	(0.450)
Top SUE	4.926***	5.019***	4.958***	5.336***				
	(0.281)	(0.339)	(0.342)	(0.372)				
Positive SUE					2.796***	2.863***	2.886***	2.974***
					(0.126)	(0.144)	(0.144)	(0.140)
Sust.Inv	−0.711*	−1.196***	−1.290***	−1.623***	−0.677***	−1.243***	−1.246***	−1.480***
	(0.390)	(0.448)	(0.454)	(0.616)	(0.208)	(0.243)	(0.244)	(0.319)
Green	−0.740*	−0.925*	−1.043**	4.687***	−0.397**	−0.902***	−0.887***	0.315
	(0.411)	(0.489)	(0.490)	(1.555)	(0.190)	(0.236)	(0.237)	(0.915)
Constant	−2.669***	1.331	1.670		−1.716***	2.989***	10.007***	
	(0.238)	(1.636)	(1.817)		(0.103)	(0.961)	(0.993)	
Observations	6,175	4,481	4,481	4,481	6,175	4,481	4,481	4,481
R^2	0.18	0.18	0.19	0.20	0.16	0.18	0.19	0.20
Stock FE	No	No	No	Yes	No	No	No	Yes
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Quarter FE	No	No	Yes	Yes	No	No	Yes	Yes

Table 7: Regression results of regression 15 using $R_{nt}^{0,1}$ as the dependent variable. As a robustness test, we define sustainable ownership based on the portfolio emission intensity of the underlying investors. Sust.Inv takes value 1 if the holding-weighted average portfolio emission intensity of the underlying investors is in quintile 1 and 0 if in quintile 5. In columns 1-4 Top SUE takes value 1 for earnings surprises in the 10th and 11th quintile and 0 for earnings surprises in the 1st and 2nd quintile. In columns 4-6, Positive SUE takes value 1 for SUE>0 and 0 for SUE<0. No. analysts measures the number of analysts tracking the stock, No. announcements is the number of announcement happening on the same day, S&P500 is an indicator for whether the stock is part of the S&P500, emission intensity the sum of scope 1 and 2 emissions divided by sales and climate news is the shock indicator by Ardia et al. (2023). Standard errors are clustered by stock and day of the announcement and are reported in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	2-day announcement AR							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top SUE × Sust.Inv	0.34*	0.57**	0.59**	0.55*				
	(0.20)	(0.26)	(0.26)	(0.32)				
Top SUE	5.40***	5.64***	5.59***	5.68***				
	(0.13)	(0.18)	(0.18)	(0.21)				
Positive SUE × Sust.Inv					0.48***	0.97***	0.97***	1.13***
					(0.11)	(0.14)	(0.14)	(0.16)
Positive SUE					3.67***	3.76***	3.76***	3.77***
					(0.08)	(0.10)	(0.10)	(0.11)
Sust.Inv	0.17	−0.05	−0.09	0.50	−0.19**	−0.69***	−0.72***	−0.31
	(0.16)	(0.22)	(0.22)	(0.35)	(0.09)	(0.12)	(0.12)	(0.19)
Constant	−2.92***	−3.88***	−0.94		−2.19***	0.13	0.12	
	(0.10)	(1.09)	(3.94)		(0.06)	(0.65)	(2.35)	
Observations	21,515	11,365	11,365	11,365	54,084	30,638	30,638	30,638
R^2	0.13	0.17	0.17	0.17	0.08	0.11	0.11	0.13
Stock FE	No	No	No	Yes	No	No	No	Yes
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Quarter FE	No	No	Yes	Yes	No	No	Yes	Yes

Table 8: Regression results of regression 18 using $jump$ as the dependent variable. $jump$ captures the fraction of the cumulative abnormal return from 21 days prior to 1 day after the earnings announcement data that occurs after the earnings release. $jump$ is inversely related to pre-earning price informativeness. It *Sust.Inv* takes the value 1 if the stock is held by investors whose holding-weighted demand coefficient on emission intensity is in quintile 1, and 0 if in quintile 5. As controls, we include log market equity, returns from month t$-$12 to t$-$2, log market-to-book, number of analysts that cover the firm, number of announcements on the same day and whether the stock is part of S&P500. Standard errors are clustered by stock and day of the announcement and are reported in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Jump			
	(1)	(2)	(3)	(4)
Sust.Inv	0.075***	0.055**	0.056**	−0.036
	(0.023)	(0.027)	(0.027)	(0.039)
Constant	0.316***	0.463**	0.346	
	(0.016)	(0.230)	(0.272)	
Observations	57,923	46,709	46,709	46,709
R^2	0.00	0.00	0.00	0.00
Stock FE	No	No	No	Yes
Quarter FE	No	No	Yes	Yes
Controls	No	Yes	Yes	Yes

Table 9: Regression results of regression 15 using $R_{nt}^{0,1}$ as the dependent variable. 'ΔE XQ ahead' denotes the percentage change in firm earnings between the current quarter and X quarters ahead. Low and high denote firms below and above the median based on 'ΔE XQ ahead'. Sust.Inv takes value 1 if the stock is held by investors whose holding-weighted demand coefficient on emission intensity is in quintile 1 and 0 if in quintile 5. Positive SUE takes value 1 for SUE>0 and 0 for SUE<0. As controls, we include log market equity, log market-to-book, the number of analysts tracking the stock, the number of announcement happening on the same day, an indicator for whether the stock is part of the S&P500 and climate news is the shock indicator by Ardia et al. (2023). *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	2-day announcement AR							
	ΔE 1Q ahead		ΔE 2Q ahead		ΔE 3Q ahead		ΔE 4Q ahead	
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Positive SUE $\times$ Sust.Inv	1.096***	1.120***	0.739**	1.221***	1.047***	1.047***	1.237***	0.595*
	(0.273)	(0.249)	(0.296)	(0.274)	(0.318)	(0.292)	(0.326)	(0.310)
Positive SUE	3.950***	3.692***	4.146***	3.644***	3.837***	3.773***	3.734***	4.125***
	(0.191)	(0.179)	(0.203)	(0.192)	(0.212)	(0.202)	(0.216)	(0.215)
Sust.Inv	−0.479*	−0.787***	−0.521*	−0.642**	−0.894***	−0.590**	−0.815**	−0.285
	(0.266)	(0.246)	(0.291)	(0.276)	(0.319)	(0.296)	(0.332)	(0.313)
Observations	12,460	12,620	10,774	10,901	9,423	9,529	8,755	8,710
R^2	0.127	0.134	0.129	0.135	0.127	0.134	0.127	0.133
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Regression results of regression 20 using $R_{nt}^{0,1}$ as the dependent variable. *Sust.Inv* takes the value 1 if the stock is held by investors whose holding-weighted demand coefficient on emission intensity is in quintile 1, and 0 if in quintile 5. SUE^{idio} and SUE^{sys} are the idiosyncratic and systematic news components estimated from regression 19, respectively. As controls, we include log market equity, log market-to-book, the number of analysts tracking the stock, the number of announcement happening on the same day, emission intensity, an indicator for whether the stock is part of the S&P500 and the climate news indicator by Ardia et al. (2023). Standard errors are clustered by stock and day of the announcement. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	2-day announcement AR			
	(1)	(2)	(3)	(4)
$\text{SUE}^{\text{idio}} \times \mathbb{1}_{\text{SUE}^{\text{idio}}>0} \times$ Sust.Inv	1.698***	2.812***	2.890***	2.390**
	(0.401)	(0.853)	(0.891)	(1.041)
$\lvert\text{SUE}^{\text{idio}}\rvert \times \mathbb{1}_{\text{SUE}^{\text{idio}}\leq 0} \times$ Sust.Inv	−0.060	−0.246	−0.239	−0.446
	(0.120)	(0.211)	(0.203)	(0.284)
$\text{SUE}^{\text{sys}} \times \mathbb{1}_{\text{SUE}^{\text{sys}}>0} \times$ Sust.Inv	−0.101	0.119	0.149	0.163
	(0.096)	(0.124)	(0.122)	(0.143)
$\lvert\text{SUE}^{\text{sys}}\rvert \times \mathbb{1}_{\text{SUE}^{\text{sys}}\leq 0} \times$ Sust.Inv	−0.007	0.119	0.118	0.105
	(0.079)	(0.099)	(0.100)	(0.129)
$\text{SUE}^{\text{idio}} \times \mathbb{1}_{\text{SUE}^{\text{idio}}>0}$	0.364***	0.446	0.481	1.047**
	(0.135)	(0.284)	(0.294)	(0.491)
$\lvert\text{SUE}^{\text{idio}}\rvert \times \mathbb{1}_{\text{SUE}^{\text{idio}}\leq 0}$	−0.344***	−0.233*	−0.204*	−0.283**
	(0.056)	(0.119)	(0.113)	(0.130)
$\text{SUE}^{\text{sys}} \times \mathbb{1}_{\text{SUE}^{\text{sys}}>0}$	0.097	−0.077	−0.065	−0.003
	(0.064)	(0.087)	(0.087)	(0.104)
$\lvert\text{SUE}^{\text{sys}}\rvert \times \mathbb{1}_{\text{SUE}^{\text{sys}}\leq 0}$	−0.012	−0.029	−0.006	0.033
	(0.055)	(0.068)	(0.069)	(0.093)
Observations	57,924	33,040	33,040	33,040
R^2	0.00	0.02	0.02	0.04
Stock FE	No	No	No	Yes
Quarter FE	No	No	Yes	Yes
Controls	No	Yes	Yes	Yes

Table 11: Regression results of regression 21 using daily excess stock returns as the dependent variable. Sust.Inv takes value 1 if the stock in a given quarter is held by investors whose holding-weighted demand coefficient on emission intensity is in quintile 1 and 0 if in quintile 5. The variable Green stock takes value 1 if in a given quarter the stock's emission intensity is in quintile 1 and 0 in quintile 5. As controls, we include the MKT, HML, SMB, RMW, CMA factors, crude oil price index, natural gas price index, propane index, TED-spread, US climate policy index and the VIX. Newey-West standard errors are reported in parentheses. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

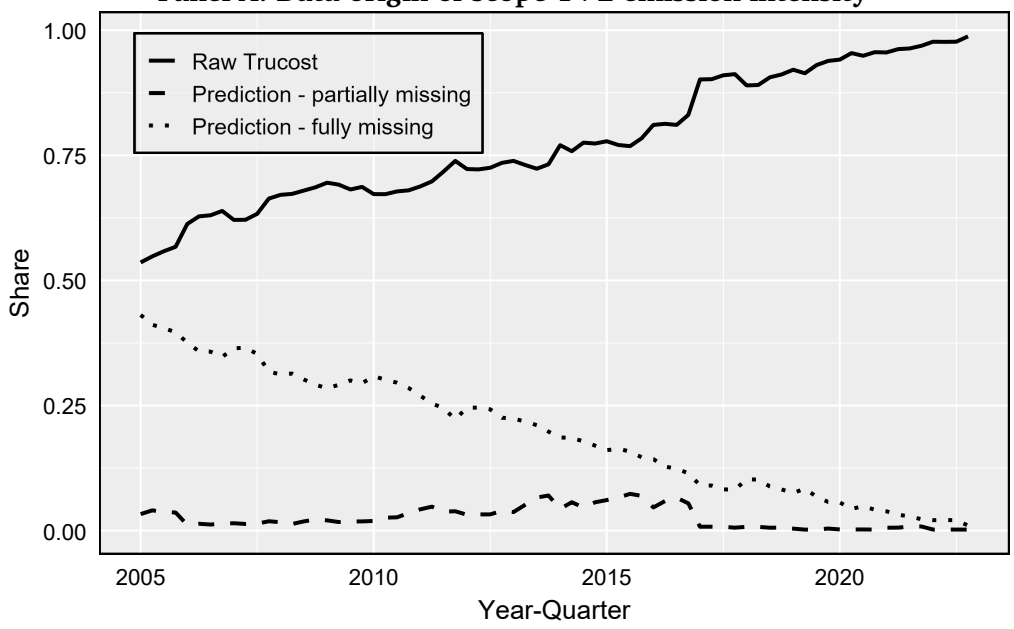
	Daily excess return			
	(1)	(2)	(3)	(4)
Climate news × Green stock	0.040***	0.080***	0.058***	0.060***
	(0.016)	(0.022)	(0.020)	(0.021)
Climate news × Sust.Inv		0.100***	0.073***	0.074***
		(0.023)	(0.021)	(0.021)
Climate news × Green stock × Sust.Inv		−0.115***	−0.089***	−0.091***
		(0.033)	(0.031)	(0.031)
Green stock × Sust.Inv		−0.001	0.006	−0.005
		(0.010)	(0.009)	(0.017)
Climate news	−0.042***	−0.073***	−0.055***	−0.055***
	(0.010)	(0.012)	(0.011)	(0.012)
Green stock	−0.010**	−0.013*	−0.019***	0.012
	(0.005)	(0.007)	(0.006)	(0.038)
Sust.Inv		0.012*	0.015**	0.022*
		(0.007)	(0.006)	(0.013)
Constant	0.052***	0.048***	0.046***	
	(0.003)	(0.004)	(0.011)	
Observations	1,245,417	1,245,417	1,245,417	1,207,066
R^2	0.00	0.00	0.17	0.17
Controls	No	No	Yes	Yes
Stock FE	No	No	No	Yes

Appendices

A Additional results

Figure A1: Panel A shows the data origin of scope 1+2 emission intensity among inside assets. Raw Trucost is data reported by the data provider, Prediction - partially missing is data estimated for firms who have at least one year in which there is a non-missing observations, Prediction - fully missing is data estimated for firms who have no emissions data in any of the years. Panel B shows the trend in firm scope 1+2 emission intensity measured in tCO2e/$ mn.

Panel A: Data origin of scope 1+2 emission intensity



Panel B: Trend in firm scope 1+2 emission intensity

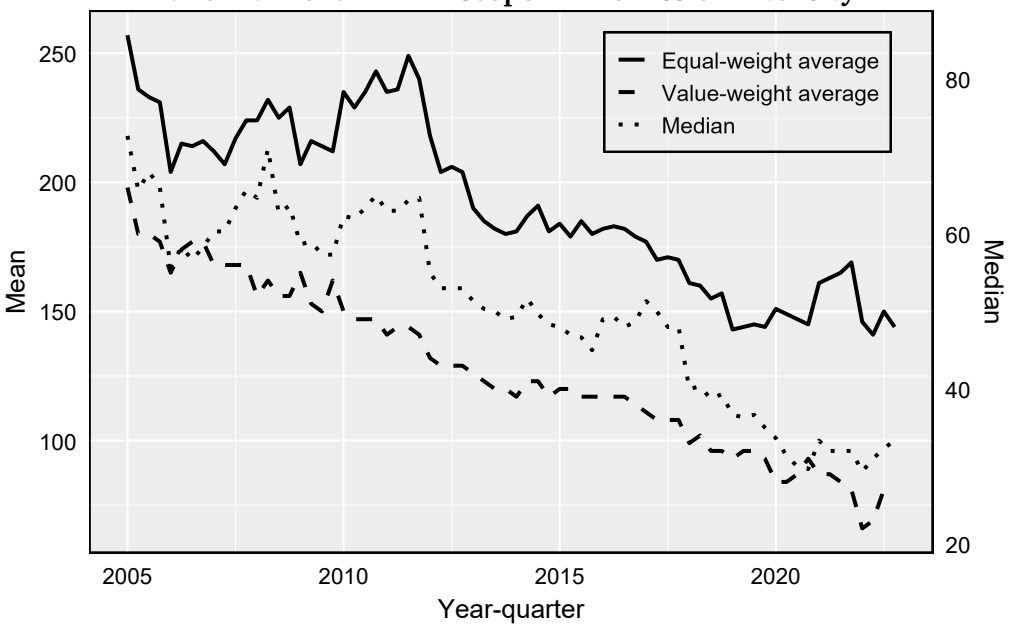
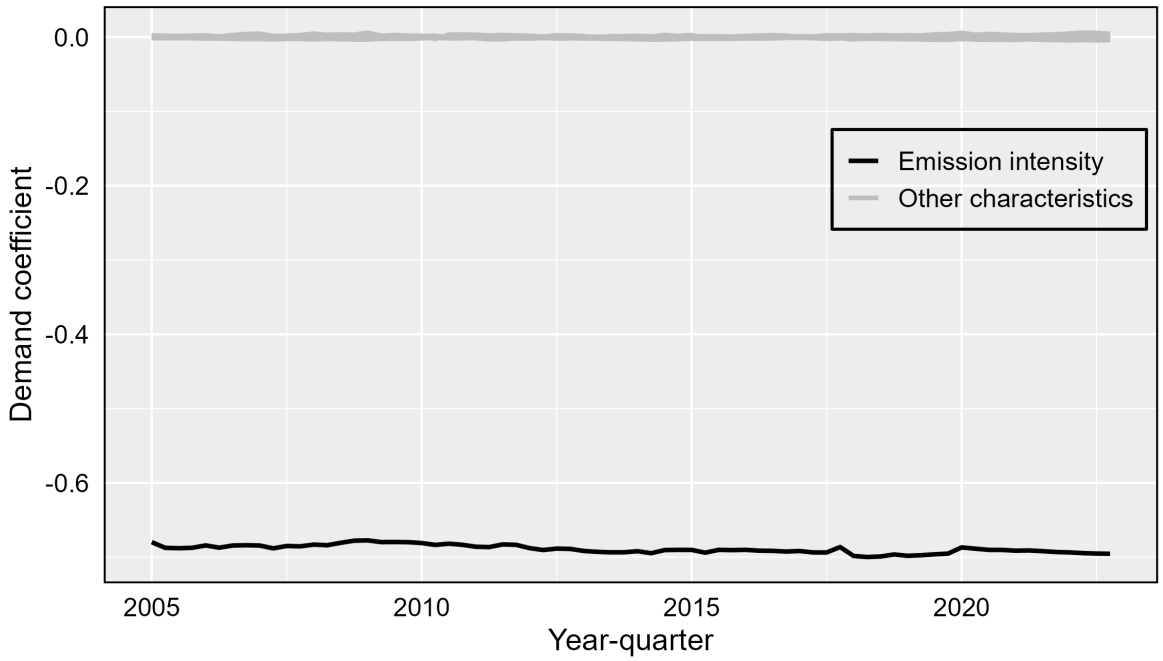


Figure A2: Demand coefficient of hypothetical sustainable funds. Panel A: Quarterly demand coefficients on characteristics of the fund 'Vanguard' for which we replace the actual weights with hypothetical weights inversely proportional to emission intensity. We estimate equation 4. Panel B: Quarterly demand coefficient on emission intensity of the fund 'Vanguard' for which we replace the actual weights with hypothetical weights proportional to market equity à la an index fund. We estimate equation 4 removing all characteristics except the constant and emission intensity.

Panel A: Hypothetical fund - weights inversely proportional to emission intensity



Panel B: Hypothetical fund - weights proportional to market equity

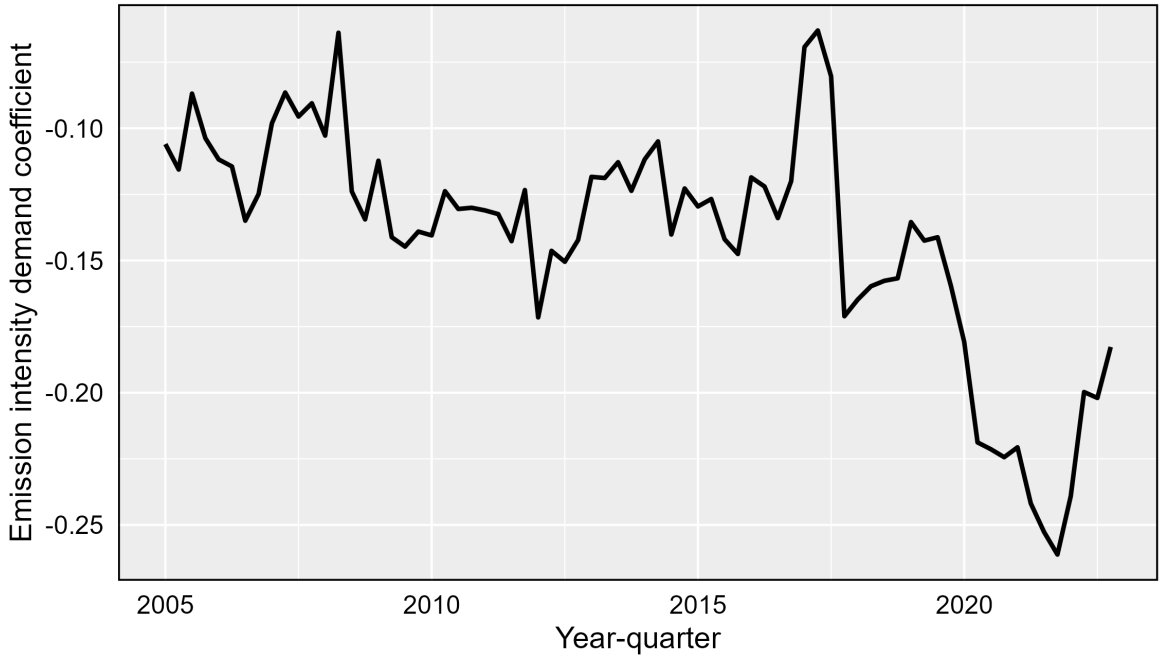


Figure A3: Relation between investor-level price elasticity and demand coefficient for emission intensity. Investor price elasticity is defined as 1 minus the demand coefficient on market-to-book, denoted by $\beta_{0,it}$ in equation 4. In Panel A and B, we sort investors each quarter into 3,000 percentiles by their emission intensity demand. For each percentile, we calculate the AUM-weighted (Panel A) and equal-weight (Panel B) average coefficient on price elasticity and average emission intensity demand coefficient. Panel C plots the raw investor demand coefficients without binning.

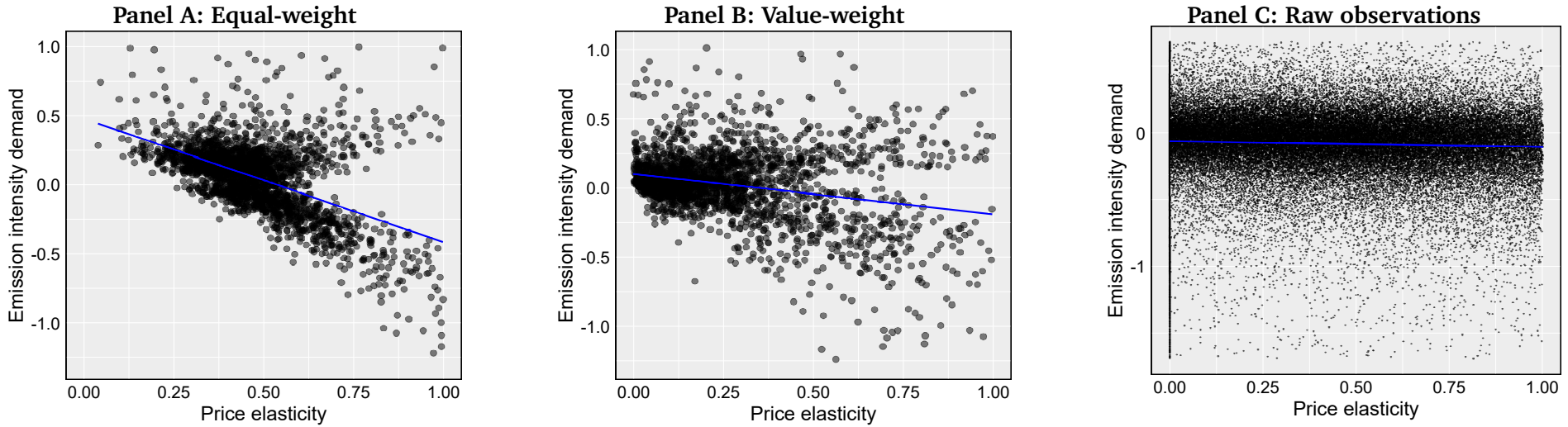


Figure A4: Active share for different levels of emission intensity demand. We sort investors each quarter into 3,000 percentiles by their emission intensity demand. For each percentile, we calculate the holding-weighted average active share and average emission intensity demand coefficient. Active share is computed as $AS_{i,t} = \frac{1}{2}\sum_{n\in\mathcal{N}_{i,t}} \left| w^I_{i,t}(n) - w^M_{i,t}(n) \right|$ and quantifies the share of an investor's portfolio that deviates from market weights.

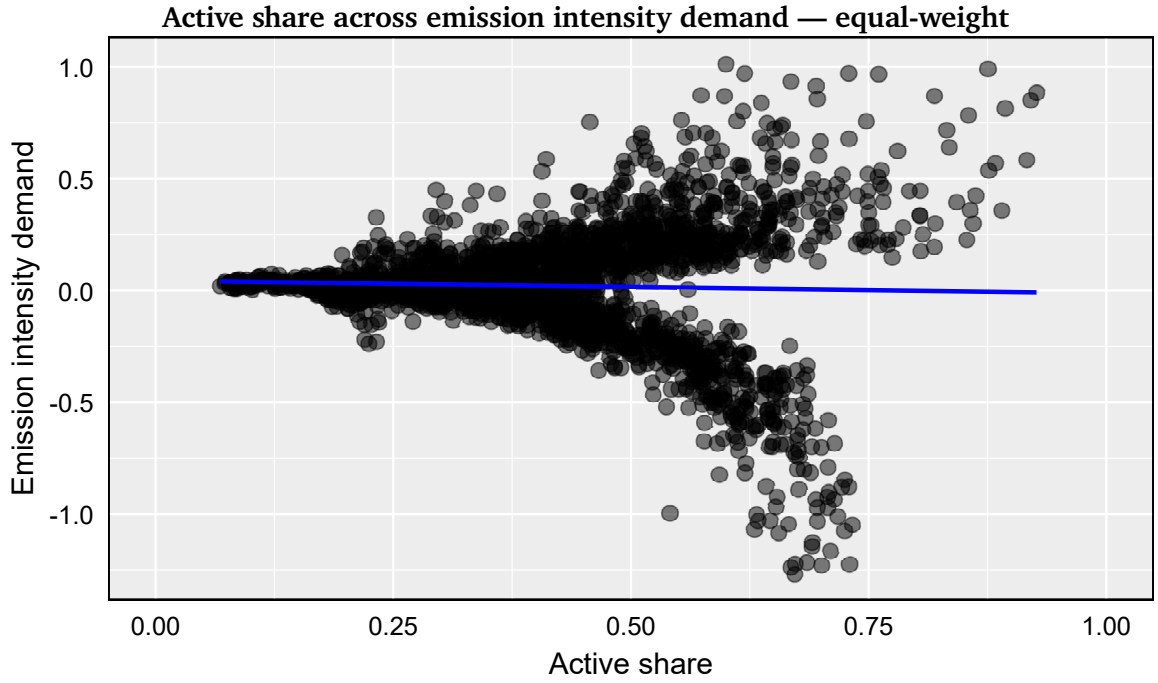


Table A1: Summary statistics of inside assets. Inside assets are stocks in the top 90% by market equity and with non-missing stock characteristics. Variables marked with an asterix winsorized at the 2.5% level.

	No. obs	Mean	Std. Dev.	Q10	Q50	Q90
Market cap. (bn)	38,314	31.72	83.09	3,58	11,95	65,45
Market-to-book	38,314	8.83	223.21	0.86	2.70	9.81
Sales-to-book	38,314	2.14	2.45	0.42	1.29	4.74
Dividends-to-book (annualized)*	38,314	0.04	0.05	0	0.02	0.11
Asset growth*	38,314	0.10	0.18	-0.05	0.06	0.28
Market beta*	38,314	1.20	0.64	0.48	1.16	1.97
Scope 1+2 emissions (mn tons)	38,314	4.53	15.33	0.02	0.31	8.63
Scope 1+2 emissions intensity*	38,314	192.55	374.37	6.85	42.23	582.80
Number of green patents - past 5yrs	38,314	20.19	127.84	0	0	19
Unique stocks p.q.	38,314	535.35	40.53	487	535	585

Table A2: Summary statistics of institutional investors.

Year	Funds	AUM ($mn)			Stocks in Portfolio		
	Unique	Q10	Q50	p90	Q10	Q50	Q90
2,005	2,195	69	297	4,531	18	62	320
2,010	2,428	55	239	4,236	31	98	437
2,015	3,178	51	282	5,107	29	97	431
2,020	4,081	37	210	4,191	28	96	384
2,022	4,500	38	217	4,334	31	103	419

Table A3: Summary statistics of the quarterly earnings announcements sample. Variables marked with an asterix winsorized at the 1% level.

	No. obs	Mean	Std. Dev.	Q10	Q50	Q90
2-day announcement CAR (%)*	144,753	0.25	6.44	-8.23	0.06	8.95
# announcements per day	144,753	6.31	5.66	1	5	14
# covering analysts	144,753	6.29	5.63	1	4	14
Realized earnings	144,753	0.52	8	-0.21	0.32	1.29
Median analyst forecast	144,753	0.48	5.94	-0.19	0.30	1.19
SUE (*10e3)	144,753	0.17	15.18	-5.56	0.60	7.45

B Theory

Recall that for each stock n, we define the market-to-book equity in period 0 as $MB(n) = \frac{P(n)}{B(n)}$. We define the productivity gain in book equity terms as $d(n) = \frac{D(n)}{B(n)}$. The economy consists of I investors indexed by $i = 1, \ldots, I$, who choose an optimal portfolio in period 0 and receive the claim on the firm in period 1. Let $q_i(n)$ be the number of shares of stock n that investor i holds in period 0. We denote the investor's holdings of stock n in units of book equity as $Q_i(n) = B(n)q_i(n)$. N-dimensional vectors are in bold.

The investor's wealth in period 0 is:

$$\begin{aligned} A_i &= \mathbf{P}'\mathbf{q}_i + O_i \\ &= \mathbf{MB}'\mathbf{Q}_i + O_i, \end{aligned} \tag{22}$$

where O_i is the dollar investment in the riskless asset. The investor's wealth in period 1 is:

$$\begin{aligned} A_{i,1} &= A_i + (\mathbf{D}_1 - \mathbf{P})'\mathbf{q}_i \\ &= A_i + (\mathbf{d}_1 - \mathbf{MB})'\mathbf{Q}_i \end{aligned} \tag{23}$$

Investors have exponential utility of the form:

$$U(A_{i1}, Q_i) = -\exp\left(-\gamma_i A_{i,1} - \mathbf{b}_i'\mathbf{Q}_i\right). \tag{24}$$

Investor have heterogeneous coefficients of absolute risk aversion vary, parameterized by $\gamma_i = \frac{1}{\tau_i A_i}$, where τ_i denotes risk tolerance. In the spirit of Pástor et al. (2021), the vector b captures non-pecuniary benefits of investor i:

$$\mathbf{b}_i = d_i \mathbf{x}^s, \tag{25}$$

where x^s is an $N \times 1$ vector whose nth element is x_n^s, and $d_i \geq 0$ is a scalar measuring the degree of agent i's sustainability taste. Investor i hence derives a non-financial benefit of $\mathbf{b}_i$ from holding stock n. Agents with higher values of d_i have stronger tastes for the sustainability characteristics of their holdings.

Investors optimize expected utility conditional on their internal signal s_i. Given normally dis-

tributed returns, we can rewrite expected utility as:

$$\begin{aligned}
\mathbb{E}_i[U(A_{i1}, Q_i) \mid \mathbf{s}_i] &= \mathbb{E}_i\left[-e^{-\gamma_i A_{i1} - \mathbf{b}_i'\mathbf{Q}_i} \mid \mathbf{s}_i\right] \\
&= \mathbb{E}_i\left[-e^{-\gamma_i (A_i + (\mathbf{d}_1 - \mathbf{MB})'\mathbf{Q}_i) - \mathbf{b}_i'\mathbf{Q}_i} \mid \mathbf{s}_i\right] \\
&= \mathbb{E}_i\left[-e^{-\gamma_i (A_i + (\mathbf{d}_1 - \mathbf{MB} + \frac{\mathbf{b}_i}{\gamma_i})'\mathbf{Q}_i)} \mid \mathbf{s}_i\right] \\
&= -e^{-\gamma_i A_i}\mathbb{E}_i\left[e^{-\gamma_i (\mathbf{d}_1 - \mathbf{MB} + \frac{\mathbf{b}_i}{\gamma_i})'\mathbf{Q}_i} \mid \mathbf{s}_i\right] \\
&= -e^{-\gamma_i A_i} e^{-\gamma_i (\mathbb{E}_i[\mathbf{d_1}|\mathbf{s}_i] - \mathbf{MB} + \frac{\mathbf{b}_i}{\gamma_i})'\mathbf{Q}_i + \frac{\gamma_i^2}{2}\mathbf{Q}_i'\mathbf{Var}(\mathbf{d_1}|\mathbf{s_i})\mathbf{Q}_i}.
\end{aligned} \tag{26}$$

Maximizing expected utility is equivalent to maximizing the term in the second exponent in equation 26. Taking the first-order condition with respect to $\mathbf{Q}_i$ yields:

$$-\mathbb{E}_i\left[\mathbf{d_1} \mid \mathbf{s}_i\right] + \gamma_i \mathbf{Var}(\mathbf{d_1} \mid \mathbf{s_i})\mathbf{Q}_i = 0. \tag{27}$$

Solving for optimal demand yields:

$$\mathbf{Q}_i = \frac{1}{\gamma_i}\mathbf{Var}(\mathbf{d_1} \mid \mathbf{s_i})^{-1}(\mathbb{E}_i\left[\mathbf{d_1} \mid \mathbf{s}_i\right] - \mathbf{MB} + \frac{\mathbf{b}_i}{\gamma_i}). \tag{28}$$

We next consider that $\mathbb{E}_i\left[\mathbf{d_1} \mid \mathbf{s}_i\right] = \mu_i$. We also assume that stocks have constant idiosyncratic risk σ_s^2, such that we can define $\mathbf{Var}(\mathbf{d_1} \mid \mathbf{s_i})^{-1} = \rho_i\rho_i' + \sigma_s^2\mathbf{I}$. Demand becomes

$$\begin{aligned}
\mathbf{Q}_i &= \frac{1}{\gamma_i}(\rho_i\rho_i' + \sigma_s^2\mathbf{I})^{-1}(\mu_i - \mathbf{MB} + \frac{\mathbf{b}_i}{\gamma_i}) \\
&= \frac{1}{\gamma_i\sigma_s^2}(\mathbf{I} - \frac{\rho_i\rho_i'}{\rho_i'\rho_i + \sigma_s^2})^{-1}(\mu_i - \mathbf{MB}) \\
&= \frac{1}{\gamma_i\sigma_s^2}(\mu_i - \mathbf{MB} - c_i\rho_i),
\end{aligned} \tag{29}$$

where

$$c_i = \frac{\rho_i(\mu_i - \mathbf{MB} - \gamma_i)}{\rho_i'\rho_i + \sigma_s^2}. \tag{30}$$

Using the information that expected productivity and loadings on the systematic risk factor can be expressed as a function of stock characteristics, we express demand as a function of these characteristics.

Investors base their expectations on public firm characteristics. Let $\mathbf{x}(n)$ represent a vector of observed characteristics for stock n, ordered such that the first element is book equity and the last

is a constant. Investor i's beliefs about the expected profitability of stock n are influenced by its observed characteristics and an unobserved (to the econometrician) characteristic $\phi_i^\mu(n)$:

$$\mu_i(n) = \Phi_i^\mu \mathbf{x}(n) + \phi_i^\mu(n), \tag{31}$$

where Φ_i^μ is a vector of coefficients on firm characteristics. Similarly, beliefs about the factor exposure of stock n depend on observed characteristics and an unobserved characteristic $\phi_i^\rho(n)$:

$$\rho_i(n) = \Phi_i^\rho \mathbf{x}(n) + \phi_i^\rho(n), \tag{32}$$

where Φ_i^ρ is a vector of coefficients on firm characteristics. The model assumes that observed and unobserved characteristics are exogenous. Loadings on characteristics are constant across assets, so that the only variation of portfolio weights stems from asset characteristics. The resulting heterogeneity across investors suggests that investors pay attention to particular characteristics and are agnostic to others.

Substituting equations 31 and 32 into 29 yields investor i's optimal demand for stock n:

$$Q_i(n) = \frac{1}{\gamma_i \sigma_s^2}\Bigg(- \text{MB}(n) + \frac{1}{\gamma_i} b_i(n) + \underbrace{(\Phi_i^\mu - c_i \Phi_i^\rho)}_{\beta_i} \mathbf{x}(n) + \underbrace{(\phi_i^\mu - c_i \phi_i^\rho)}_{\epsilon_i(n)} \Bigg), \tag{33}$$

Optimal demand is increasing in $\frac{1}{\gamma_i} b_i$: the stronger the non-pecuniary benefit investor i receives the stronger the demand, though this mechanism is weaker when the investor is more risk-averse. Next to the non-pecuniary benefit, the investor is paying attention to fundamentals characteristics $\mathbf{x}(n)$, which includes sustainability characteristics. Sustainability characteristics as in Pedersen et al. (2021) thus enter twice, for non-pecuniary- and fundamental reasons.

Equilibrium prices

Market clearing, i.e., supply of stocks is equal to the demand of stocks, implies:

$$B(n) = \sum_{i=1}^{I} Q_i(n). \tag{34}$$

Let $\mathbf{e}_1$ be a vector with the first element equal to one and the other elements equal to zero, so that $\mathbf{e}_1' \mathbf{x}(n) = \mathbf{B}(n)$ (i.e., the first element of $\mathbf{x}(n)$ is book equity). Substituting equation 33 in market-clearing 34 yields equilibrium prices:

$$
\begin{aligned}
\sum_{i=1}^{I} \frac{1}{\gamma_i \sigma_s^2} \text{MB}(n) &= \sum_{i=1}^{I} \frac{1}{\gamma_i^2 \sigma_s^2} b_i(n) + \sum_{i=1}^{I} \frac{1}{\gamma_i \sigma_s^2} \beta_i' \mathbf{x}(n) + \sum_{i=1}^{I} \frac{1}{\gamma_i \sigma_s^2} \epsilon_i(n) - B(n) \\
\text{MB}(n) &= \Big(\sum_{i=1}^{I} \frac{1}{\gamma_i \sigma_s^2}\Big)^{-1} \Big(\sum_{i=1}^{I} \frac{1}{\gamma_i^2 \sigma_s^2} b_i(n) + \sum_{i=1}^{I} \frac{1}{\gamma_i \sigma_s^2} \beta_i' \mathbf{x}(n) + \sum_{i=1}^{I} \frac{1}{\gamma_i \sigma_s^2} \epsilon_i(n) - B(n) \Big) \\
\text{MB}(n) &= \bar{b}(n) + \bar{\beta}' \mathbf{x}(n) + \bar{\epsilon}(n).
\end{aligned} \tag{35}
$$

where[19]

$$
\begin{aligned}
\bar{\beta} &= \sum_{i=1}^{I} a_i \beta_i - \frac{\sigma_s^2 e_1}{\sum_{i=1}^{I} \tau_i A_i}, \\
\bar{\epsilon}(n) &= \sum_{i=1}^{I} a_i \epsilon_i(n), \\
\bar{b}(n) &= \sum_{i=1}^{I} v_i b_i(n), \\
a_i &= \frac{\tau_i A_i}{\sum_{j=1}^{I} \tau_j A_j}, \quad v_i = \frac{\tau_i^2 A_i^2}{\sum_{j=1}^{I} \tau_j A_j}.
\end{aligned}
$$

Prices are increasing in the non-pecuniary benefit $\bar{b}(n)$ stock n provides to investors and whenever stocks have characteristics that proxy for larger expected return or lower risk. Lastly, prices change with investor's demand component $\bar{\epsilon}(n)$ that is not observable to the econometrician.

[19] Recall that $\gamma_i = \frac{1}{\tau_i A_i}$.