Greenness Demand For US Corporate Bonds*

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We characterize the demand for green securities based on institutional holdings of US corporate bonds. The generally positive demand for greenness shows significant time variation, peaking around the Paris Agreement and declining sharply during the first Trump administration. The demand variations significantly affect prices and investors' wealth. At the corporate level, we document several real effects of investor preferences: increases in greenness demand are followed by improvements in firms' environmental performance, more frequent and larger bond issuances, higher capital expenditures, and reduced reliance on bank debt.

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1. Introduction

In the 2010s, sustainable investing emerged as a prominent strategy in financial markets. This approach directs capital towards companies with positive impact while steering away from those with adverse effects. Thereby, this capital allocation potentially influences firms' financing conditions and, subsequently, real policies. While there is (still) debate around the impact of sustainable investing, the theoretical literature also points out that green investments can provide value to investors beyond expected risk and return (see, e.g., Heinkel et al., 2001; Pedersen et al., 2021; Pástor et al., 2021; Baker et al., 2022; Dangl et al., 2025a,b).[1] Overall, the attention and investment in sustainable funds saw a massive increase until 2021, when net inflows peaked at USD 69 billion. However, the landscape has changed recently, as the sector experienced a net outflow of over USD 13 billion in 2023 (Morningstar, Inc., 2024). Fluctuations in attitudes toward sustainable initiatives are also mirrored by the public debate and policymakers, especially in the US. Thus, investor preferences for sustainability-related investments do not seem to follow a steady rise, as has long been taken for granted.

In this paper, we investigate the demand for green investments and its effects on investors and firms based on institutional holdings. We identify investors' preferences by developing a demand-based asset pricing system inspired by Koijen and Yogo (2019) for the US corporate bond market.[2] Corporate bonds constitute an ideal empirical laboratory, as we can jointly analyze bond holdings data, traded prices, as well as issue and issuer characteristics. Furthermore, in contrast to stocks, corporate bond investors' return expectations can be estimated directly from yields. From a corporate finance perspective, our evidence can, therefore, identify the effects of greenness on firms' financing costs via bond yields, and we can exploit the fact that firms issue corporate bonds more frequently than equity. Thus, corporate bonds represent a direct and more timely link between investors' preferences and firms' policies. Overall, our approach can uncover greenness-related effects even when observable bond prices already reflect equilibrium corporate supply reactions.

[1] For the remaining paper, we will use the terms "sustainable" and "green" interchangeably.

[2] While demand-based asset pricing is commonly applied in equity markets, evidence from fixed-income markets is limited. For example, Bretscher et al. (2025) also consider demand systems in corporate bonds, but they do not include the awareness for sustainability.

Therefore, our insights are consistent with the recent theoretical literature highlighting the need to account for endogenous firm decisions (see, e.g., Favilukis et al., 2023; Dangl et al., 2025a,b). Given that our analysis centers on investors' holdings, our results go beyond studying observable price differences for green securities - a common, simplified view adopted by the earlier literature.

Our goals for this project are threefold. First, we wish to characterize the greenness preferences within a demand-based asset pricing framework. Based on the empirical calibration of our model to the US corporate bond market, we analyze the aggregate greenness demand over time and explore differences across investors. Second, we present the resulting valuation effects and discuss the implications of greenness demand shocks for investors' wealth. Third, motivated by the evolving greenness awareness, questions about the real effects of these demand shocks arise. By focusing on the time-series variation in greenness demand for corporate bonds, we can investigate the firm-level reactions to shifts in this demand. This allows us to contribute to the ongoing debate on the effects of green investments on economic outcomes. In particular, we analyze the change in firms' environmental performance and explore the differences in bond issuance activity and firm fundamentals for green and brown firms. In summary, the project employs state-of-the-art empirical methods to identify the time-varying interactions between firms' greenness, their financing and investment decisions and investors' demand for sustainable investments, thereby providing relevant insights for investors, corporate managers, and policymakers.

We start by developing an asset pricing framework based on the model introduced by Koijen et al. (2024), tailored specifically to the corporate bond market. In this framework, investors have heterogeneous beliefs about expected return and risk, and/or sentiment based on a bond's greenness. After combining optimal portfolio allocation derived from these heterogeneous beliefs with market clearing, the model delivers an important insight for our analysis of greenness demand. It implies that bond prices are a function of bonds' greenness, where the slope is a weighted sum of investors' demand elasticities with respect to environmental performance. Thus, bond prices and holdings change when those demand elasticities change in response to market trends or regulatory changes.

In our comprehensive analysis, we focus on the US corporate bond market from 2012 to the end of 2022. This market allows us to use bond holdings data from Refinitiv eMAXX, which is the defining part of identifying individual investors and their demand for environmental performance. We combine the holdings with secondary bond market transactions from TRACE and aggregated bond-issuer-level characteristics from Mergent FISD and Compustat. Most importantly, we add firm-level environmental performance information from MSCI. In total, our sample comprises 6,939 unique institutional investors of varying sizes and investment approaches, split across five types. In particular, we group the investors in (1) life insurers, (2) property, casualty, and health insurers, (3) mutual funds, (4) variable annuity funds, and (5) federal, state government, pension, and retirement funds. These investors' holdings combined cover 13,522 individual bonds issued by 9,398 firms. At the end of 2022, this represents an outstanding par amount of almost USD 4.9 trillion. Following that, to estimate the asset-demand system, we resort to the instrumental variables ridge estimation procedure employed by Koijen et al. (2024). Ultimately, this method allows for a more granular estimation of different demand coefficients across investors and time.

We find that greenness demand is generally positive over our sample period. While the aggregate demand is close to zero initially, the demand significantly increased around the 2015 United Nations Climate Change Conference (COP21), resulting in the Paris Agreement. In fact, the greenness demand reaches the highest observed level in the second half of 2016, when the agreement came into force. At the peak, on average, investors would wish to raise portfolio weights by around 14% for bonds whose environmental performance increases by one standard deviation, thereby inducing significant price increases in the market. Thereafter, the greenness demand decreases, reaching its lowest level in 2019, even going into negative territory. This episode coincides with the time of the first Trump administration, culminating in the official withdrawal of the US from the Paris Agreement. In 2020, greenness demand increases again. However, at the end of our sample period in 2021/22, the greenness demand again decreases and approaches zero, coinciding with several US states introducing restrictions associated with ESG investment strategies. Thus, the greenness demand aligns with important political events and related investors' attention.

Our research design allows us to estimate the greenness demand of each individual investor, enabling an analysis of how the demand evolves across different investor types over time. In particular, we can compare insurance companies and investment funds, the two most important institutional investor groups. Regression results show that insurance companies exhibit a relatively stable positive demand for bonds issued by greener firms compared to other investors, controlling for various characteristics. Their demand was already significantly positive before the Paris Agreement, consistent with the notion that their business models are more exposed to the physical risk of climate change.

By contrast, mutual funds and variable annuity funds closely mirror the aggregate trends and react more strongly to major climate-related events. Our regression analysis shows that, prior to COP21, their greenness demand was significantly negative, but increased markedly thereafter. Overall, these findings reveal significant heterogeneity in greenness demand across investor types.

In the next step, we study the valuation effects of the greenness demand in greater detail. Specifically, we simulate counterfactual bond prices based on our model parameters by muting investors' preferences for greenness - that is, generating equilibrium prices unaffected by these observable preferences. Comparing the counterfactual and observed bond yields reveals substantial valuation effects. On average, bonds issued by firms with superior environmental performance (E-scores above 7.5) exhibit yields that are 33 basis points lower due to greenness demand. Before COP21, the price impact is essentially zero, whereas in 2016 the yield differential peaks, with greener bonds trading at yields 63 basis points below their counterfactual levels.

In a regression setup, we further assess the contribution of specific investor groups to these price effects by selectively muting their greenness demand. The results show that the valuation effects are primarily driven by insurance companies, consistent with their relatively strong and stable demand for green securities.

In addition, our model allows us to discuss the wealth effects experienced by individual investors in various scenarios. First, we analyze the impact of the rise in greenness demand, following COP21. Our results show that mutual and variable annuity funds were most affected, as their portfolios were least tilted towards greener assets. On average, institutional investors experienced a value loss of approximately 0.23%, while life insurance companies incurred only slightly more than half of this loss. Property, casualty, and health insurers proved the most resilient, with an average loss of just 0.06%. Although average effects appear modest, our detailed results reveal that the most adversely affected investors suffered losses exceeding 6%.

In a second exercise, we use investors' portfolio holdings as of the end of 2022 to simulate the impact of a hypothetical increase in greenness demand of the same magnitude as that observed around COP21. The results indicate that investors are now considerably better positioned for such an event. While mutual and variable annuity funds would still be most affected, their average losses would decline to about 0.05%, with even the most exposed funds losing only around 2%. These findings suggest that institutional investors have substantially improved the greenness orientation of their portfolios since the period surrounding COP21.

To examine firm-level reactions to shifts in greenness demand, we quantify the potential bond-yield reductions associated with improvements in environmental performance. Based on our estimated demand system, a 2.5-point increase in a firm's E-score corresponds to a yield reduction of roughly 20 basis points. We find that brown firms exhibit substantial potential for yield declines across most of the sample period, whereas green firms benefit from such reductions only during periods of elevated aggregate greenness demand.

Motivated by these findings, we test whether greenness demand predicts subsequent changes in firms' E-scores. Regression analyses reveal that lagged greenness demand forecasts improvements in environmental performance, but only among already-green firms. Thus, although the yield benefits from improving environmental performance are greatest for the brownest firms, we do not observe an immediate response from them, consistent with higher adjustment costs and/or longer implementation lags for environmental policies.

We further examine how greenness demand influences firms' financing and investment decisions. When lagged greenness demand is high, firms with higher E-scores issue bonds more frequently and in larger amounts. Economically, following such periods, greener firms are about one percentage point more likely to issue a bond (versus a 9.1% unconditional quarterly issuance probability), and their issuance amounts are 14.3% higher. These patterns indicate that greener firms face both lower borrowing costs and improved access to bond financing. Turning to capital structure and risk, we find that the additional funds are used to substitute away from bank debt and to invest in long-term assets, while leverage remains stable. After episodes of elevated greenness demand, a one-standard-deviation greener firm reduces bank debt by roughly 4.5% and increases capital expenditures (capex) by about 1%.

In summary, we study greenness demand using institutional holdings of US corporate bonds and find that it is positive on average but highly time-varying, spiking around the 2016 Paris Agreement and receding during the Trump years. These swings affect prices and investors' wealth and, crucially, induce real effects: in response to an increase in greenness demand, greener firms issue more and larger bonds and improve environmental performance, deploying proceeds to adjust capital structure and investment. Together, the evidence underscores that investor sustainability preferences affect corporate behavior and can catalyze broader environmental improvements.

2. Literature Review

Our research relates to various aspects of the literature on asset pricing (i.e., primarily corporate bond pricing) and green investing. First, in the broader context of asset pricing research, our paper contributes to the growing body of literature that investigates asset demand across various markets, encompassing equity, corporate bonds, and country-level assets (see, e.g., Koijen and Yogo, 2019, 2020; Koijen et al., 2024; Bretscher et al., 2025, among others). Specifically, our study aligns with those exploring the implications of demand estimation for asset pricing questions. Recent theoretical contributions have extended this framework and discussed its limitations (e.g., Fuchs et al., 2023; Haddad et al., 2025), particularly with respect to substitution elasticity and macro- and "meso"-demand shocks. We acknowledge these perspectives and see our work as complementary, offering bond-market-specific evidence on greenness demand under a widely used empirical implementation. Connected works include van der Beck and Jaunin (2021) investigating retail investor demand, Huebner (2023) investigating the origins of equity momentum, Gabaix et al. (2024) investigating US households' asset demand, Noh et al. (2024) investigating sustainable equity investing, Jansen (2025) focusing on the demand of pension funds and insurance companies, and Bretscher et al. (2025) investigating demand-based corporate bond pricing. Our contribution lies in the structural analysis of sustainable bond investing. We emphasize the asset demand of individual institutional bond investors within the context of green investments.

Second, our research aligns with the more general strand of literature concerning the asset-pricing implications of sustainable investing. Theoretical research on sustainable investing commonly integrates investor sustainability preferences, arguing that some investors favor greener assets, considering specific sustainability characteristics beyond traditional risk-return attributes. Works such as Heinkel et al. (2001), Fama and French (2007), and Baker et al. (2022) assert that securities of greener companies have lower expected returns due to higher prices compared to assets with identical risk structures. In the recent model of Pástor et al. (2021), unexpected shifts in greenness preferences are emphasized in explaining the evolution of realized returns for greener assets. This model suggests that, despite lower expected returns, greener assets can outperform less sustainable assets when customers' tastes for sustainable products or investors' preferences for sustainable holdings unexpectedly strengthen. Several empirical studies align with the theoretical predictions regarding the asset-pricing implications of a firm's sustainability. Among these, Hong and Kacperczyk (2009) widely cited work investigates "sin stocks", revealing that companies in the tobacco, alcohol, and gambling sectors exhibit higher expected returns. In a more recent study, Bolton and Kacperczyk (2021) adopt a similar methodology to explore the impact of carbon emissions on US stock returns, finding that firms with higher emissions also earn higher returns. Both studies argue that these outcomes primarily signify reduced demand stemming from the reluctance to hold companies with subpar sustainability performance. Therefore, we make a contribution to understanding the dynamics of greenness preferences over time, which is crucial for comprehending the impact of a firm's sustainability on financing conditions.

Our research also directly relates to the empirical literature examining the interplay between sustainability characteristics and corporate debt pricing. On the one hand, studies by Bauer and Hann (2010), Halling et al. (2021), and Seltzer et al.

(2022) focus on primary market yields for US corporate bonds. On the other hand, Schneider (2011), Oikonomou et al. (2014), Handler et al. (2022), and Amiraslani et al. (2023) explore effects on secondary market yields. Despite a consensus that investors' greenness preferences reduce bond yields, reported results significantly vary from 6 to 32bp on average and peak at around 100bp. Thus, differences arise in how, when, and through which channels these preferences manifest themselves. These papers implicitly assume a static supply of corporate bonds, which could significantly influence their results. In particular, recent theoretical advances (see, e.g., Favilukis et al., 2023; Dangl et al., 2025a,b) discuss endogenous adjustments of firms' policies, which imply that firms respond to demand shocks. For example, an increase in greenness demand leads to green firms issuing more securities and/or all firms improving their greenness performance in equilibrium. Such supply-side adjustments reduce observed price differences and, thus, static comparisons of yield reductions as applied in the previous empirical literature cannot precisely analyze the dynamic nature of greenness demand effects. Relative to this empirical literature, we make two contributions. First, we uncover greenness demand based on investors' holdings, which implicitly incorporates supply-side effects, allowing us to discuss its evolution over time and across different investor types in detail. Our second contribution quantifies how alterations in the greenness demand impact the valuations of bonds and investors' wealth through counterfactual scenarios.

Fourth, our paper significantly contributes to the expanding literature investigating green investments. While some studies utilize survey instruments (see, e.g., Krüger, 2015), we primarily analyze portfolio choice decisions. Notably, Gibson et al. (2021) compute a portfolio-level sustainability measure for institutional investors and finds higher returns for institutions with elevated portfolio greenness post-2010. Pástor et al. (2023) evaluates ESG-related tilts for institutional investors, revealing approximately 6% of invested AUM dedicated to sustainable considerations. Hartzmark and Sussman (2019) and van der Beck (2021) focus on subsets of investors. Both study inflows into sustainable mutual funds. Koijen et al. (2024) and Noh et al. (2024) investigate investors' sustainability demand in the US stock market. We contribute by offering a comprehensive estimate of the sustainability demand of institutional investors in the US corporate bond market. Our estimates point to significant time variation.

Lastly, our work contributes to the literature on the effects of sustainable investing on firms' policy choices. As an extension to their asset pricing model, Pástor et al. (2021) show that the pressure from sustainable investing indeed leads to real impact. Ancillary, the model of Broccardo et al. (2022) suggests divestment is less effective than engagement, and Edmans et al. (2022) underscores the limitations of blanket exclusion strategies. Similarly, Berk and Van Binsbergen (2025) argues that a substantial shift from less sustainable to more sustainable stocks would only minimally impact the cost of capital for the less sustainable firms. As Dangl et al. (2025a) propose, even if the cost of capital difference between green and brown sectors is minimal, in a model where firms' investment decisions are endogenous, green preferences can significantly influence corporate decisions. By investigating the impact of different forms of investor preferences on equilibrium capital allocation, they postulate that a gap in the cost of capital is counteracted by changes in supply. Following that, Dangl et al. (2025b) reframes those assertions in a setting with stochastic preferences. Respective empirical evidence on the impact of sustainable investing on real firm decisions is mixed (see, e.g., Gantchev et al., 2022; Hartzmark and Shue, 2023; Heath et al., 2023, among others). Noh et al. (2024) finds that equity investors' pressure for greenness only weakly predicts future improvements in a firm's environmental performance, whereas Luneva and Sarkisyan (2024) and Beyene et al. (2025) provide first indications of a trade-off between bank and bond financing in relation to environmental performance. We provide further evidence that firms indeed react to bond investors' demand for greenness. Our findings show that heightened greenness demand induces firms to improve environmental performance and more sustainable firms to issue more bonds, as well as make adjustments to their capital structure and investment decisions. These findings highlight the advantages of focusing on the corporate bond market when investigating the effects of greenness on corporate policy: Bonds provide a clear cash-flow structure and are issued much more frequently than equity. These characteristics enable the measurement of the cost of capital and its determinants, as well as the analysis of the effect of greenness on corporate financing and real policies.

3. Theoretical Framework

In this section, we outline the asset pricing framework that we adapt to a bond-market setting from existing work of Koijen et al. (2024). It remains intentionally stylized to focus on the core economic mechanisms of how demand for greenness affects bond prices. While we adjust details for the empirical calibration later, the exposition in this chapter allows for a closed-form solution and, thus, provides important insights. In particular, we show how asset prices change when the elasticities of demand to characteristics change in response to market trends, e.g., sustainable investing. Additionally, the model highlights that the degree to which shifts in asset demand affect asset prices depends on heterogeneity in asset demand and demand elasticities.

3.1. Financial Market Setup

Our model features two periods indexed by $t = 0, 1$.[3] N corporate bonds, indexed by $n = 1, \ldots, N$. For simplicity, we assume all of them to be zero-coupon bonds with a face value of one. A riskless asset with a constant interest rate of zero also exists. Let $\mathbf{P}$ and $\mathbf{P}_1$ be N-dimensional vectors of bond prices in period 0 and 1, respectively. Let $\mathbf{r_1}$ be the N-dimensional vector of returns from period 0 to 1. Then, we define $\mathbf{R}_1 = \mathbf{P}_1 - \mathbf{P} = \text{diag}(\mathbf{P})\mathbf{r}_1$ as the N-dimensional vector of dollar returns from period 0 to 1.

3.2. Optimal Portfolio Choice and Asset Demand

There are I investors indexed by $i = 1, \ldots, I$. Each investor chooses an optimal portfolio in period 0 based on a set of bond characteristics from their investment universe. Here, we consider a comprehensive investment universe that includes all bonds. However, in reality, the investment universe is usually restricted by particular investment mandates or regulations, which we consider in the empirical calibration.[4]

[3] For simplicity of notation, we remove the time subscript in period 0 (e.g., $\mathbf{P}_0 = \mathbf{P}$) in the following derivations.

[4] For example, some mutual funds have mandates prohibiting investments in speculative-grade bonds or other restrictions based on specific bond characteristics.

Let $q_i(n)$ be the share of bond n that investor i holds in period 0. Then, we can express the dollar holdings of investor i as $Q_i(n) = P(n)q_i(n)$. Let Q_i^0 be the dollar investment in the riskless asset. Thus, investor i's wealth in period 0 is

$$\begin{aligned} A_i &= \mathbf{q}_i'\mathbf{P} + Q_i^0 \\ &= \mathbf{Q}_i'\mathbf{1} + Q_i^0. \end{aligned} \tag{1}$$

Investor i's wealth in period 1 is given as the sum of the initial investment plus the return on the asset, i.e.,

$$\begin{aligned} A_{1,i} &= A_i + \mathbf{q}_i'\mathrm{diag}(\mathbf{P})\mathbf{r}_1 \\ &= A_i + \mathbf{Q}_i'\mathbf{r_1}. \end{aligned} \tag{2}$$

We assume investors have heterogeneous constant absolute risk aversion utility and derive expected return and risk from bond characteristics. In addition, considering greenness, investors could overweight green assets due to expected returns, risks, or sentiment. Intuitively, if greenness performance is informative about expected returns and risk, it should enter the characteristics-based demand. However, even if greenness is not informative about bonds' expected future cash flows and risk, it may still enter investors' demand when they derive non-pecuniary benefits (see, e.g., Pástor et al., 2022; Dangl et al., 2025a). In particular, let $d_i \geq 0$ be a scalar representing investor i's greenness sensitivity. Let $\mathbf{f}$ be an N-dimensional vector of greenness performance. If $f(n) > 0$, bond n is perceived to generate positive externalities for society and the environment, and vice versa for $f(n) < 0$. Hence, investors choose an optimal portfolio in period 0 to maximize their expected utility in period 1:

$$\max_{\mathbf{Q}_i} \mathbb{E}_i[-\exp(-\gamma_i A_{1,i} - d_i \mathbf{f}'\mathbf{Q}_i)]. \tag{3}$$

We follow Koijen et al. (2024) and define the risk aversion parameter to be $\gamma_i = \frac{1}{\tau_i A_i}$, where τ_i represents the risk tolerance. This ensures constant relative risk aversion while keeping the tractability of an exponential utility.

Investors have heterogeneous return expectations, where we model investor i's beliefs about the return through a factor model:

$$\mathbf{r}_1 = \mathbf{g}_i + \boldsymbol{\rho}_i F_1 + \boldsymbol{\eta_1}. \tag{4}$$

The vector $\mathbf{g}_i$ represents investor i's belief about the expected return. The vector $\boldsymbol{\rho}_i$ represents investor i's belief about exposures to a systematic factor F_1, a standard normal random variable. Additionally, the vector $\boldsymbol{\eta_1}$ is a normally distributed idiosyncratic shock with a mean of zero and a diagonal covariance matrix $Var(\boldsymbol{\eta_1}) = \sigma^2\mathbf{I}$. Therefore, the heterogeneity in the return-generating process is driven by differences in the beliefs $\mathbf{g}_i$ and $\boldsymbol{\rho}_i$, which are determined by an investor-specific function of observable and empirically unobservable characteristics. Thus, based on the same observed characteristics, they might have different expectations about the period return. Moreover, each investor could form expectations based on unobserved characteristics.

Let $\mathbf{x}(n)$ be a vector of observed characteristics of bond n (which includes the issuers' greenness next to other bond-specific information). Following that, investor i's beliefs about expected returns and factor exposure are

$$g_i(n) = \boldsymbol{\lambda}_i^{g\prime}\mathbf{x}(n) + \nu_i^g(n) \text{ and} \tag{5}$$

$$\rho_i(n) = \boldsymbol{\lambda}_i^{\rho\prime}\mathbf{x}(n) + \nu_i^\rho(n), \tag{6}$$

where investor i's $\boldsymbol{\lambda}_i^g$ and $\boldsymbol{\lambda}_i^\rho$ are constant vectors across assets. $\nu_i^g(n)$ and $\nu_i^\rho(n)$ are scalars that represent unobserved characteristics of bond n that relate to expected return and factor exposure.

Under the normality assumption, we can solve the first-order condition for the optimal portfolio choice to find investor i's optimal demand for bond n, which is given by[5]

$$q_i(n) = \frac{1}{P(n)\gamma_i\sigma^2}\left(\underbrace{(\boldsymbol{\lambda}_i^g - c_i\boldsymbol{\lambda}_i^\rho + \boldsymbol{\zeta}_i)'}_{\tilde{\boldsymbol{\beta}}_i}\mathbf{x}(n) + \underbrace{\nu_i^g(n) - c_i\nu_i^\rho(n)}_{\epsilon_i(n)}\right), \tag{7}$$

where c_i is an investor-specific constant that scales risk perception.

[5] We show the formal derivations in Appendix A.1.

From this specification, we can gain important economic insights. In particular, bond demand is a linear function of characteristics. Based on the first term in Equation (7), bond demand is downward-sloping and decreasing in price. The second term reveals that bond demand rises in observed characteristics associated with a higher expected return, lower risk, and non-pecuniary benefits derived from higher greenness performance (i.e., ζ_i). However, the expression for $\boldsymbol{\beta}_i$ does not reveal whether investors' tilts towards specific characteristics are due to expected return, risk, or sentiment. The last term represents investors' latent demand. Similarly to the second term, we can not infer the reasons for the relation between bond demand and unobserved characteristics. Overall, Equation (7) relates the cross-section of bond holdings to characteristics. It implies different elasticities with respect to characteristics due to heterogeneous risk preferences and beliefs. Relevant to our analysis, we see that bond demand is more elastic to a characteristic like the greenness performance for investors with stronger beliefs about the impact of climate change or related potential regulation on expected return and risk.

Note that Equation (7) is implicitly based on the assumption of identical unit bonds. Therefore, in the empirical calibration, the variation in the amount outstanding across bonds has to be accounted for. Following Koijen and Yogo (2019), this is done by explicitly modeling portfolio weights and approximating the demand with an exponential function embedding a linear structure. This also ensures that the economic intuition derived here remains valid and matches the empirical relation between characteristics and holdings.

3.3. Equilibrium Bond Prices

By imposing market clearing, i.e., aggregating investors' demands and equating them to the supply of each bond, we can now solve for equilibrium bond prices $P(n)$. Recall that we have normalized each bond's total face value to one. Thus, we have

$$1 = \sum_{i=1}^{I} q_i(n) \text{ and}$$
$$P(n) = \sum_{i=1}^{I} P(n) q_i(n).$$

Then, substituting optimal demand from Equation (7) into market clearing implies

$$P(n) = \bar{\boldsymbol{\beta}}' \mathbf{x}(n) + \bar{\boldsymbol{\epsilon}}(n), \tag{8}$$

where

$$\bar{\boldsymbol{\beta}} = \sum_{i=1}^{I} \frac{A_i \tau_i}{\sigma^2} \boldsymbol{\beta}_i \text{ and}$$
$$\bar{\boldsymbol{\epsilon}}(n) = \sum_{i=1}^{I} \frac{A_i \tau_i}{\sigma^2} \epsilon_i(n).$$

The vector $\bar{\boldsymbol{\beta}}$ is a weighted sum of the coefficients on observed characteristics in the investors' demands, see Equation (7). Hence, investors with more extreme beliefs about expected return, risk, or sentiment with larger $\boldsymbol{\beta}_i$ have a stronger impact on asset prices. Additionally, investors with more wealth or higher risk tolerance also have a stronger impact on asset prices. Similarly, $\bar{\boldsymbol{\epsilon}}(n)$ is a weighted sum of latent demand across investors. Again, investors with more extreme beliefs about expected returns or risk with greater latent demand have a stronger impact on asset prices.

4. Data

To construct the sample for our analysis of greenness demand, we utilize four main sources of data. We obtain bond and issuer characteristics from the Mergent Fixed Income Securities Database (FISD), secondary bond market trade data from the Trade Reporting and Compliance Engine (TRACE), issuer-level environmental performance measures from the MSCI ESG database, and institutional bond holdings data from the Refinitiv eMAXX database. We complement these main data with issuer-specific accounting data from Compustat and macroeconomic variables.[6]

We start the sample construction with data on corporate bonds with Mergent's FISD. Following the relevant literature, we restrict our sample to senior, unsecured corporate bonds denoted in USD with a fixed coupon. We require the bonds to be straight, callable, or puttable, and remove all others with complex structures, such as asset-backed and convertible securities. Based on this sample of corporate bonds, we utilize the transactions reported in TRACE to determine bond prices, bond yields, and the liquidity proxy price dispersion (see Jankowitsch et al., 2011).[7] Additionally, where possible, we retrieve the last quarterly credit ratings from S&P, Moody's, and Fitch and convert them to numeric values (i.e., one corresponds to AAA/Aaa, two to AA+/Aa1, etc.). Next, we obtain firm-level E-scores from the MSCI ESG dataset.[8] For our analyses, we use the last available E-score per quarter for each bond. These ratings range between 0 and 10, with 10 being the best score, indicating no risk exposure.

Our final bond sample covers the period from 2012 to the end of 2022 and includes 13,522 individual bonds issued by 9,398 unique firms. We summarize the bond characteristics in Table 1. The average yield in our sample is 3.79%. The bonds have, on average, a remaining time to maturity of 9.09 years, a price dispersion of 0.22%, a rating of 8.49 (i.e., on average, between BBB+ and BBB), and an E-score of 5.70. The average amount outstanding per bond issuance totals USD 870.68 million.

Finally, we obtain information on the quarterly holdings of bonds by institutional investors from Refinitiv eMAXX. The Refinitiv eMAXX dataset covers individual investors' holdings for different types of institutional investors. The investors are split into two types of insurers (life insurers and property, casualty, and health insurers), two types of funds (mutual funds and variable annuity funds), and a group of federal, state government, pension, and retirement funds. The notional amount

[6] Additional implementation details are covered in Appendix A.2.

[7] We clean bond prices following Dick-Nielsen (2009) using code from Scheuch et al. (2023).

[8] Berg et al. (2022) finds that the ratings provided by MSCI might be the most relevant ESG performance metric for institutional investors. Furthermore, next to Sustainalytics ESG Risk Ratings, ESG ratings from MSCI are seen by professional investors as one of the more useful ESG performance metrics, as well as one of the better ratings in terms of quality.

Table 1: Bond Characteristics.
This table shows summary statistics for all bonds in our sample. The bond-specific variables are yield to maturity in percent, time to maturity in years, price dispersion in percent, rating as a numeric variable between 1 (best) and 24 (worst), the environmental score (E-score) from MSCI, and the amount outstanding in 1,000 USD.

	Mean	SD	10th	Median	90th
Yield to Maturity	3.79	5.78	1.19	3.37	6.03
Time to Maturity	9.09	9.18	1.41	5.79	25.83
Price Dispersion	0.22	0.48	0.01	0.07	0.53
Rating	8.49	3.16	5.00	8.00	13.00
E-score	5.70	2.27	2.80	5.53	9.20
Amount Outstanding	870,683	693,879	300,000	700,000	1,666,940

of all bonds in our sample not covered by the holdings of the institutional investors is subsumed into the residual sector.[9] The residual sector represents households, small institutions, and other institutional investors that are not required to report their bond holdings (e.g., foreign banks). For each investor, we compute the dollar holdings of each bond, defined as the held par amount times the price, and the respective portfolio weights.

We summarize the investor characteristics from 2012 to 2022 in Table 2.[10] In the years 2012 and 2013, our sample consists of 4,197 individual institutional investors. This number grew to 5,088 at the end of our sample period. From 2020 to 2022, the median investor managed assets worth USD 46.40 million with a set of holdings of 79 bonds. The largest 10% of investors managed more than USD 571 million and the 10% with the most diversified holdings held more than 321 bonds. Over the full sample period, the median size of the investment universe is about 40 to 60% larger than the median number of bonds that are actually held.[11]

At the end of 2022, our merged sample represents a total outstanding par amount of about USD 4.89 trillion. The two largest types of institutional investors are mutual funds and life insurers. They respectively hold about 46% and 39% of the notional

[9] On average, we find that the residual sector's greenness demand is not distinguishable from zero.
[10] We also show the largest and smallest investors within each institutional investor type in Table IA-1.
[11] A precise definition of the investment universe is provided in Appendix A.3 and discussed in Section 5.

amount covered by the observed institutional investors. Property, casualty, and health insurers have a market share of 13%, variable annuity funds of 2%, and federal, state government, pension, and retirement funds hold a marginally small share of much less than 1%. This distribution of the total amount outstanding held by the different investor types is relatively stable over the full sample period. The only exception is the type of federal, state government, pension, and retirement funds. Their market share intermittently drops to zero since there are no observations of this type in the holdings data from the first quarter of 2019 up to the first quarter of 2022.[12]

Table 2: Investor Characteristics.
This table shows summary statistics for all institutional investors in our sample grouped into periods. The investors' assets under management (AUM) are in USD 1,000. The investment universe (Inv. Universe) is defined for each investor in each quarter as the set of all bonds held at one point in the preceding three years. The residual sector is not included in this exposition.

Period	No. of	Investor AUM		Bonds held		Bonds in Inv. Universe	
	Investors	Median	90th	Median	90th	Median	90th
2012-'13	4,197	45,660	445,889	65	221	93	317
2014-'15	4,248	49,080	501,066	71	248	109	398
2016-'17	4,425	49,613	549,249	77	282	117	439
2018-'19	4,676	49,008	559,629	80	301	119	438
2020-'22	5,088	46,397	571,007	79	321	128	497

5. Methodology

The demand system of Section 3 is highly tractable for obtaining a closed-form solution for bond demand and prices, and it provides a clear intuition of how heterogeneous investors' beliefs affect them. Here, we describe how we empirically fit this asset pricing framework to our data. Next, we introduce the counterfactual estimation used to investigate the impact of greenness demand. Finally, we establish the regression framework for investigating real effects.

[12] Figure IA-1 provides a visual representation of the wealth distribution.

5.1. Empirical Asset-Demand System

We start the empirical calibration by specifying the investment universe $\mathcal{N}_{i,t} \subseteq \{1, \dots, N\}$ of each investor i, which is defined by the set of bonds observed in the investor's holdings over the past three years (following Koijen and Yogo, 2019). This set spans current bond holdings and all bonds held at one point in the defined period. The next calibration step is to define the characteristics. Similar to Bretscher et al. (2025), we use yield, time to maturity, price dispersion, rating, and amount outstanding. Given our focus, we additionally include the bond issuer's environmental performance.[13]

In each quarter, each investor allocates their wealth $A_{i,t}$ among their investment universe and the outside asset, which consists of all bonds with available prices but missing characteristics.[14] To complete the notation, let $n = 0$ be the outside asset and investor $i = 1$ be the residual sector.[15] Correspondingly, we can now define investors' portfolio weights $w_{i,t}(n)$ for each bond $n \in \mathcal{N}_{i,t}$. Analogous to the observation in equity markets in Koijen et al. (2024), we consider these weights to follow a lognormal distribution and, thus, a non-linear relation between characteristics and weights. Hence, jointly with the budget constraint of each investor, our empirical implementation is a logit demand system (see Koijen and Yogo, 2019) that encapsulates the linear specification from Section 3.

Following that, investor i's portfolio weight on bond $n \in \mathcal{N}_{i,t}$ in period t is

$$w_{i,t}(n) = \frac{\delta_{i,t}(n)}{1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m)}, \tag{9}$$

where

$$\delta_{i,t}(n) = \frac{w_{i,t}(n)}{w_{i,t}(0)} = \exp\left(\alpha_{i,t} + \beta_{0,i,t} y_t(n) + \boldsymbol{\beta}'_{1,i,t} \boldsymbol{x}_t(n)\right) \epsilon_{i,t}(n). \tag{10}$$

[13] Note that we do not incorporate bond-level greenness labels. We do not expect controlling for this to significantly alter our results for two reasons. First, issuers of labeled green bonds already have a significantly better environmental performance (see, e.g., Flammer, 2021). Second, the total amount of green bonds outstanding is minuscule compared to the total bond market.

[14] Note that the outside asset mainly represents unrated bonds in our setup.

[15] Further implementation details are covered in Appendix A.3.

Thus, the portfolio weights depend on investor-time fixed effects $\alpha_{i,t}$, the bond's yield $y_t(n)$, a vector of observed characteristics $\boldsymbol{x}_t(n)$ that includes the environmental performance variable, and latent demand $\epsilon_{i,t}(n)$. Since the portfolio weights must sum to one, the weight on the outside asset is

$$w_{i,t}(0) = \frac{1}{1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m)}. \tag{11}$$

We denote the supply of a bond n as $S_t(n)$, which is represented by the amount outstanding. The market value $P_t(n) \cdot S_t(n)$ should be equal to the sum of asset demand across all investors. Therefore, in line with Section 3, we close the market by imposing market clearing for each bond n as

$$P_t(n) S_t(n) = \sum_{i=1}^{I} A_{i,t} w_{i,t}(n), \tag{12}$$

where we emphasize that the portfolio weight for bond n depends on the N-dimensional vector of bond prices through the yield. Thus, the logit demand system provides unique equilibrium bond prices comparable to Equation (8). However, here, the solution is numerical rather than in a closed form.

While recent critiques (e.g., Haddad et al., 2025) emphasize limitations in substitution patterns and identification of relative elasticities, we note that our primary object of interest is investor-specific demand for greenness within empirically defined investment universes, where logit-based substitution across bonds is a reasonable first-order approximation.

5.2. Estimating the Asset-Demand System

In principle, we can directly estimate the empirical demand system introduced before. However, we further improve the accuracy of our results by combining two refinements suggested in the previous literature.

First, as suggested by Bretscher et al. (2025), we estimate an instrument for the bond yield to complement the set of characteristics. This is prudent because the yield can be endogenously determined with latent demand if investors are not atomistically small or latent demand shocks are correlated. In particular, the investment universes of other investors are used as an exogenous instrument that only affects investor i's portfolio choice through prices. Let $|\mathcal{N}_{j,t}|$ be the number of bonds in the investment universe of investor j, and $\mathbb{1}_{\{n\in\mathcal{N}_{j,t}\}}$ be an indicator function that is equal to one if bond n is in investor j's investment universe. Then, we construct an instrument for the yield of bond n as

$$z_{i,t}(n) = \log\left(\sum_{j\notin\{i,1\}} A_{j,t}\frac{\mathbb{1}_{\{n\in\mathcal{N}_{j,t}\}}}{1+|\mathcal{N}_{j,t}|}\right). \tag{13}$$

By this definition, a bond should have a higher price if it is part of the investment universe of more and/or larger investors, which results in lower yields. The instrument is clearly independent of latent demand, and, as Bretscher et al. (2025) demonstrate, this instrument achieves high first-stage t-statistics, successfully passing the test for weak instruments of Stock and Yogo (2005).

Second, we see that institutional investors tend to hold concentrated portfolios. This can make coefficient estimates less reliable. Therefore, we resort to the two-step instrumental variables ridge estimation procedure developed in Koijen et al. (2024). Specifically, within the investor types, we rank investors by wealth and aggregate them so each group has at least 1,000 holdings. On a group level, we use non-linear GMM to estimate the demand coefficients through the following moment condition:

$$\mathbb{E}\left[\left(\underbrace{\delta_{i,t}(n)\exp\left(-\beta_{0,i}y_t(n)-\boldsymbol{\beta}_{1,i}'\boldsymbol{x}_t(n)\right)}_{\epsilon_{i,t}(n)}-1\right)\begin{pmatrix}z_{i,t}(n)\\ \boldsymbol{x}_t(n)\end{pmatrix}\right]=\mathbf{0}, \tag{14}$$

where $\mathbf{0}$ is a vector of zeros.[16]

Finally, we use the group-level estimates $\hat{\beta}_0$ and $\hat{\boldsymbol{\beta}}_1$ as the shrinkage target and add the ridge penalty (i.e., $\lambda = 10$ and $\xi = 0.7$) as a linear term in Equation (14).[17]

[16] Equivalent to Koijen and Yogo (2019), to ensure convergence in later counterfactual analysis, we impose the restriction of $\beta_0 > 0$ in the estimation.

[17] For investors that exceed 1,000 bond holdings, we use the estimates of Equation (14) directly.

Hence, we now estimate the coefficients on the other characteristics of each investor based on the following moment condition:

$$\mathbb{E}\left[\left(\hat{\delta}_{i,t}(n)\exp\left(-\boldsymbol{\beta}_{1,i}'\boldsymbol{x}_t(n)\right)-1\right)\boldsymbol{x}_t(n)\right]-\frac{\lambda}{|\mathcal{N}_i|^{\xi}}\left(\boldsymbol{\beta}_{1,i}-\hat{\boldsymbol{\beta}}_{1,i}\right)=\mathbf{0}, \tag{15}$$

where $\hat{\delta}_{i,t}(n)=\delta_{i,t}(n)\exp(-\hat{\beta}_0 y_t(n))$. This ridge procedure allows us to get precise estimates even for individual investors with concentrated portfolios.

We acknowledge recent debates surrounding the identification of price elasticities in cross-sectional demand estimation (e.g., Fuchs et al., 2023; Haddad et al., 2025). These critiques highlight that in the presence of strong substitution across assets, the cross-sectional instrumental variables approach may only identify a relative elasticity or local slope. In our corporate bond setting, however, substitution is naturally more limited as bonds differ along multiple features (e.g., maturity, rating, liquidity), investor mandates restrict eligible holdings, and arbitrage across bonds is constrained by frictions. Thus, the relative price elasticity we recover is economically meaningful and sufficiently informative for our analysis of greenness demand.

5.3. Estimating Counterfactuals

The demand system defined in Section 5.1, together with the market-clearing condition, allows for the quantification of the impact of counterfactual scenarios. By market clearing, equilibrium bond prices are a function of supply, bond characteristics, the wealth distribution, the coefficients on characteristics, and latent demand. Thus, we compute bond prices and yields under alternative market conditions, where we can alter demand coefficients and bond characteristics. Subsequently, we get associated counterfactual bond prices $\mathbf{P}_t^C$ as a solution to

$$P_t^C(n)=\frac{\sum_{i=1}^{I}A_{i,t}w_{i,t}^C(n;\mathbf{P}_t^C)}{S_t(n)}. \tag{16}$$

We solve for the counterfactual bond prices using the algorithm devised in Koijen and Yogo (2019).[18]

[18] We document the algorithm for counterfactual prices in Section III of the Internet Appendix.

Once we have counterfactual bond prices, we get the respective counterfactual wealth distribution from

$$A_{i,t}^{C}(P_t^C(n)) = A_{i,t}\left(w_{i,t}(0) + \sum_{n\in\mathcal{N}_{i,t}} \frac{P_t^C(n)}{P_t(n)} w_{i,t}(n)\right). \tag{17}$$

In particular, we use these counterfactual scenarios to examine the effects of changes in individual investors' greenness preferences. Moreover, we also simulate a counterfactual in which firms have different greenness performances.

5.4. Real Effects

For some of our results, we investigate whether greenness demand (GD_t) influences the behavior of firms.[19] To do so, we first define the market-wide aggregate measure for greenness demand as the wealth-weighted average coefficient on greenness performance

$$GD_t = \frac{\sum_{i=1}^{I} A_{i,t}\beta_{k,i,t}}{\sum_{i=1}^{I} A_{i,t}}, \tag{18}$$

where $\beta_{k,i,t}$ is the estimated coefficient of investor i on the kth characteristic in quarter t, which we assume is the greenness performance.

We use a panel regression model to test the impact of greenness demand on the firm's decision to improve its greenness performance. Since there is usually only a single major update in the E-score per year by MSCI, we use yearly frequency. The detailed specification is as follows

$$E\text{-}score_{i,y} = \beta E\text{-}score_{i,y-1} + \gamma\overline{GD}_{y-1} + \delta\mathbf{X}_{i,y-1} + \epsilon_{i,y}, \tag{19}$$

where $E\text{-}score_{i,y}$ represents the environmental performance of firm i at the end of year y, $\overline{GD}_y$ is the average greenness demand over year y, and $\mathbf{X}_{i,y}$ is the set of firm-specific variables at the end of year y. For easier interpretation, we standardize

[19] In Section V.1 of the Internet Appendix, we also provide this set of analyses using a measure for firm-level greenness demand similar to the *investor pressure* used in Noh et al. (2024).

the greenness demand measure.

In a further analysis, we employ a regression setup to investigate how greenness demand affects a firm's financing policies. Here, we consider several variables that describe investment decisions and regress them on the lagged environmental performance. Most importantly, we include the interaction of the greenness demand averaged over the previous four quarters and the environmental performance. The detailed specification is as follows:

$$\begin{aligned} Y_{i,t} =& \beta E\text{-}score_{i,t-1} + \gamma \overline{GD}_{t-1} \times E\text{-}score_{i,t-1} \\ &+ \delta \mathbf{X}_{i,t-1} + \zeta \mathbf{M}_{t-1} + \epsilon_{i,t}. \end{aligned} \tag{20}$$

$Y_{i,t}$ represents the level or changes in bond issuance activity and various capital structure variables for firm i in quarter / year t, and $\mathbf{M}_t$ is the set of macroeconomic variables. As before, we standardize the greenness demand.

6. Results

In this section, we present our results on investors' greenness preferences and the demand effects from three distinct angles. Initially, we discuss the greenness demand itself in Section 6.1. Then, we consider the demand's effects on the valuation of corporate bonds issued by firms with varying greenness (see Section 6.2), and we discuss the effects of shocks that exogenously change the demand for greenness on investors' wealth in Section 6.3. Finally, we consider the real effects on firms' behavior. To this end, Section 6.4 shows the incentives for firms to improve their greenness performance, highlights differences in how green and brown firms issue corporate bonds, and empirically investigates how firm fundamentals react to these changes.

6.1. Investors' Greenness Demand

The main goal of this paper is to deepen the understanding of investors' preferences for greenness. The model developed in Section 3 shines a light on this demand component and differentiates it from the demand for other bond features. The results from fitting the model to corporate bond market data deliver insights into the aggregate level of greenness demand and both time and cross-investor variation in these heterogeneous preferences. While these demand estimates provide important insights, they also form the basis for the subsequent analyses.

Figure 1: Overall Greenness Demand.
This figure shows the time series of the average demand coefficient on the environmental score. The solid line represents the average, and the shaded area represents the 95% confidence interval.

In Figure 1, we plot the average greenness demand, which represents the estimated coefficients on the environmental performance in Equation (10).[20] Given the characteristic's standardization, the coefficient represents the change in demand per one-standard-deviation change in environmental performance. Overall, greenness demand is predominantly positive from 2012 until the end of 2022. However, we also see significant variation over time, which aligns with regulatory changes and is in accordance with the media attention surrounding events that arguably raised awareness for climate issues. In particular, until 2015, the average greenness demand is around zero, as general climate awareness and other environmental concerns were

[20] For completeness, we also provide the remaining coefficients for all other bond characteristics in Section II of the Internet Appendix.

still low among the public as well as institutional investors. Yet, investors' preferences for greenness changed in 2015 when demand spikes up. This trend aligns with the 2015 United Nations Climate Change Conference (COP21) in Paris, culminating in the highest level of greenness demand in the third quarter of 2016 when the Paris Agreement was enacted. At this peak, we observe a greenness demand of around 0.14. For the average investor, this estimate implies that a bond's portfolio weight increases by 14% for a one-standard-deviation improvement in the E-score, ceteris paribus. Following this peak, however, a period of marked decline in the greenness demand started, which coincides with the first Trump administration. In fact, greenness demand reaches the lowest, marginally negative levels in 2019, simultaneously with the US withdrawing from the Paris Agreement in November 2019. Then, the next significant upward trend in greenness demand happens alongside another policy-shifting event, as Biden won the presidential elections in 2020. The Biden administration committed to rejoining the Paris Agreement and took a generally favorable stance on climate change mitigation. Finally, we see another drop in greenness demand towards the end of our sample. Again, this drop coincides with regulatory changes as several US states introduced restrictions regarding ESG investment strategies. Overall, the observed patterns in investors' preferences correlated with the public debate on climate-related issues and the US administration's regulatory interventions.

While the aggregate demand is clearly relevant, it masks significant cross-sectional heterogeneity between investors. Figure 2 reports the cross-sectional distribution of greenness demand over time.[21] In Panel A, we plot the wealth-weighted average greenness demand by investor types. On the one hand, both insurance types have a relatively stable positive demand for greener securities over the full sample period. This demand reflects the understanding that their underlying business models are potentially affected by physical risks associated with climate change. In particular, the group of property, casualty, and health insurers is especially affected by damages and disruptions caused by extreme weather events such as hurricanes, floods, droughts, and rising sea levels. On the other hand, most mutual funds presumably channel or reflect their investors' preferences. Thus, the greenness demand

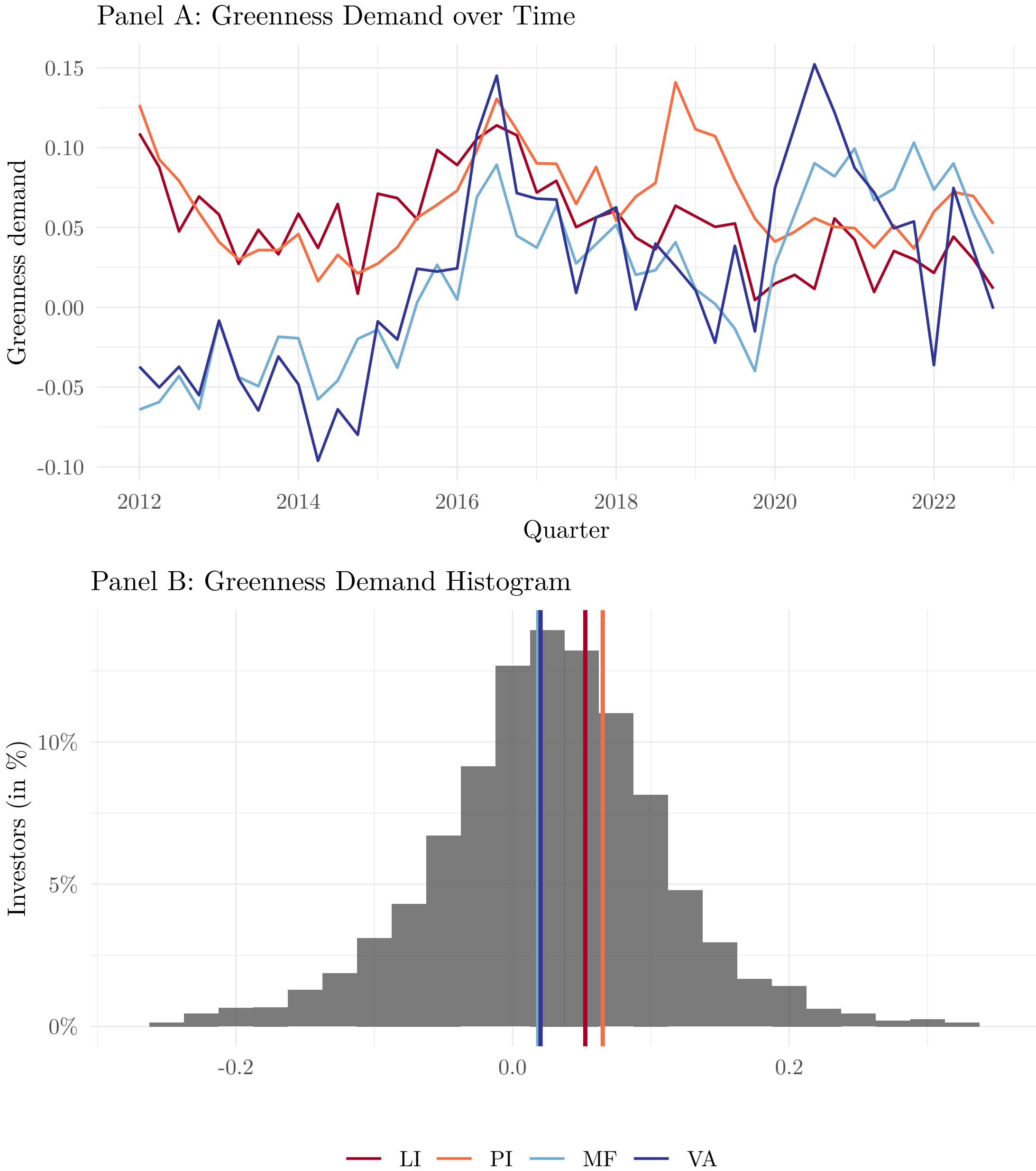
[21] Since the time series for federal, state government, pension, and retirement funds is incomplete due to the absence of holding data for certain quarters, we omit this investor type here.

of mutual funds and variable annuity funds fluctuates more over time and seems to be significantly influenced by exogenous events. Most notably, we see a slightly negative demand for greener securities at the beginning of the sample period, when sustainable investing or ESG investing were not yet established terms in the finance industry. Then, while the demand across all investor types moves up in unison related to the Paris Agreement's enactment at the end of 2016, the fund industry sees the biggest increase. Later, we see another strong demand boost from the fund industry at the end of 2020, again potentially linked to the Biden administration and its proposed environmental protection programs. Simultaneously, the beginning of this decade was marked by the uptake in the inception of funds with a specific sustainability objective in the investment process.[22]

Panel B of Figure 2 shows a histogram of the time-series average of the estimated greenness demand for each individual investor over the sample period (truncated at the 2.5% level in both tails). The colored vertical lines represent the wealth-weighted averages of the greenness demand of the different investor types. Panel B also reveals that there is much heterogeneity in greenness demand across individual investors. The highest observed average greenness demand of an individual investor is around 1.29. Vice versa, the lowest observed value is around -0.53.

[22] To further validate our estimates, we also inspect how ESG-focused mutual funds differ from other mutual funds in terms of their estimated greenness demand coefficients. In the Internet Appendix, Figure IA-8 shows that green mutual funds have significantly higher greenness demand than their competitors.

Figure 2: Greenness Demand.
Panel A shows the development of the value-weighted greenness demand coefficients for each investor type. Panel B shows the histogram of the time-series averages of demand coefficients of the respective asset characteristic for each individual investor. The colored vertical lines represent the time-series averages of the value-weighted demand coefficients of the investor types. We abbreviate life insurers (LI), property, casualty, and health insurers (PI), mutual funds (MF), and variable annuity funds (VA).



Finally, we employ a regression setup to check whether investor characteristics can explain this heterogeneity in greenness demand. In Table 3, we regress the estimated greenness demand coefficients on institutional-type dummies, controlling for the investor's size, active share, and quarterly portfolio turnover as suggested by Koijen et al. (2024). The full sample estimates in the first column show that larger institutional investors tend to have a higher greenness demand, and a higher active share and a higher turnover are also associated with a stronger demand for greener securities. Confirming the visual results above, we observe generally positive and statistically significant coefficients on the institutional-type dummies ranging between 0.02 and 0.04 over the full sample. Then, to examine a potential systematic shift during COP21, we also investigate the periods before and after COP21 separately in the second and third columns. In line with our other evidence, the insurance industry has a stable positive demand for environmental performance, whereas, for mutual and variable annuity funds, we see a switch in signs. Before COP21, the fund industry has a generally negative stance towards green securities with coefficient estimates of -0.03 and -0.06. However, this changes in the second sample period, when we observe positive demand from mutual and variable annuity funds at levels of 0.05 and 0.06.

Table 3: Greenness Demand of Institutional Investors
This table shows the results of quarterly regressions of the environmental performance demand coefficient on institution-type dummies. In the first column, we report the results for the whole sample period. The sample is restricted to the period before (after) COP21 in 2015:Q4 in the second (third) column. The controls log of assets under management (AUM), active share, and portfolio turnover are standardized on a quarterly basis. We indicate significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

	2012-2022	Pre COP21	Post COP21
LI	0.031***	0.048***	0.022***
	(0.001)	(0.001)	(0.001)
PI	0.041***	0.067***	0.030***
	(0.001)	(0.001)	(0.001)
MF	0.022***	−0.029***	0.044***
	(0.001)	(0.001)	(0.001)
VA	0.015***	−0.057***	0.056***
	(0.002)	(0.002)	(0.002)
log(AUM)	0.010***	0.005***	0.013***
	(0.001)	(0.001)	(0.001)
Active Share	0.008***	0.003***	0.009***
	(0.001)	(0.001)	(0.001)
Turnover	0.003***	−0.001**	0.004***
	(0.000)	(0.001)	(0.001)
Num. obs.	154,693	48,513	106,180
Adj. R^2	0.008	0.097	0.009

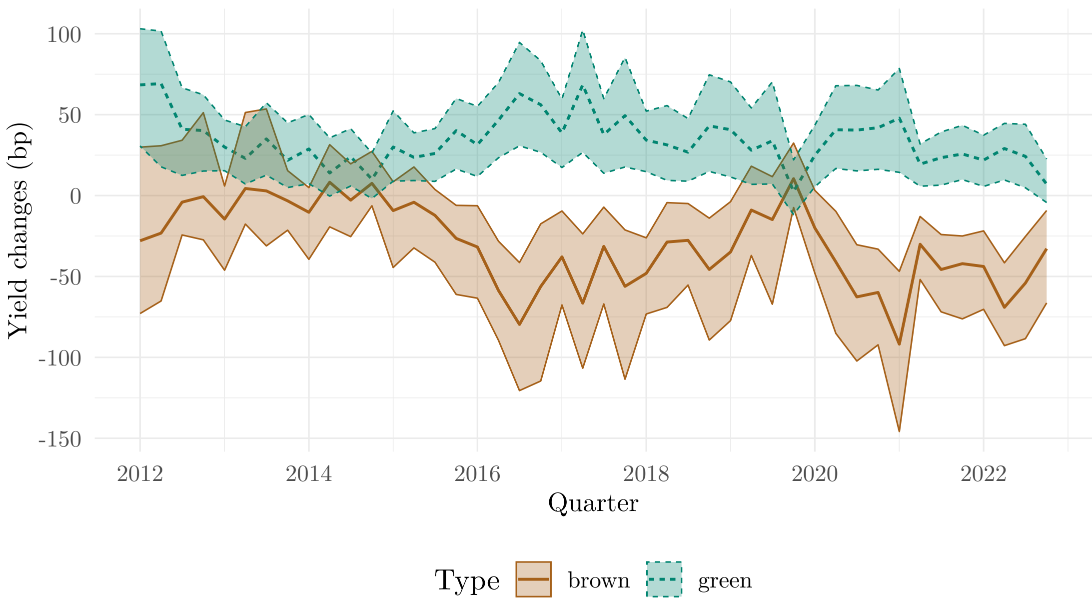
6.2. Greenness' Price Effects

Building on the finding that investors generally exhibited a positive greenness demand, we next study corresponding price effects. In particular, our results reveal how much the yields of green or brown bonds are impacted by these preferences. To investigate the demand's contribution to observed yields, we simulate a counterfactual that mutes institutional investors' greenness demand and, thereby, creates an equilibrium with yields unaffected by these preferences. Specifically, we set the demand coefficient for environmental performance to zero for institutional investors and solve for the market-clearing price (see Section 5.3).[23] Then, we compare the observed and counterfactual yields to provide evidence for greenness-induced price effects. Thereby, we complement the recent theoretical literature (see, e.g., Favilukis et al., 2023; Dangl et al., 2025a,b) that discusses firms' endogenous reaction to demand. Given such supply adjustments, any direct comparison between bond prices cannot cleanly identify the effect of investors' preferences. However, our counterfactual analyses implicitly account for such supply effects and, thus, are a feasible way to estimate the valuation effects of greenness demand.

Figure 3 shows the difference between counterfactual and actually observed yields, where the counterfactual scenario has zero institutional investors' greenness demand. We can clearly observe that yields of bonds of green issuers (i.e., having an E-score above 7.5) are higher without institutional investors' greenness demand. Moreover, the variation over time in the yield impact is strongly connected to the time-series variation in average greenness demand in Figure 1. The yield impact is relatively small in the years before COP21, intermittently marginally different from zero. However, in the years after COP21, we see a strong price impact. In the third quarter of 2016, the median difference between the counterfactual yield and the actual yield is 63bp. Subsequently, the price impact of greenness demand enters a downward trajectory until the end of 2019, reaching zero. We see another spike of about 48bp in the first quarter of 2021, followed by the yield impact flattening out again. Over the full sample period, the yield change averages out at 33bp for

[23] It is worth noting that our counterfactual simulations focus on cross-sectional tilts within a given quarter, holding fixed the distribution of investor types, investment universes, and assets. Thus, while we do not separately identify aggregate multipliers (as emphasized by Haddad et al., 2025), the analysis isolates the marginal contribution of greenness preferences under equilibrium conditions that reflect real-world frictions and constraints.

Figure 3: Impact of Environmental Preferences on Bond Yields.
This figure shows the time series of the counterfactual changes in bond yields (in basis points) if institutional bond investors had no preferences for issuers' environmental performance. Bonds with issuers' E-scores above 7.5 are considered "green" and bonds with issuers' E-scores below 2.5 are considered "brown". The solid, brown (dashed, green) line represents the median for brown (green) bonds. The respective first and third quartiles are shown as shaded areas.



greener securities. If we broaden the focus to bonds of issuers with an E-score above 5, the average observed yield change is 11.4bp. When analyzing the bonds of brown firms (i.e., having an E-score below 2.5 or 5), the variation and magnitude of the price impact generally mirror those of their green counterparts.

We test this price impact and the contribution of the demand of the different investor types in a regression setup. This analysis not only sheds light on which investors drive the yield wedge but also controls for other bond-specific characteristics. Therefore, we regress the difference between counterfactual yield and actual yields on the bond characteristics in the demand function. Table 4 provides these regression results. The first column depicts the counterfactual scenario in which mutual and variable annuity funds have no greenness demand, where the regression coefficients represent the change compared to the actual yields. This implies that if we remove the greenness demand of the fund industry, then the yield decrease due to a one-standard-deviation increase in the environmental score is 5.2bp smaller. Likewise, the second column is based on the counterfactual scenario where insurers and the group of federal, state government, pension, and retirement funds have no greenness demand. Here, we see a stronger change in the regression coefficient on the environmental score of 14.3bp. In the last column, we mute the demand for greenness for all institutional investors. These coefficients represent approximately the cumulative changes found in columns one and two. In summary, the greenness demand of the two types of insurers, together with pension and other federal funds, has, on average, a stronger impact on bond yields than the demand of mutual and variable annuity funds. Moreover, as expected, if no institutional investors had greenness demand, the overall effects represent an order of magnitude that basically fully offsets the decreasing effect of environmental performance on bond yields discussed previously.

Overall, our results point towards a significant impact of investors' preferences for greenness. While the exact size of the effect depends on the specific demand changes, the potential yield savings for green firms are high, creating meaningful incentives for real policy changes. In fact, our valuation evidence goes well beyond simply observing and measuring yield differences of bonds issued by firms with different environmental performances, which have been studied in the literature so far. The counterfactual analyses shown here document the effects of greenness demand, fully taking possible corporate supply effects into account. In other words, in response to greenness demand, green firms may have substantially increased the supply of green bonds in the past and/or initially brown firms may have become greener. This may lead to vanishing yield differences across bonds of issuers with different environmental performances. Therefore, simply measuring yield differences may lead to the conclusion that an issuer's greenness does not matter for bond prices. However, even in this case, investors' greenness preferences can be relevant and reflected in market prices, and this is precisely what we document. Given the existing supply of bonds and the resulting prices, we analyze what happens to corporate bond prices if greenness demand by particular investor groups vanishes. We show that this has substantial effects on bond prices and is consistent with significant corporate supply effects in response to greenness demand. Consequently, Section 6.4 analyzes firm reactions to changing greenness demand in more detail.

Table 4: Impact of Environmental Preferences on Bond Yields
This table shows the results of quarterly regressions of the bond yield and counterfactual yield changes on characteristics. All characteristics are standardized on a quarterly basis. In the first column, the dependent variable is the difference between the counterfactual yield if mutual funds had no preferences for environmental performance and the actual observed yield (in basis points). In the second column, the dependent variable is the difference between the counterfactual yield if insurers, pension funds, and federal institutions had no preferences for environmental performance and the actual yield. In the third column, the dependent variable is the difference between the counterfactual yield if all institutional bond investors had no preferences for issuers' environmental performance and the actual yield. All specifications include quarter-fixed effects and a dummy variable for a missing environmental score. The standard errors shown in parentheses are clustered at the firm-quarter level. We indicate significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

	Counterfactual		
	MF, VA	LI, PI, PF	All
E-score	5.218***	14.260***	19.513***
	(1.651)	(1.301)	(2.041)
Time to Maturity	−0.718	−0.013	−0.716
	(0.527)	(0.391)	(0.801)
Price Dispersion	0.312	0.555***	0.867**
	(0.341)	(0.183)	(0.400)
Rating	−0.354	0.981**	0.637
	(0.635)	(0.378)	(0.638)
Amt. Outstanding	−0.532	−0.731**	−1.254**
	(0.441)	(0.335)	(0.578)
Num. obs.	175,275	175,275	175,275
Adj. R^2	0.300	0.340	0.406

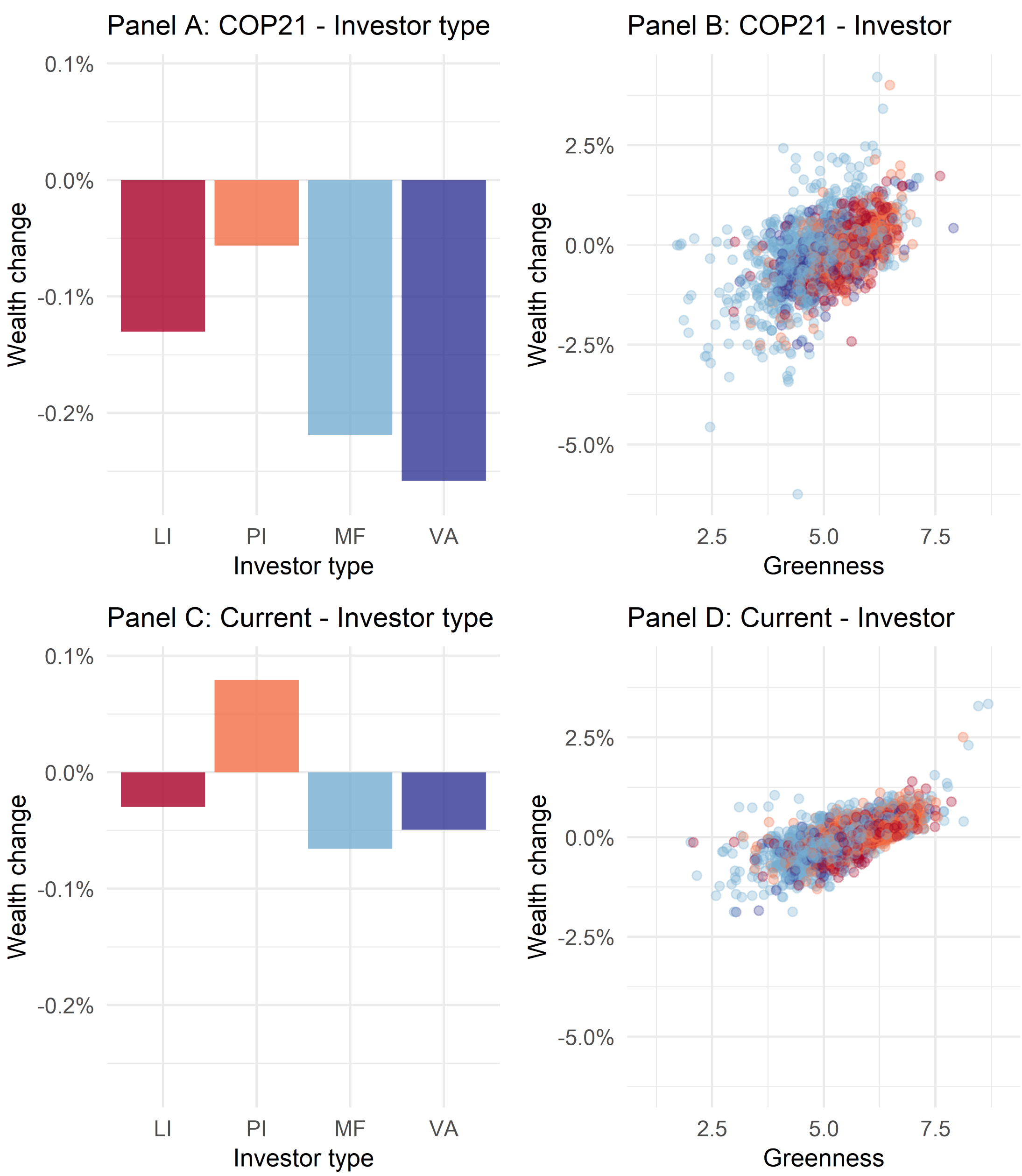
6.3. Greenness-related Regulatory Interventions

The estimated time series of greenness demand suggests a relation to regulatory and political events. In particular, the signing of the Paris Agreement and the beginning of the first Trump administration are plausibly exogenous events that align with significant changes in investors' preferences for greenness. Consequently, combining these exogenous shocks with the previously shown price impact raises questions about how sensitive investors' wealth is to these events. To understand this sensitivity, we build on the previous section's quantification of the yield impact of greenness demand based on counterfactual prices. In this part, we take these counterfactual prices to compute a counterfactual wealth for each investor, as shown in Equation (17). Figure 4 shows the distribution of relative wealth changes due to greenness demand.[24]

COP21 shock. Panel A and B of Figure 4 provide relative wealth changes due to the rise in greenness demand after COP21. Panel A shows the average wealth impact per investor type in the third quarter of 2016. Here, we use portfolio weights directly before COP21, where we do not observe any stark increases in greenness demand yet.[25] In the next step, we calculate investors' wealth using counterfactual prices, which assume that greenness demand remains artificially unchanged by COP21, and contrast this with actual prices observed after COP21. With this approach, we ensure that the investors' estimated wealth change is exclusively driven by the rise of the greenness demand leading up to the Paris Agreement. On average, mutual and variable annuity funds are affected the most since their portfolios least incorporate environmental aspects in that period. An average mutual fund and an average annuity fund lose 22bp and 26bp in value, respectively. Compared to that, insurers are less impacted. An average life insurer has a loss of 13bp, and an average investor in the group of property, casualty, and health insurers only loses approximately 6bp. Similar to our previous analysis, grouping institutions into a few types masks considerable cross-investor heterogeneity. Therefore, we show the full distribution of individual investors' wealth changes across the average environmental performance spectrum of their holdings in Panel B. As can be seen, there is a clear association between the wealth impact and the investor's E-score. The worst wealth change by an individual investor is -6.2%, and on the opposite side, the highest wealth gain by an individual investor is 4.2%. Consequently, we conclude that the demand shock around COP21 had a marked wealth effect on investors.

[24] In Section IV of the Internet Appendix, we provide this analysis with absolute wealth changes.
[25] The results remain unchanged if we use weights from the third quarter of 2016.

Figure 4: Impact of Greenness Demand on Investors' Wealth.
This figure shows relative wealth changes due to changes in the aggregate greenness demand. Panels A and B show wealth changes due to increased greenness demand following COP21. Panels C and D show the wealth changes from a counterfactual greenness demand shock at the end of 2022. Panels A and C provide average changes per investor type. Panels B and D provide changes in relation to the value-weighted average E-score of an investor's holdings. We abbreviate life insurers (LI), property, casualty, and health insurers (PI), mutual funds (MF), and variable annuity funds (VA).



Current shock. Next, we model the regulatory or stakeholder risk as a shock to greenness demand at the end of our sample period. To this end, we simulate what would happen if an event of the magnitude of the Paris Agreement happened today, i.e., if a similar exogenous shock hit investors at the end of 2022. To do so, we increase the coefficient on the environmental performance of all institutional investors by 0.1 (approximately equal to the elevated level around the COP21 demand spike) and again estimate counterfactual prices. As in Panel A, Panel C of Figure 4 provides the average relative wealth changes for each investor type due to this hypothetical policy shock to greenness demand. As in 2016, average life insurers, mutual funds, and variable annuity funds would lose value. However, the losses are now comparably smaller with 3bp, 7bp, and 5bp, respectively. An average property, casualty, and health insurer even gains in value by 8bp. Panel D shows the full distribution of wealth changes across the investors' greenness profiles. Now, the worst wealth impact amounts to only -1.9%. Thus, overall, institutional investors appear to be less impacted if an event such as the Paris Agreement had happened again in December of 2022. There are several potential explanations for this. First, the relatively lower yield elasticity of the institutional investors may lead to less pronounced wealth changes compared to the Paris Agreement.[26] Second, institutional investors seem to be better prepared for such scenarios. Although the actual average greenness demand is approaching zero in the last quarter of 2022, as can be seen in Figure 1, investors have increased their portfolios' E-score since COP21 on average. This aggregate change is only possible because firms have significantly improved their environmental performance and/or greener firms have issued more bonds over this period. Thereby, firms' decisions insulate investors from another positive shock in greenness demand.

6.4. Firm-level Reactions to Greenness Demand

In this final subsection, we focus on firm-level responses to identify the real effects of greenness demand. First, we estimate the magnitude of firms' incentives to improve their greenness performance from our demand system. These incentives are the mechanism through which greenness demand can impact firm-level decisions to

[26] We show the yield elasticity over time (alongside other demand coefficients) in Table IA-4 in the Internet Appendix.

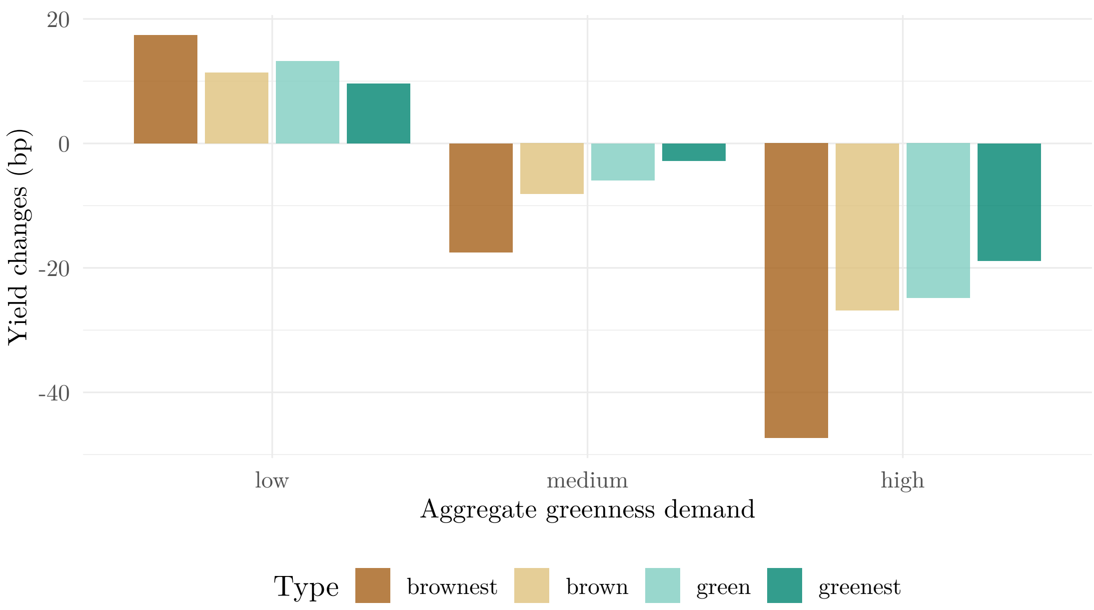
adopt green policies. Then, we leverage the time variation in greenness demand to empirically identify the real effect of investors' preferences on firms' environmental performance. In our second empirical analysis, we show how greenness demand affects bond issuance activity. Finally, we analyze the reactions of firm fundamentals to changes in greenness demand.

Greenness performance improvements. So far, we have established the yield impact of institutional investors' demand for environmental performance. Now, we take the opposite route. We change the firms' environmental performances and estimate the resulting counterfactual yields. To maintain parsimony, we categorize bonds by their issuers' environmental performance. Bonds with an E-score below 2.5 are "brownest", between 2.5 and 5 "brown", between 5 and 7.5 "green", and above 7.5 "greenest". For each category, we estimate counterfactual yields based on collectively improving the types' E-score of all bonds by 2.5. For the "greenest" bonds, we set the E-scores to 10.

Figure 5 shows the average counterfactual yield changes for three aggregate demand regimes (with "low" being quarters in the bottom quartile, "high" being quarters in the top quartile, and "medium" being the quarters in the intermediate quartiles). In the low-demand regime, we find no incentives to improve greenness performance as expected. In periods with medium greenness demand, we only observe a significant potential for yield reductions for "brownest" firms. These incentives are roughly 18bp, whereas yield reductions for firms in the other categories are below 10bp. Finally, all firms see significant yield savings during times of high greenness demand. Particularly impressive are the results for "brownest" firms with a decline in their bonds' yields of about 47bp when improving their environmental performance by one notch. On the other side of the greenness spectrum, for "greenest" firms, the efforts to improve the environmental performance are met with yield savings of 19bp.

Given these potentials for yield improvements, we investigate whether firms change their real decisions to take advantage of the reduction in their cost of debt. Pástor et al. (2021) postulates that the asset pricing effects, on the one hand, lead firms to become greener, and on the other hand, more environmentally-friendly firms to

Figure 5: Environmental Performance Improvement and Bond Yields. This figure shows average counterfactual changes in bond yields (in basis points) if bond issuers' environmental performance improves to the next 2.5-step (i.e., by at most 2.5). We split the sample period into three aggregate greenness demand levels: Quarters with greenness demand outside the top (bottom) quartile are classified as "high" ("low") demand, and all intermediate quarters are categorized as "medium". Additionally, we group the bonds based on their issuer's environmental performance. If the E-score is above 7.5, the bond is considered "greenest", if the E-score is between 5 and 7.5, the bond is considered "green", if the E-score is between 2.5 and 5, the bond is considered "brown", and if the E-score is below 2.5, the bond is considered "brownest".



invest more and polluting firms to invest less. First, we investigate a potential improvement in environmental performance. Table 5 provides the regression results for the model in Equation (19). In particular, we use the variation in greenness demand to identify firms' incentives to improve their environmental performance, which is the dependent variable, controlling for firm-specific variables. In Panel A, we present the regression estimated with the level of the E-score as the response variable explained by the greenness demand lagged by one year. Panel B shows results for a lag of two years. Pooling all firms (in the first column), we do not find that the greenness demand impacts future improvements in environmental performance within one year. However, this average effect masks differences between green (i.e., firms with E-scores above five in the second column) and brown issuers (i.e., firms with E-scores below five in the third column). Again, there are no effects for the sample of brown firms. However, for the green firms, we find a statistically significant coefficient on the average greenness demand. This positive coefficient shows that green firms react to the incentives to become greener. In terms of magnitude, a one-standard-deviation change in greenness demand leads greener firms to improve their E-score in the succeeding year by 0.053. Shifting our attention to a two-year period (Panel B), we find a significant positive effect when jointly analyzing all firms, and the coefficient for green firms increases to 0.083. For brown firms, the coefficient is positive, but still insignificant. The size of the effects for green firms is comparable to the aggregate annual E-score improvement of around 0.14. This trend is significantly boosted, particularly following periods of heightened greenness demand. For example, while a one-point E-score improvement takes roughly seven years in regular conditions, this speeds up to four years, assuming the COP21 environment persists.[27]

Overall, we find that firms benefit from improving their greenness performance, particularly during periods of high greenness demand. Theoretically, these yield savings are strongest for the brownest firms. However, we find that the green firms are the firms that react faster to changes in the demand for greenness. Greener firms improve their environmental performance following high demand for it within one year. On the other hand, brown firms do not immediately improve their greenness performance following heightened aggregate greenness demand. This difference in our findings provides potential insights into the cost and duration of implementing green policies, which seem significantly higher for brown firms as they do not take advantage of the potentially high reductions in their cost of debt.

Bond issuance activity. The documented effects of greenness demand on corporate bond valuation raises the question whether it also induces a reallocation of capital. We therefore explore issuance behavior, relating offering amounts and is-

[27] We complement this analysis by investigating changes in firm-level emission intensities instead of aggregated scores in Table IA-6 in the Internet Appendix. We find that our results hold similarly for emission intensities, i.e., firms reduce emissions more when greenness demand is high, providing, in part, an explanation for the overall E-score improvement. However, emission data is only available for around 50% of the firms in our sample.

Table 5: Impact of Greenness Demand on Environmental Performance. This table shows the results of regressions of future firms' environmental performance on the standardized wealth-weighted greenness demand and environmental performance. In Panel A (B), the dependent variable is the environmental performance in one year (two years). In the first column, we use the full sample. For the second and third columns, we restrict the sample to issuers with an E-score above five and below five, respectively. We control for rating, leverage, profitability, firm size, and tangibility in all specifications. The standard errors shown in parentheses are clustered at the industry level. We indicate significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

Panel A: One year

	All	Green	Brown
$\overline{\text{GD}}_{y-1}$	0.017	0.053**	−0.016
	(0.016)	(0.024)	(0.017)
E-score$_{y-1}$	0.914***	0.923***	0.867***
	(0.010)	(0.015)	(0.016)
Num. obs.	10,165	5,120	5,045
Adj. R^2	0.875	0.759	0.620

Panel B: Two years

	All	Green	Brown
$\overline{\text{GD}}_{y-2}$	0.043*	0.083**	0.007
	(0.025)	(0.035)	(0.023)
E-score$_{y-2}$	0.847***	0.855***	0.745***
	(0.017)	(0.025)	(0.022)
Num. obs.	9,153	4,539	4,614
Adj. R^2	0.781	0.608	0.449

suance frequency to firms' environmental performance and greenness demand, while controlling for firm characteristics and macroeconomic conditions. Table 6 provides the results from the corresponding regression, specified in Equation (20).

In the first column, the response variable is the logarithm of the overlapping four-quarter cumulative offering amount.[28] Consistent with our earlier findings, a higher E-score by itself does not raise the cumulative offering amount. However, the coefficient on the interaction term of the E-score and greenness demand is significantly positive, telling us that the issuance of greener firms increases in the four quarters succeeding heightened greenness demand. Quantitatively, a one-standard-deviation increase in greenness demand amplifies the effect of a one-point increase in E-score on the subsequent four-quarter cumulative offering amount by up to 6.3%. Evaluated at high greenness demand, this implies that a firm with a one-standard-deviation higher E-score issues about 14.3% more.

In the second column, we replace the dependent variable with an indicator for whether a firm issues at least one bond within the four-quarter window. Greener firms issue more frequently: a one–standard deviation higher E-score raises the issuance probability by about one percentage point. Relative to the unconditional quarterly issuance probability of 9.1%, this effect is economically meaningful.

Firm fundamentals. We next examine how firm fundamentals respond to greenness demand and environmental performance. Given the lower financing costs and higher issuance activity of greener firms in periods of elevated greenness demand, an important question is how the additional funds are deployed and how this deployment affects capital structure and risk. One possibility is that firms channel the proceeds into additional green investments, thereby increasing leverage. Alternatively, firms may substitute away from costlier sources of funding (e.g., bank loans) or raise equity to keep leverage stable. Related work (such as Luneva and Sarkisyan, 2024; Beyene et al., 2025) provides first evidence of a financing trade-off linked to environmental performance: banks offer relatively lower rates to brown firms, making bank credit less attractive for green firms. Against this backdrop,

[28] In Table IA-7 of the Internet Appendix, we report consistent results using a non-overlapping specification.

Table 6: Impact of Greenness Demand on Bond Issuance.
This table shows the results of regressions of bond issuance on the standardized wealth-weighted greenness demand over the preceding four quarters and firms' environmental performance. In the first column, the dependent variable is the logarithmic offering amount over the current and succeeding three quarters. In the second column, the dependent variable is a dummy variable indicating whether a firm issued bonds in the current and succeeding three quarters. In all specifications, we control for firm characteristics (i.e., rating, leverage, profitability, firm size, and tangibility) and macroeconomic variables (i.e., GDP changes, default spread, term spread, T-Bill rate, and CPI changes). As the dependent variables are overlapping, we report Newey-West standard errors with four lags in parentheses. We indicate significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

	$\log(\text{Amt.}_q{+}1)$	$\text{Amt.}_q > 0$
E-score_{q-1}	0.038	0.002
	(0.028)	(0.002)
$\overline{\text{GD}}_{q-1} \times$ E-score_{q-1}	0.063**	0.005**
	(0.029)	(0.002)
Num. obs.	44,066	44,066
Adj. R^2	0.271	0.269

our design isolates the mechanism operating through bond investors' preferences and traces its implications for firms' funding mix and risk profile.

We analyze firms' balance-sheet responses by relating changes in capital-structure variables to environmental performance and greenness demand, controlling for firm characteristics and macroeconomic conditions. We reuse the regression design in Equation (20) and report results for changes in leverage, bank debt, book equity, and capital expenditures (capex) as dependent variables (Table 7).

Leverage shows no significant response to the lagged E-score or to the interaction of lagged greenness demand with the E-score, providing no evidence that greener firms lever up relative to equity. By contrast, the interaction term is significantly negative for bank debt: for a one-standard-deviation increase in greenness demand, bank debt falls by 2% for a one-point increase in the E-score; for a firm that is one standard deviation greener, this implies a decline of roughly 4.5%. Consistent with a funding mix shift, we also find a positive effect on book equity: greener firms raise book equity by about 1.1% in periods of elevated greenness demand, leaving leverage broadly unchanged. Finally, capex rises by roughly 1%, indicating that part of the additional bond financing is deployed into real investment while bank borrowing is partially substituted.

Table 7: Impact of Greenness Demand on Fundamentals.
This table shows the results of regressions of different accounting variables on the standardized wealth-weighted average greenness demand and firms' environmental performance. In the first column, the dependent variable is the change in leverage (Lev). In the second column, we show results for changes in bank debt (BD). In the third column, the dependent variable is the change in book equity (BE). In the fourth column, we show results for changes in capital expenditures (CAPEX). In all specifications, we control for firm characteristics (i.e., rating, profitability, firm size, and tangibility) and macroeconomic variables (i.e., GDP changes, default spread, term spread, T-Bill rate, and CPI changes). Furthermore, models two to four also control for leverage. The standard errors shown in parentheses are clustered at the industry level. We indicate significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

	ΔLev_y	$\Delta\log(\text{BD}_y{+}1)$	$\Delta\log(\text{BE}_y{+}1)$	ΔCAPEX_y
E-score_{y-1}	0.298	0.012	−0.003	0.017
	(0.228)	(0.014)	(0.003)	(0.017)
$\overline{\text{GD}}_{y-1} \times \text{E-score}_{y-1}$	−0.029	−0.020**	0.005***	0.017*
	(0.044)	(0.008)	(0.002)	(0.009)
Num. obs.	9,350	8,873	9,183	9,398
Adj. R^2	0.009	0.013	0.049	0.022

Overall, higher greenness demand in bond markets elicits a clear corporate response. Greener firms issue more frequently and in larger amounts, partially substitute away from bank debt, and raise book equity, leaving leverage unchanged. The additional funds are deployed into long-term assets. Taken together, these patterns show how investors' preferences for greenness translate into firms' real financing and investment policies.

7. Conclusion

In this paper, we provide comprehensive evidence on institutional investors' demand for corporate bond greenness. Our findings are based on a demand system building on Koijen and Yogo (2019), calibrated to institutional holdings of US corporate bonds. This framework enables us to identify preferences for greenness that cannot be observed solely from yield differences between bonds issued by firms with varying environmental performance.

We document that institutional investors have a positive demand for greener assets. However, the strength of this demand changes substantially over time and does not follow a linear trend. Our estimates indicate that greenness demand responds significantly to environment-related events with regulatory relevance. In particular, the Paris Agreement signed at COP21 coincides with the highest observed greenness demand, whereas the US withdrawal from the agreement is associated with a pronounced decline. Across investor types, mutual funds closely mirror these dynamics, showing a marked increase in greenness demand after COP21. By contrast, insurance companies maintain a consistently high and relatively stable demand for green assets.

From counterfactual simulations with muted environmental preferences, we isolate the bond price effects arising from shifts in greenness demand. Comparing observed and counterfactual yields reveals significant valuation impacts: bonds issued by firms with strong environmental performance exhibit significantly lower yields attributable to greenness demand, whereas bonds of environmentally weaker firms command higher yields. Furthermore, our findings reveal that insurance companies, with their consistent positive greenness demand, play a key role in driving these valuation effects.

Exploiting arguably exogenous regulatory shocks, we further demonstrate that greenness demand has significant implications for investors' wealth. Our analyses quantify both the losses incurred by portfolios tilted towards brown assets and gains realized by investors with a greenness tilt. Together, these results point to the potential regulatory risks faced by investors amid uncertain future environmental policies.

We further show that greenness demand has significant real effects on firms' decisions. First, firms benefit from meaningful yield reductions when improving environmental performance; these benefits are largest for the brownest firms and increase with greenness demand across the environmental spectrum. However, only green firms appear to respond in the short run: they further improve their greenness following periods of elevated demand, whereas brown firms do not, plausibly reflecting higher implementation costs or longer technology-adjustment lags. Second, following an increase in investors' demand for greenness, green firms raise more capital via corporate bonds than brown firms, issuing more frequently and at higher face values, and they use the proceeds to substitute away from bank debt and to invest in long-term assets, while maintaining overall leverage.

Taken together, the paper documents the dynamics of greenness demand in corporate bond markets and the resulting feedback mechanism. As environmental concerns, such as regulatory or political developments, become more salient, investor preferences for greenness intensify, prompting firms to adjust financing and investment policies.

Appendix

A. Implementation Details

A.1. Model Derivations

Derivation of Equation (7): Given the normality assumptions, we can rewrite investor i's objective function from Equation (3) as

$$\max_{\mathbf{Q}_i} -\exp\left(-\gamma_i(A_{0,i} + \mathbf{g}_i'\mathbf{Q}_i) - d_i\mathbf{f}'\mathbf{Q}_i + \frac{\gamma_i^2}{2}\mathbf{Q}_i'(\boldsymbol{\rho}_i\boldsymbol{\rho}_i' + \sigma^2\mathbf{I})\mathbf{Q}_i\right). \tag{A-1}$$

This leads to the first-order condition for the optimal portfolio choice

$$-\mathbf{g}_i - \frac{d_i}{\gamma_i}\mathbf{f} + \gamma_i(\boldsymbol{\rho}_i\boldsymbol{\rho}_i' + \sigma^2\mathbf{I})\mathbf{Q}_i = \mathbf{0}. \tag{A-2}$$

Solving for the optimal demand results in

$$\begin{aligned} \mathbf{Q}_i =& \frac{1}{\gamma_i}\left(\boldsymbol{\rho}_i\boldsymbol{\rho}_i' + \sigma^2\mathbf{I}\right)^{-1}\left(\mathbf{g}_i + \frac{d_i}{\gamma_i}\mathbf{f}\right) \\ =& \frac{1}{\gamma_i\sigma^2}\left(\mathbf{I} - \frac{\boldsymbol{\rho}_i\boldsymbol{\rho}_i'}{\boldsymbol{\rho}_i'\boldsymbol{\rho}_i + \sigma^2}\right)\left(\mathbf{g}_i + \frac{d_i}{\gamma_i}\mathbf{f}\right) \\ =& \frac{1}{\gamma_i\sigma^2}\left(\mathbf{g}_i + \frac{d_i}{\gamma_i}\mathbf{f} - c_i\boldsymbol{\rho}_i\right). \end{aligned} \tag{A-3}$$

In the second line, we applied the Woodbury matrix identity. The scalar

$$c_i = \frac{\boldsymbol{\rho}_i'\left(\mathbf{g}_i + \frac{d_i}{\gamma_i}\mathbf{f}\right)}{\boldsymbol{\rho}_i'\boldsymbol{\rho}_i + \sigma^2}$$

encodes information about all assets and does not vary across bonds. The last line of Equation (A-3) reveals that demand for bond n increases in the expected return $\mathbf{g}_i$, in the greenness performance $f(n)$ if $d_i > 0$, and decreases in the factor exposure $\boldsymbol{\rho}_i$ if $c_i > 0$. The direction the demand changes with respect to the greenness sensitivity d_i, depends on the greenness performance. The demand for bond n increases in d_i if $f(n) > 0$, and, vice versa, decreases if $f(n) < 0$.

Lastly, we substitute Equations (5) and (6) in Equation (A-3). Assuming the greenness performance to be at the kth position of $\mathbf{x}(n)$, we additionally define $\boldsymbol{\zeta}_i = \frac{d_i}{\gamma_i}\mathbf{e}_k$, where $\mathbf{e}_k$ is a vector with the kth element being one and all other elements being zero. This vector captures the additional risk-aversion-scaled utility of investor i from holding greener assets. Thus, investor i's optimal demand for bond n is given by

$$q_i(n) = \frac{1}{P(n)\gamma_i\sigma^2}\left(\underbrace{(\boldsymbol{\lambda}_i^g - c_i\boldsymbol{\lambda}_i^\rho + \boldsymbol{\zeta}_i)'}_{\tilde{\boldsymbol{\beta}}_i}\mathbf{x}(n) + \underbrace{\nu_i^g(n) - c_i\nu_i^\rho(n)}_{\epsilon_i(n)}\right). \tag{A-4}$$

A.2. Data Construction

Quarterly price and liquidity For each bond, we compute a volume-weighted price per week and respective yield-to-maturity from the trades recorded in TRACE. Here, we require a minimum of five observations in a week. To match the frequency of the holdings data, which is at a quarterly frequency, we convert the data obtained from TRACE to quarterly data by using the last available price and yield of each bond in a given quarter. However, we restrict the last price to be in the last month of the quarter. For simplicity in later calculations, we reformulate the yield-to-maturity to (pseudo, implied) zero coupon yields following Bretscher et al. (2025). To measure liquidity, we average the price dispersion measure on a quarterly basis (see Jankowitsch et al., 2011). To avoid outliers driving our results, we truncate the yield at the 0.5% level in both tails and winsorize the liquidity measure by 1% in the right tail.

E-scores The ratings are re-evaluated by MSCI annually and are available from 2007 onward. However, in 2012 MSCI greatly extended the coverage of their ratings.[29] Since the coverage does not reach adequate levels until then, we restrict our sample to start in 2012. For bonds that are not covered by MSCI, following Koijen et al. (2024), we construct an indicator variable that is one if the E-score is missing and add it to the set of bond characteristics in our demand system. For the missing

[29] We report more detailed insights into the coverage in Table IA-3 in the Internet Appendix.

E-score, we insert the average environmental performance of the corresponding SIC major group.

Outside asset Bonds with missing characteristics are aggregated into the outside assets of each investor. Thus, in our sample, the outside asset mainly comprises bonds without a credit rating. Bonds without price information are not considered as part of the assets.

Investor-specific characteristics and restrictions For each investor, we compute the quarterly portfolio turnover and active share, which is one-half of the sum of the absolute difference between the weight of each bond in the portfolio and the market weight. To make the demand estimation more robust, we allocate small institutional investor with less than USD 2.5 million in total holdings, less than USD 0.25 million in outside assets, or fewer than eleven bonds in their investment universe (see Paragraph *Investment universe* in Section A.3) to the residual sector.

Firm-specific characteristics We gather firm-specific characteristics for our analysis from Compustat. In particular, we collect firms' leverage (equal to long-term debt *dltt* and current debt *dlc* over book equity *seq* - *preferred_stock* + *txditc*), profitability (equal to EBITDA *ebitda* over total assets *at*), firm size (equal to the logarithm of total assets *at*), tangibility (equal to property, plant, and equipment *ppent* over total assets *at*), and capex (equal to capital expenditures *capx* over total assets *at*). Additionally, from Capital IQ, we obtain firms' total bank debt (*totbankdbt*). To merge the firm characteristics with our bond sample, we rely on the linking table of Fang (2024).[30]

Macroeconomic variables We consider several market-wide variables. In particular, we retrieve the three-month T-Bill rate, GDP growth rate, CPI changes, and the term spread, which is computed as ten-year minus three-month treasury constant maturity yield, from FRED. Following Welch and Goyal (2008), we obtain the

[30] The Bond-Compustat/CRSP linking table is provided by Chuck Fang via OpenBondAssetPricing.com

default spread, which is the spread between BBB and AAA-rated corporate bond yields.

A.3. Estimation Specifics

Investment universe We define the investment universe of each investor in each quarter as the holdings that are held at this point in time or have been held in the portfolio in the previous eleven quarters. Therefore, a bond that was part of an investor's portfolio in the previous eleven quarters but is no longer held in the current quarter appears with a weight of zero. Bretscher et al. (2025) show that the investment universe of bond investors is very stable over time. Furthermore, by using realized holdings to define investor-specific universes, we ensure that substitution occurs only across economically reasonable alternatives. This helps mitigate concerns about unrealistic substitution patterns in the logit demand model and supports the plausibility of the exclusion restriction for our instrumental variable.

Ridge penalty term The penalty is defined such that it is inversely related to the number of investor i's holdings $|\mathcal{N}_i|$. The penalty shrinks the demand coefficients toward the group-level estimator. We employ cross-validation to select the penalty parameters, λ and ξ. By randomly splitting the sample in half within each quarter for each investor, we estimate asset demand in the first subsample and compute the mean squared error of predicted demand in the second subsample. The final parameters are $\lambda = 10$ and $\xi = 0.7$.

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Internet Appendix to "Greenness Demand for US Corporate Bonds"

In the Internet Appendix, we provide additional evidence for the findings in the main body, which maintains a reasonable length. In particular, Section I provides additional summary statistics. In Section II, we provide a comprehensive look at all estimated demand coefficients. We detail the algorithm used for estimating equilibrium prices in the counterfactual analyses in Section III. Then, we show the effect of demand shocks on investor wealth in absolute terms in Section IV. In Section V, we study the real effects of (firm-level) greenness demand. Finally, we provide a colophon of all packages we use in Section VI.

I. Summary Statistics

Table IA-1: Largest Investors.
This table lists the largest investors in terms of assets under management (AUM, in 1,000 USD) per investor type at the start and end of the sample period. We abbreviate life insurers (LI), property, casualty, and health insurers (PI), mutual funds (MF), variable annuity funds (VA), federal, state government, pension, retirement funds, and other institutions (PF), and the residual (RES).

Quarter	Type	Investor name	AUM
Q1 2012	LI	Northwestern Mutual Life Insurance Co	17,222,778
Q4 2022	LI	Northwestern Mutual Life Insurance Co	30,815,252
Q1 2012	MF	PIMCO Total Return Fund	21,429,878
Q4 2022	MF	Vanguard Total Bond Market Index Fund	34,760,582
Q1 2012	PF	New York State Common Retirement Fund	2,595,759
Q4 2022	PF	GRS North American High Yield Bond Putnam	56,380
Q1 2012	PI	Allstate Insurance Co	4,647,671
Q4 2022	PI	State Farm Mutual Automobile Insurance Co	8,563,997
Q1 2012	VA	CREF Bond Market Account	1,636,186
Q4 2022	VA	Advanced Srs MultiSector Fixed Income Portfolio	3,261,755
Q1 2012	RES	Residual Sector	1,210,216,970
Q4 2022	RES	Residual Sector	1,982,237,797

Figure IA-1: Par Amount over Time.
Panel A shows the development of the total par amount (in trillion USD) held by the respective investor types (Type). Panel B shows the development of the par amount share of the four main investor types. We abbreviate life insurers (LI), property, casualty, and health insurers (PI), mutual funds (MF), variable annuity funds (VA), federal, state government, pension, retirement funds, and other institutions (PF), and the residual (RES).

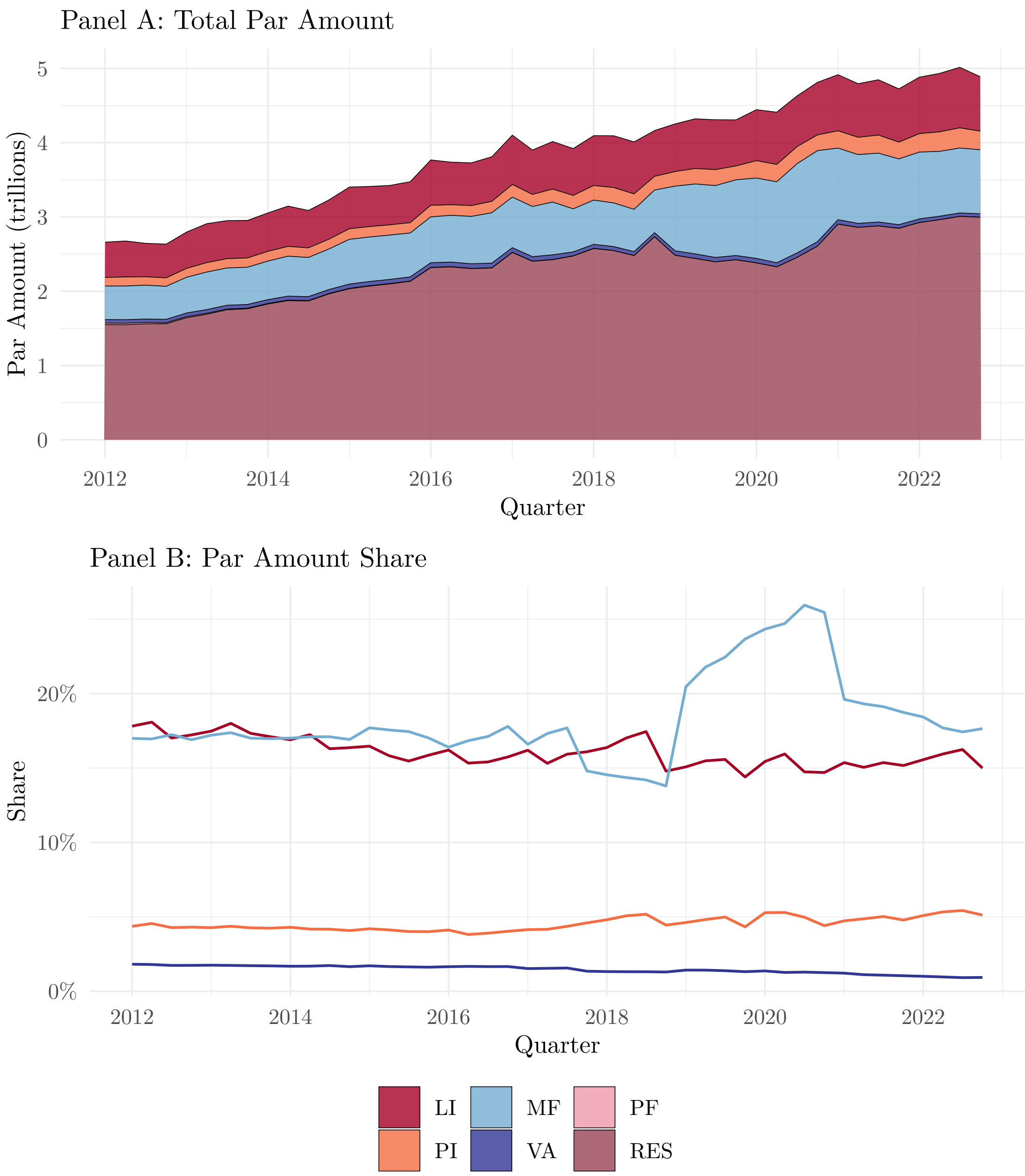


Figure IA-2: Average Bond Characteristics over Time.
This figure shows the development of the par amount-weighted averages for the respective asset characteristics of each investor type. We abbreviate life insurers (LI), property, casualty, and health insurers (PI), mutual funds (MF), and variable annuity funds (VA).

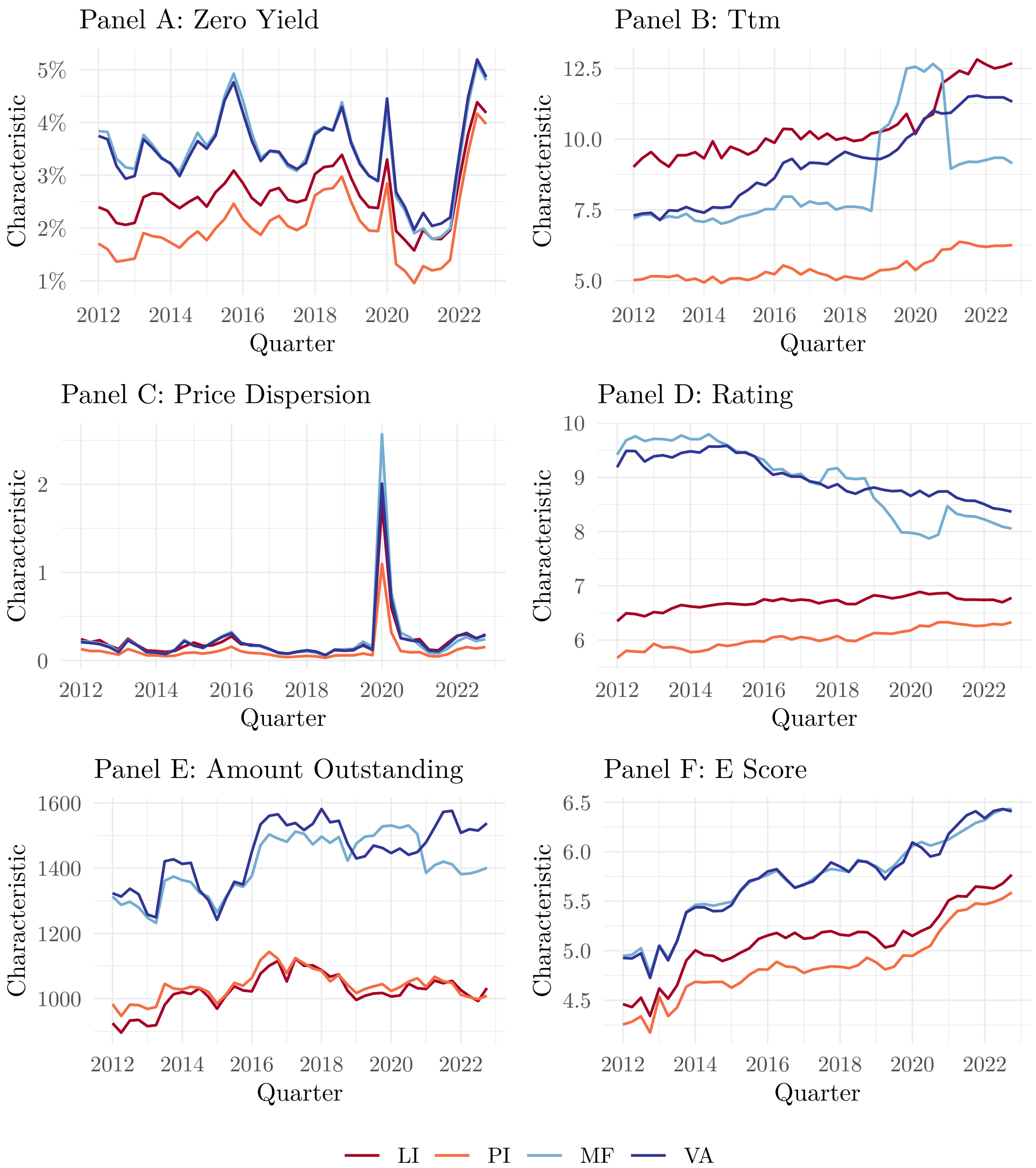
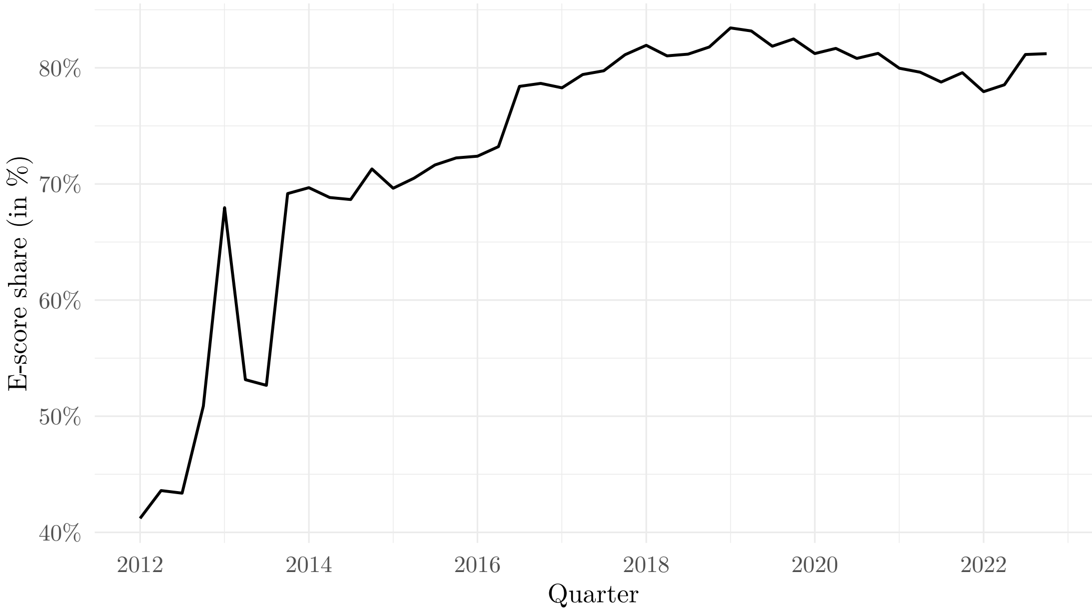


Figure IA-3: E-score Coverage.
This figure shows the share of bonds in our sample with an E-score.



II. Demand Coefficients

In this part, we provide additional insights into the demand coefficients not reported in the main part of the paper. While we exclusively focus on the greenness demand (the coefficients on the e-score) before, this section shows all estimated coefficients in various dimensions.

We also inspect how ESG-focused mutual funds differ from other mutual funds in terms of their estimated greenness demand coefficients. To identify ESG funds, we search for an extended list of keywords in a mutual fund's name (see, e.g., Baker et al., 2022; Handler et al., 2022; Csiky et al., 2024).[1] We present the results in Figure IA-8.

[1] The list of strings we used to select ESG funds: Calvert, Catholic, Church, Climate, Clean, CSR, Domini, Environ, ESG, Faith, Green, Impact, KLD, Parnassus, Responsib, Social, SRI, Sustain, Walden.

Table IA-2: Demand Curves of Institutional Investors

This table shows the results of quarterly regressions of the demand coefficients on institution-type dummies. The controls log of assets under management (AUM), active share, and portfolio turnover are standardized on a quarterly basis. We indicate significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

	Zero Yield	Time to Maturity	Price Dispersion	Rating	Amt. Outstanding	E-score
LI	0.163***	−0.257***	−0.070***	−0.312***	−0.007***	0.031***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
PI	0.133***	−0.366***	−0.114***	−0.331***	−0.000	0.041***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
MF	0.241***	−0.326***	−0.154***	0.026***	0.015***	0.022***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
VA	0.213***	−0.302***	−0.197***	−0.003	0.004***	0.015***
	(0.003)	(0.005)	(0.002)	(0.003)	(0.001)	(0.002)
log(AUM)	−0.009***	0.040***	−0.028***	0.007***	−0.002***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Active Share	0.006***	−0.015***	−0.007***	0.045***	−0.003***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Turnover	0.007***	0.018***	−0.000	−0.000	−0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Num. obs.	154,737	154,737	154,737	154,737	154,737	154,737
Adj. R^2	0.024	0.019	0.043	0.234	0.007	0.008

Figure IA-4: Demand Coefficients over Time (Value-Weighted Average). This figure shows the development of the value-weighted demand coefficients for the respective asset characteristics of each investor type. We abbreviate life insurers (LI), property, casualty, and health insurers (PI), mutual funds (MF), and variable annuity funds (VA). The bond characteristics used for estimating the demand coefficients are zero yields (Panel A), times to maturity (Panel B), price dispersions (Panel C), ratings (Panel D), amounts outstanding (Panel E), and environmental scores (Panel F). All bond characteristics were standardized on a quarterly basis.

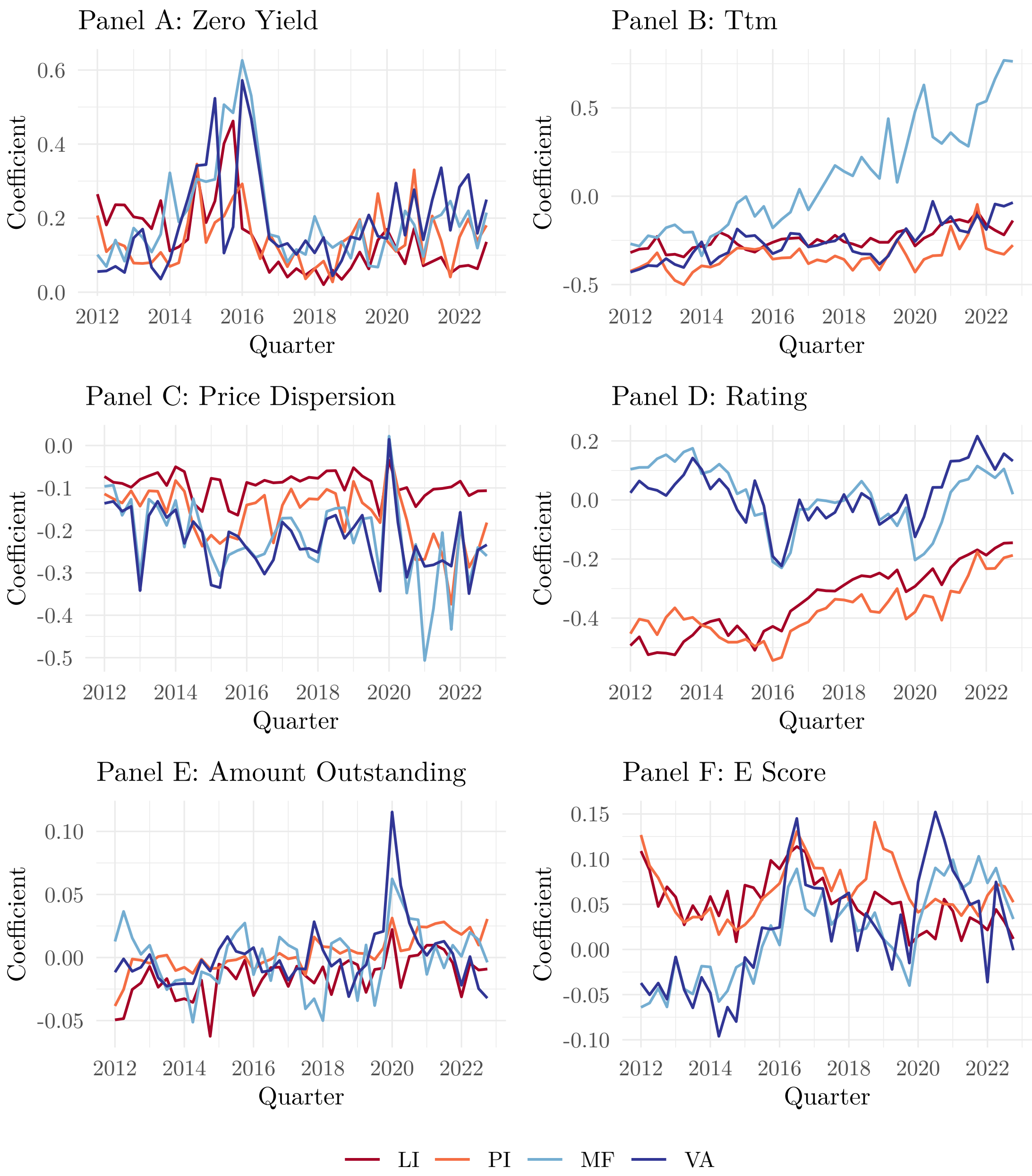


Figure IA-5: Demand Coefficients over Time (Arithmetic Average).
This figure shows the development of the average demand coefficients for the respective asset characteristics of each investor type. We abbreviate life insurers (LI), property, casualty, and health insurers (PI), mutual funds (MF), and variable annuity funds (VA). The bond characteristics used for estimating the demand coefficients are zero yields (Panel A), times to maturity (Panel B), price dispersions (Panel C), ratings (Panel D), amounts outstanding (Panel E), and environmental scores (Panel F). All bond characteristics were standardized on a quarterly basis.

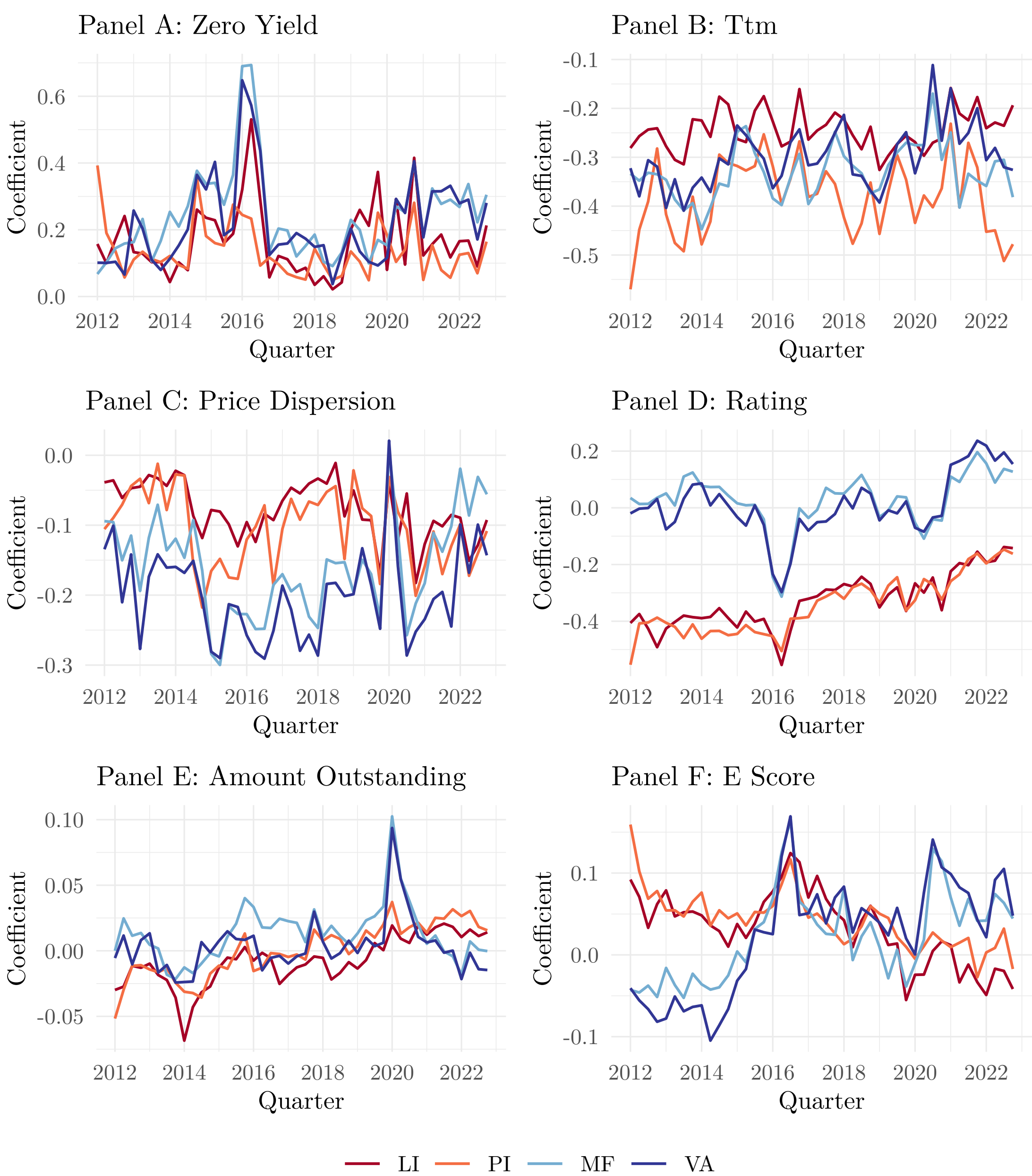


Figure IA-6: Average Demand.
This figure shows the overall time-series average of the demand coefficients for the respective asset characteristics of each investor type. We abbreviate life insurers (LI), property, casualty, and health insurers (PI), mutual funds (MF), and variable annuity funds (VA). The bond characteristics used for estimating the demand coefficients are zero yields (Panel A), times to maturity (Panel B), price dispersions (Panel C), ratings (Panel D), amounts outstanding (Panel E), and environmental scores (Panel F). All bond characteristics were standardized on a quarterly basis.

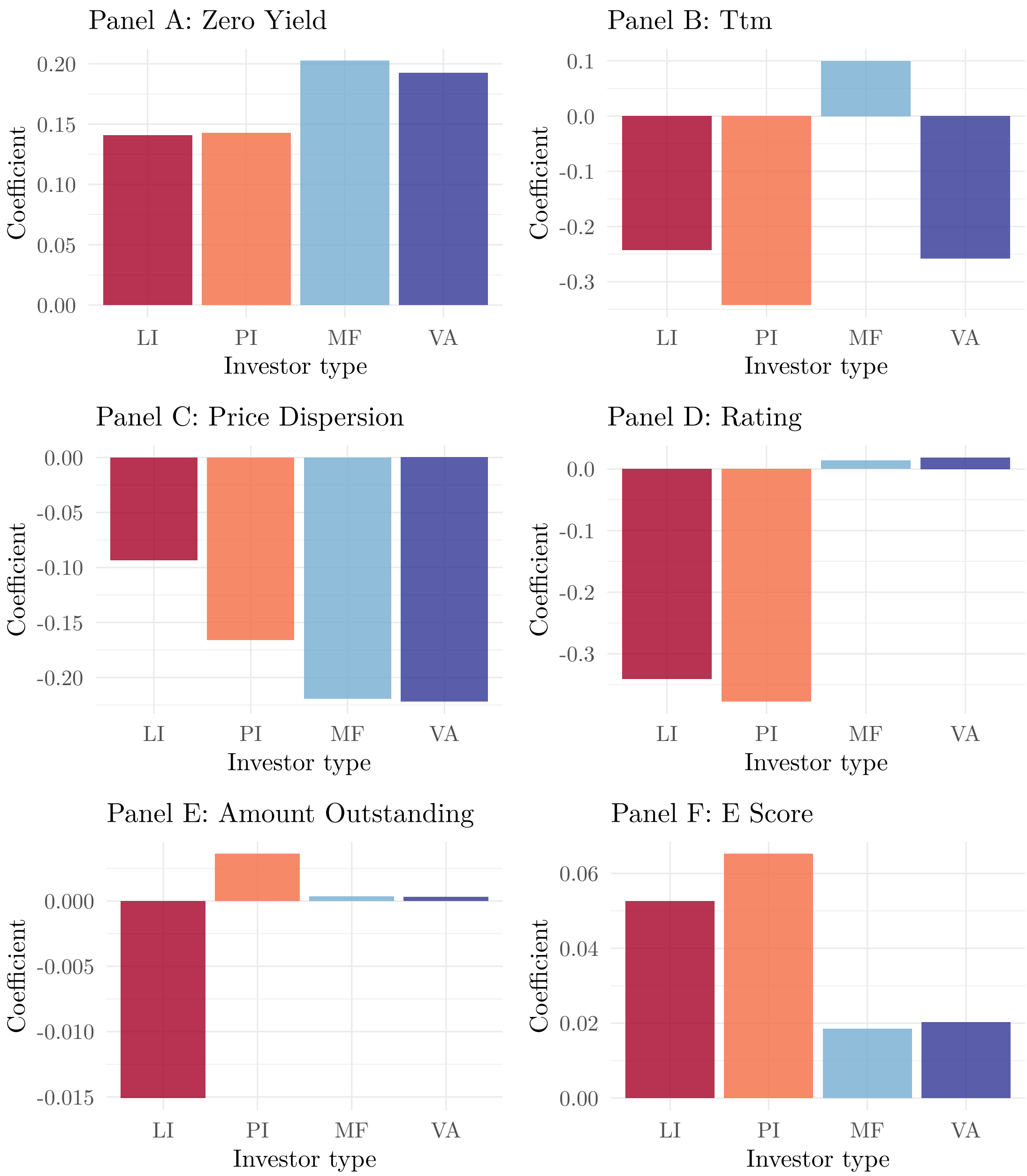


Figure IA-7: Histogram of Demand.
This figure shows histograms of the investor-level averages of demand coefficients of the respective asset characteristics. The colored vertical lines represent the time-series averages of the value-weighted demand coefficients of the investor type. We abbreviate life insurers (LI), property, casualty, and health insurers (PI), mutual funds (MF), and variable annuity funds (VA). The bond characteristics used for estimating the demand coefficients are zero yields (Panel A), times to maturity (Panel B), price dispersions (Panel C), ratings (Panel D), amounts outstanding (Panel E), and environmental scores (Panel F). All bond characteristics were standardized on a quarterly basis.

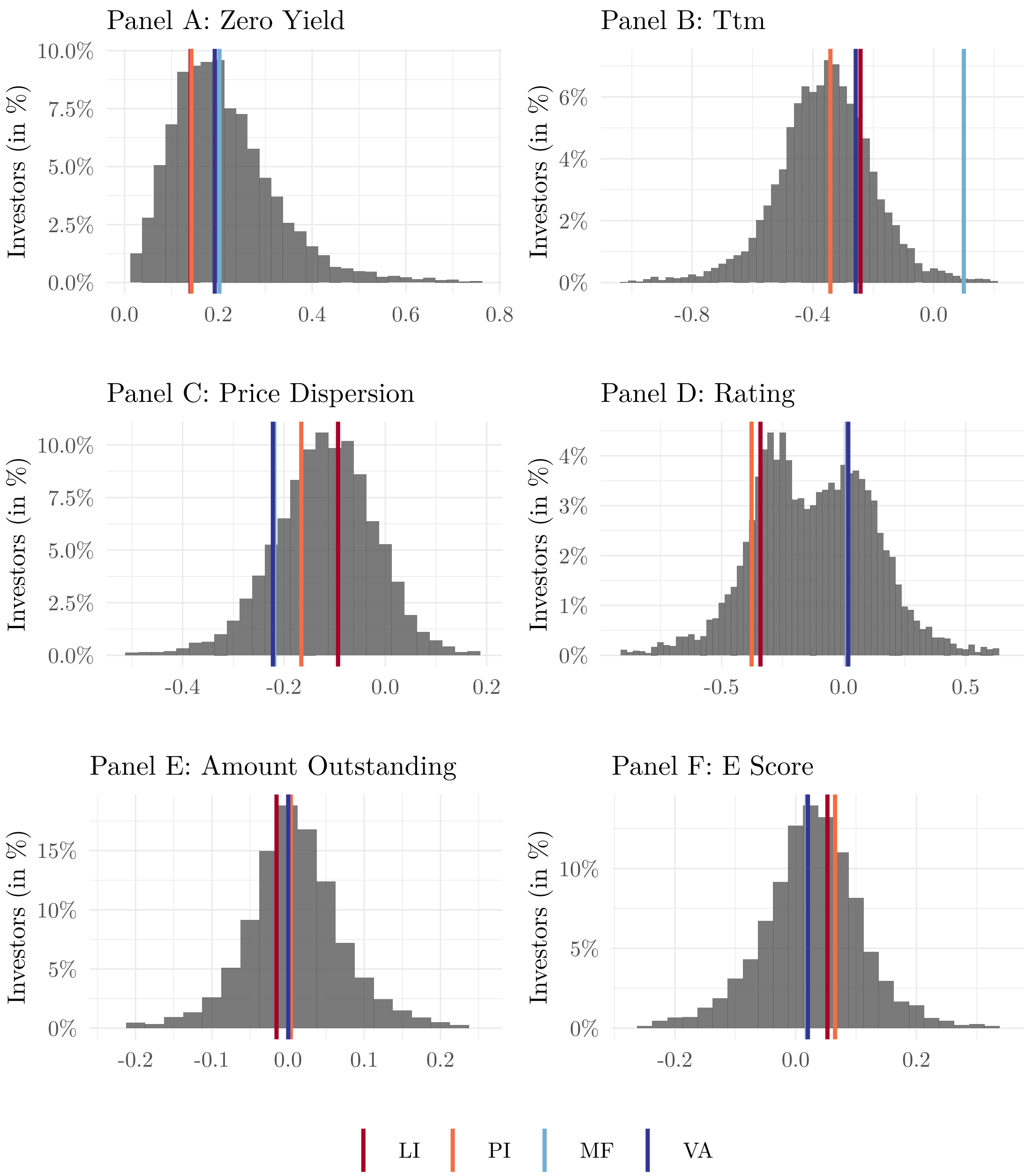
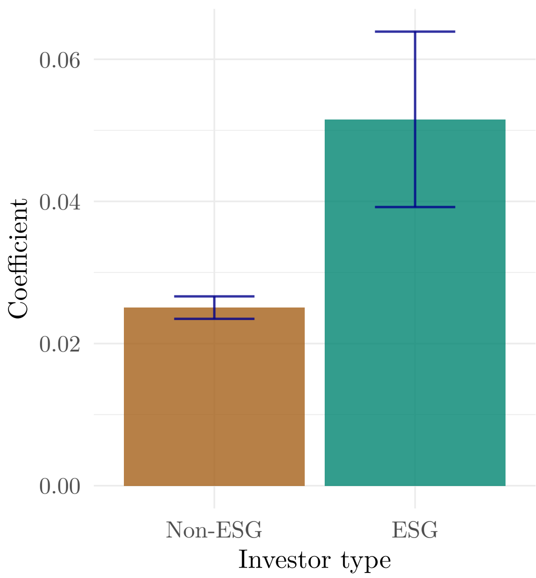


Figure IA-8: Average Demand of ESG and Non-ESG Funds.
This figure shows the overall time-series average of the greenness demand coefficients of two groups of institutional investors. We distinguish ESG mutual funds that have a clear ESG focus based on their name from the other regular mutual funds (i.e., Non-ESG). Alongside the average demand, we indicate 95% confidence intervals. All bond characteristics used for estimating the demand coefficients were standardized on a quarterly basis.



III. Algorithm for Computing Equilibrium Prices

The following numerical algorithm was devised in Koijen and Yogo (2019) Appendix C and is used for estimating equilibrium bond prices. Our demand system, outlined in Section 5.1, along with market clearing (see Equation (12)), enables us to find the equilibrium price. Therefore, we rewrite market clearing in logarithms and vector notation as

$$\mathbf{p}_t = \mathbf{g}(\mathbf{p}_t) = log\left(\sum_{i=1}^{I} A_{i,t}\mathbf{w}_{i,t}\right) - \mathbf{s}_t. \tag{IA-1}$$

Then, starting with any price vector $\mathbf{p}_t^{(m)}$, the Newton's method would update the price vector through

$$\mathbf{p}_t^{(m+1)} = \mathbf{p}_t^{(m)} + \left(\mathbf{I} - \frac{\partial \mathbf{g}\left(\mathbf{p}_t^{(m)}\right)}{\partial \mathbf{p}_t}\right)^{-1}\left(\mathbf{g}\left(\mathbf{p}_t^{(m)}\right) - \mathbf{p}_t^{(m)}\right). \tag{IA-2}$$

We can calculate the Jacobian $\frac{\partial \mathbf{g}\left(\mathbf{p}_t^{(m)}\right)}{\partial \mathbf{p}_t}$ analytically as follows:

$$\begin{aligned}\frac{\partial \mathbf{g}\left(\mathbf{p}_t^{(m)}\right)}{\partial \mathbf{p}_t} &= \frac{\partial}{\partial \mathbf{p}_t}\left(log\left(\sum_{i=1}^{I} A_{i,t}\mathbf{w}_{i,t}\right) - \mathbf{s}_t\right)\\ &= \mathbf{H}_t^{-1}\frac{\partial}{\partial \mathbf{p}_t}\left(\sum_{i=1}^{I} A_{i,t}\mathbf{w}_{i,t}\right),\end{aligned}$$

where

$$\mathbf{H}_t := diag\left(\sum_{i=1}^{I} A_{i,t}\mathbf{w}_{i,t}\right) = \sum_{i=1}^{I} A_{i,t}diag(\mathbf{w}_{i,t}).$$

Note that for a zero-coupon bond, and using the approximation $log(1 + x) \approx x$ for small x, it holds

$$p_t(n) = -y_t(n) m_t(n),$$

where $m_t(n)$ is the time to maturity of bond n.

Thus, we have

$$\begin{aligned}
\frac{\partial \mathbf{g}\left(\mathbf{p}_t^{(m)}\right)}{\partial \mathbf{p}_t} &= \sum_{i=1}^{I} A_{i,t} \mathbf{H}_t^{-1} \frac{\partial \mathbf{w}_{i,t}}{\partial \mathbf{p}_t} \\
&= \sum_{i=1}^{I} \beta_{0,i,t} A_{i,t} \mathbf{H}_t^{-1} \mathbf{M}_t,
\end{aligned}$$

where $\mathbf{M}_t := diag(\mathbf{m}_t)^{-1} \left(\mathbf{w}_{i,t} \mathbf{1}_n' - \mathbf{I}\right)$, and $\mathbf{1}_n' = (1, 1, \ldots, 1) \in \mathbb{R}^n$.

Due to the large dimension of the Jacobian, the calculation might be computationally too expensive. Therefore, we could follow Koijen and Yogo (2019) and approximate the Jacobian with only its diagonal elements.

$$\begin{aligned}
\frac{\partial \mathbf{g}\left(\mathbf{p}_t^{(m)}\right)}{\partial \mathbf{p}_t} &\approx diag\left(\left\{\frac{\partial \mathbf{g}\left(\mathbf{p}_t^{(m)}\right)}{\partial p_t(n)}\right\}_{1 \leq n \leq N}\right) \\
&= diag\left(\left\{\frac{\sum_{i=1}^{I} \frac{\beta_{0,i,t}}{m_t(n)} A_{i,t}\left(w_{i,t}\left(\mathbf{p}_t^{(m)}; n\right) - 1\right)}{\sum_{i=1}^{I} A_{i,t} w_{i,t}\left(\mathbf{p}_t^{(m)}; n\right)}\right\}_{1 \leq n \leq N}\right).
\end{aligned}$$

We iterate through Equation (IA-2) until $\max_n |\mathbf{p}_t^{(m+1)}(n) - \mathbf{p}_t^{(m)}(n)| < 0.01$, or after 1000 iterations.

IV. Demand Shocks' Wealth Impact

Figure IA-9: Impact of Greenness Demand on Investors' Wealth.
This figure shows wealth changes (in 1,000 USD) due to changes in the aggregate greenness demand. Panels A and B show wealth changes due to increased greenness demand following COP21. Panels C and D show the wealth changes from a counterfactual greenness demand shock at the end of 2022. Panels A and C provide average changes per investor type. Panels B and D provide changes in relation to the value-weighted average E-score of an investor's holdings. We abbreviate life insurers (LI), property, casualty, and health insurers (PI), mutual funds (MF), and variable annuity funds (VA).

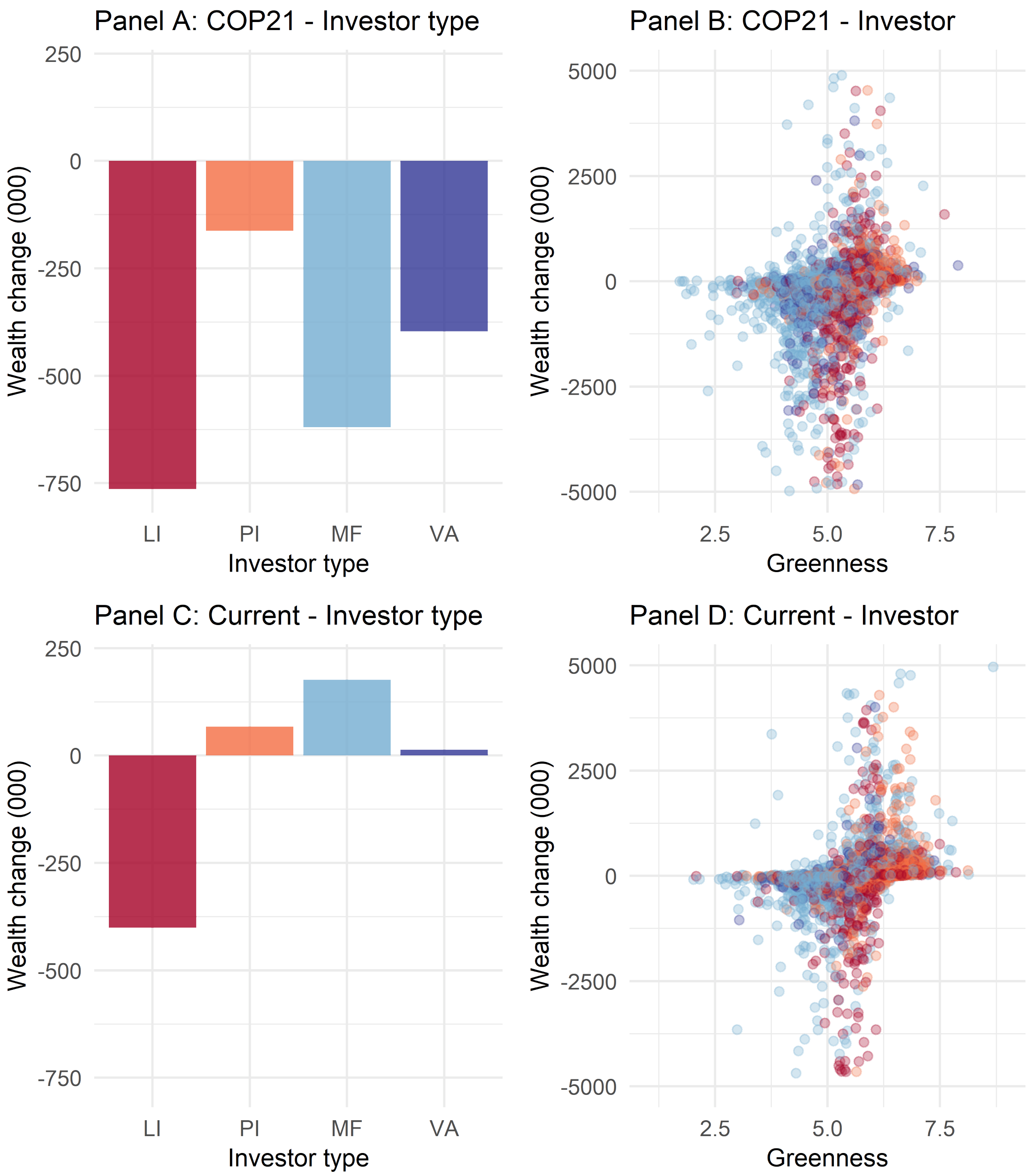


Table IA-3: Impact of Greenness Demand on Investors' Wealth.
This table shows wealth changes due to changes in the aggregate greenness demand of investors with different value-weighted average E-scores. Each investor is classified based on the investor type's greenness quartiles, where investors in the bottom (top) quartile are "brown" ("green"). Panels A (relative changes) and B (absolute changes) show wealth changes due to increased greenness demand following COP21. Panels C (relative changes) and D (absolute changes) show wealth changes from a counterfactual greenness demand shock at the end of 2022. LI are life insurers, PI are property, casualty, and health insurers, MF are mutual funds, and VA are variable annuity funds (a subtype of mutual funds). Relative changes are in percent, and absolute changes in 1,000 USD.

Panel A: COP21 - Relative Effect

Type	LI	PI	MF	VA
Green	0.18	0.29	0.17	0.04
Brown	−0.40	−0.36	−0.71	−0.63

Panel B: COP21 - Absolute Effect

Type	LI	PI	MF	VA
Green	602.06	198.79	102.48	−95.39
Brown	−1,158.31	−477.04	−1,150.33	−662.79

Panel C: Current - Relative Effect

Type	LI	PI	MF	VA
Green	0.26	0.33	0.30	0.26
Brown	−0.30	−0.15	−0.45	−0.45

Panel D: Current - Absolute Effect

Type	LI	PI	MF	VA
Green	146.08	377.56	1,165.44	332.91
Brown	−634.00	−228.43	−423.51	−182.13

V. Real Effects

Here, we show additional real effects and robustness tests for firm-level greenness demand (see Section V.1), firm emissions (see Section V.2), non-overlapping issuance activity (see Section V.3), alongside equation derivations (see Section V.4).

V.1. Firm-Level Greenness Demand

Once the demand system is estimated, we are able to compute the price impact of a change in the greenness performance analytically. Here, we assume the greenness performance to be the kth characteristic in $\mathbf{x}$. Following Koijen and Yogo (2019), we define the matrix for the price impact as

$$\frac{\partial \mathbf{p}_t}{\partial \mathbf{x}_{k,t}} = \left(\mathbf{I} - \sum_{i=1}^{I} \beta_{0,i,t} A_{i,t} \mathbf{H}_t^{-1} \mathbf{M}_t \right)^{-1} \left(\sum_{i=1}^{I} \beta_{k,i,t} A_{i,t} \mathbf{H}_t^{-1} \mathbf{G}_{i,t} \right), \tag{IA-3}$$

where

$$\begin{aligned}
\mathbf{H}_t &= \sum_{i=1}^{I} A_{i,t} diag(\mathbf{w}_{i,t}), \\
\mathbf{G}_{j,t} &= diag(\mathbf{w}_{i,t}) - \mathbf{w}_{i,t} \mathbf{w}_{i,t}^{'}, \\
\mathbf{M}_t &= diag(\mathbf{m}_t)^{-1} \left(\mathbf{w}_{i,t} \mathbf{1}_n^{'} - \mathbf{I} \right),
\end{aligned}$$

where $\mathbf{p}_t$ is the vector of log prices, $\mathbf{w}_i$ denotes the vector of portfolio weights of investor i, and $\mathbf{m}_t$ is the vector of time to maturity of each bond. The (n, m)-element of this matrix is the elasticity of the price of bond n with respect to the greenness performance related to bond m. The matrix inside the inverse in Equation (IA-3) is indeed the aggregate demand elasticity as defined in Koijen and Yogo (2019), which implies a larger price impact for assets held by less elastic investors. The n-th diagonal element of the matrix outside the inverse is $\sum_{i=1}^{I} \beta_{k,i,t} A_{i,t} w_{i,t}(n)(1 - w_{i,t}(n)) / \left[\sum_{i=1}^{I} A_{i,t} w_{i,t}(n) \right]$. Equivalent to Noh et al. (2024), this quantity can be seen as a wealth-weighted average of the coefficients on greenness performance.

Consequently, for a given bond n, the price impact for a change in its greenness performance is a weighted average of the coefficients on this characteristic, adjusted for the price elasticity of its holders. We transform this measure into a yield impact to account for differing maturities. To better align with the previous paradigm, where a greater positive value indicates a stronger impact, we multiply the yield impact measure by -1. Lastly, we calculate the paramount-weighted average of the bond-level yield impact to aggregate this measure on a firm level.

Table IA-4: Impact of Firm-Level Greenness Demand on Environmental Performance.
This table shows the results of regressions of firms' future environmental performance on standardized firm-level greenness demand and environmental performance. In Panel A (B), the dependent variable is the environmental performance in one year (two years). In the first column, we use the full sample. For the second and third columns, we restrict the sample to issuers with an E-score above five and below five, respectively. We control for rating, leverage, profitability, firm size, and tangibility in all specifications. The standard errors shown in parentheses are clustered at the industry level. We indicate significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

Panel A: One year

	All	Green	Brown
Firm-$\overline{\text{GD}}_{y-1}$	0.028	0.046	0.013
	(0.020)	(0.031)	(0.032)
E-score$_{y-1}$	0.914***	0.922***	0.866***
	(0.010)	(0.015)	(0.016)
Num. obs.	10,165	5,120	5,045
Adj. R^2	0.875	0.758	0.620

Panel B: Two years

	All	Green	Brown
Firm-$\overline{\text{GD}}_{y-2}$	0.036	0.078	0.001
	(0.035)	(0.055)	(0.044)
E-score$_{y-2}$	0.848***	0.853***	0.745***
	(0.017)	(0.025)	(0.022)
Num. obs.	9,153	4,539	4,614
Adj. R^2	0.781	0.607	0.449

Table IA-5: Impact of Firm-Level Greenness Demand on Bond Issuance. This table shows the results of regressions of bond issuance on the standardized firm-level greenness demand over the preceding four quarters and the firms' environmental performances. In the first column, the dependent variable is the logarithmic offering amount over the current and succeeding three quarters. In the second column, the dependent variable is a dummy variable indicating whether a firm issued bonds in the current and succeeding three quarters. In all specifications, we control for firm characteristics (rating, leverage, profitability, firm size, and tangibility) and macroeconomic variables (GDP changes, default spread, term spread, T-Bill rate, and CPI changes). As the dependent variables are overlapping, we report Newey-West standard errors with four lags in parentheses. We indicate significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

	$\log(\text{Amt.}_q{+}1)$	$\text{Amt.}_q > 0$
E-score$_{q-1}$	0.020	0.001
	(0.032)	(0.002)
Firm-$\overline{\text{GD}}_{q-1}\times$ E-score$_{q-1}$	0.168**	0.012**
	(0.077)	(0.005)
Num. obs.	44,066	44,066
Adj. R^2	0.276	0.273

V.2. Firm Emissions

In this section, we investigate the effect of greenness demand on firm-level emission intensities (tons CO_2-equivalent/revenue USD mill), providing a more tangible form of environmental performance. Therefore, we obtain data on annual emissions from the LSEG ESG database and match it to our firm sample. We use emission intensity based on scope one emissions, aggregated scope one, two, and three emissions, and total emissions supplemented with proprietary estimates for firms that do not disclose their emissions. Table IA-6 provides the results of regressing those three measures of emission intensity onto the lagged greenness demand. In all three cases, the estimated coefficient on the greenness demand indicates that firms reduce their emission intensity in the year following heightened greenness demand. In the case of the most direct form of emissions, scope one emissions, a one-standard-deviation rise in greenness demand leads to a reduction of up to 18.23 tons CO_2-equivalent/revenue USD million. Comparing this to the average scope one emission intensity of 347.5 documents an economically significant reduction of 5.2%.

Table IA-6: Impact of Greenness Demand on Emission Intensity.
This table shows the results of regressions of firms' annual emission intensity (tons CO_2eq/USD mill) on the standardized wealth-weighted greenness demand and environmental performance. In the first column, we use scope one emissions. For the second column, we use aggregated scope one, two, and three emissions. In the third column, we again use total emissions but also include estimated values by the data provider. We control for rating, leverage, profitability, firm size, and tangibility in all specifications. The standard errors shown in parentheses are clustered at the industry level. We indicate significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

	Scope 1 Int_y	Total Int_y	Est. Tot. Int_y
$\overline{\text{GD}}_{y-1}$	-18.229^{**}	-35.262^{*}	-25.573^{*}
	(9.122)	(20.777)	(13.285)
E-score_{y-1}	-3.102	-9.044	-9.584
	(3.514)	(10.634)	(11.424)
Scope 1 Int_{y-1}	0.999^{***}		
	(0.042)		
Total Int_{y-1}		1.064^{***}	
		(0.034)	
E-score_{y-1}			1.110^{***}
			(0.033)
Num. obs.	2,501	2,787	4,699
Adj. R^2	0.926	0.845	0.805

V.3. Non-overlapping Bond Issuance Activity

Table IA-7: Impact of Greenness Demand on Bond Issuance.
This table shows the results of regressions of bond issuance on the standardized wealth-weighted average greenness demand and firms' environmental performance. In the first column, the dependent variable is the annual logarithmic offering amount. In the second column, the dependent variable is a dummy variable indicating whether a firm issued bonds in a given year. In all specifications, we control for firm characteristics (i.e., rating, leverage, profitability, firm size, and tangibility) and macroeconomic variables (i.e., GDP changes, default spread, term spread, T-Bill rate, and CPI changes). The standard errors shown in parentheses are clustered at the industry level. We indicate significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

	log(Amt.$_y$+1)	Amt.$_y$> 0
E-score$_{y-1}$	0.058	0.003
	(0.063)	(0.005)
$\overline{\text{GD}}_{y-1}\times$ E-score$_{y-1}$	0.024**	0.002**
	(0.012)	(0.001)
Num. obs.	11,136	11,136
Adj. R^2	0.269	0.267

V.4. Derivations

Derivation of Equation (IA-3): Our demand system, outlined in Section 5.1, along with market clearing (Equation (12)), enables us to find the equilibrium price. That is, bond prices are completely determined by supply, characteristics, investors' wealth, coefficients on characteristics, and latent demand:

$$\mathbf{p}_t = \mathbf{g}(\mathbf{s}_t, \mathbf{x}_t, \mathbf{A}_t, \boldsymbol{\beta}_t, \boldsymbol{\epsilon}_t). \tag{IA-4}$$

Recalling market clearing (Equation (12)) and putting it in logarithmic terms, we know that the following identity holds:

$$\mathbf{p}_t = \log\left(\sum_{i=1}^{I} A_{i,t}\mathbf{w}_{i,t}\right) - \mathbf{s}_t. \tag{IA-5}$$

Since we are interested in the change in prices for a change in an individual characteristic, we differentiate both sides by $\mathbf{x}_{k,t}$:

$$\begin{aligned}\frac{\partial \mathbf{p}_t}{\partial \mathbf{x}_{k,t}} &= \frac{\partial}{\partial \mathbf{x}_{k,t}} \left(\sum_{i=1}^{I} A_{i,t} \mathbf{w}_{i,t} \right) \\ &= \mathbf{H}_t^{-1} \frac{\partial}{\partial \mathbf{x}_{k,t}} \left(\sum_{i=1}^{I} A_{i,t} \mathbf{w}_{i,t} \right)\end{aligned}$$

where

$$\mathbf{H}_t := diag\left(\sum_{i=1}^{I} A_{i,t} \mathbf{w}_{i,t} \right) = \sum_{i=1}^{I} A_{i,t} diag(\mathbf{w}_{i,t}).$$

In order to calculate the derivative of $\sum_{i=1}^{I} A_{i,t}\mathbf{w}_{i,t}$ with respect to $\mathbf{x}_{k,t}$, we have to recall that $\mathbf{w}_{i,t}$ is a function of characteristics and prices, but, implied by Equation (IA-4), prices themselves are also a function of characteristics. Thus, we have

$$\frac{\partial \mathbf{p}_t}{\partial \mathbf{x}_{k,t}} = \sum_{i=1}^{I} A_{i,t} \mathbf{H}_t^{-1} \left(\frac{\partial \mathbf{w}_{i,t}}{\partial \mathbf{x}_{k,t}} + \frac{\partial \mathbf{w}_{i,t}}{\partial \mathbf{p}_t} \frac{\partial \mathbf{p}_t}{\partial \mathbf{x}_{k,t}} \right),$$

which leads to

$$\frac{\partial \mathbf{p}_t}{\partial \mathbf{x}_{k,t}} = \left(\mathbf{I} - \sum_{i=1}^{I} A_{i,t} \mathbf{H}_t^{-1} \frac{\partial \mathbf{w}_{i,t}}{\partial \mathbf{p}_t} \right)^{-1} \left(\sum_{i=1}^{I} A_{i,t} \mathbf{H}_t^{-1} \frac{\partial \mathbf{w}_{i,t}}{\partial \mathbf{x}_{k,t}} \right).$$

The derivatives in the last line can be calculated analytically. We have

$$\begin{aligned}
\frac{\partial \mathbf{w}_{i,t}}{\partial \mathbf{x}_{k,t}} &= \begin{pmatrix} \frac{\partial w_{i,t}(1)}{\partial x_{k,t}(1)} & \frac{\partial w_{i,t}(1)}{\partial x_{k,t}(2)} & \dots & \frac{\partial w_{i,t}(1)}{\partial x_{k,t}(n)} \\ \frac{\partial w_{i,t}(2)}{\partial x_{k,t}(1)} & \frac{\partial w_{i,t}(2)}{\partial x_{k,t}(2)} & & \vdots \\ \vdots & & \ddots & \vdots \\ \frac{\partial w_{i,t}(n)}{\partial x_{k,t}(1)} & \dots & \dots & \frac{\partial w_{i,t}(n)}{\partial x_{k,t}(n)} \end{pmatrix} \\
&= \begin{pmatrix} \beta_{k,i,t} w_{i,t}(1)(1 - w_{i,t}(1)) & -\beta_{k,i,t} w_{i,t}(1) w_{i,t}(2) & \dots & -\beta_{k,i,t} w_{i,t}(1) w_{i,t}(n) \\ -\beta_{k,i,t} w_{i,t}(2) w_{i,t}(1) & \beta_{k,i,t} w_{i,t}(2)(1 - w_{i,t}(2)) & & \vdots \\ \vdots & & \ddots & \vdots \\ -\beta_{k,i,t} w_{i,t}(n) w_{i,t}(1) & \dots & \dots & \beta_{k,i,t} w_{i,t}(n)(1 - w_{i,t}(n)) \end{pmatrix} \\
&= \beta_{k,i,t} \mathbf{G}_{i,t},
\end{aligned}$$

where $\mathbf{G}_{i,t} = diag(\mathbf{w}_{i,t}) - \mathbf{w}_{i,t}\mathbf{w}_{i,t}^{'}$.

For the derivative of the portfolio weights with respect to prices, we have to note that for a zero-coupon bond, and using the approximation $log(1+x) \approx x$ for small x, it holds

$$p_t(n) = -y_t(n) m_t(n),$$

where $m_t(n)$ is the time to maturity of bond n.

Thus, we obtain

$$\begin{aligned}
\frac{\partial \mathbf{w}_{i,t}}{\partial \mathbf{p}_t} &= \begin{pmatrix} \frac{\partial w_{i,t}(1)}{\partial p_t(1)} & \frac{\partial w_{i,t}(1)}{\partial p_t(2)} & \dots & \frac{\partial w_{i,t}(1)}{\partial p_t(n)} \\ \frac{\partial w_{i,t}(2)}{\partial p_t(1)} & \frac{\partial w_{i,t}(2)}{\partial p_t(2)} & & \vdots \\ \vdots & & \ddots & \vdots \\ \frac{\partial w_{i,t}(n)}{\partial p_t(1)} & \dots & \dots & \frac{\partial w_{i,t}(n)}{\partial p_t(n)} \end{pmatrix} \\
&= \begin{pmatrix} -\frac{\beta_{0,i,t}}{m_t(1)}(1 - w_{i,t}(1)) & \frac{\beta_{0,i,t}}{m_t(1)} w_{i,t}(2) & \dots & \frac{\beta_{0,i,t}}{m_t(1)} w_{i,t}(n) \\ \frac{\beta_{0,i,t}}{m_t(2)} w_{i,t}(1) & -\frac{\beta_{0,i,t}}{m_t(2)}(1 - w_{i,t}(2)) & & \vdots \\ \vdots & & \ddots & \vdots \\ \frac{\beta_{0,i,t}}{m_t(n)} w_{i,t}(1) & \dots & \dots & -\frac{\beta_{0,i,t}}{m_t(n)}(1 - w_{i,t}(n)) \end{pmatrix} \\
&= \beta_{0,i,t} \mathbf{M}_t,
\end{aligned}$$

where $\mathbf{M}_t := diag(\mathbf{m}_t)^{-1}\left(\mathbf{w}_{i,t}\mathbf{1}_n' - \mathbf{I}\right)$, and $\mathbf{1}_n' = (1, 1, \ldots, 1) \in \mathbb{R}^n$.

Putting it all together results in

$$\frac{\partial \mathbf{p}_t}{\partial \mathbf{x}_{k,t}} = \left(\mathbf{I} - \sum_{i=1}^{I} \beta_{0,i,t} A_{i,t} \mathbf{H}_t^{-1} \mathbf{M}_t\right)^{-1} \left(\sum_{i=1}^{I} \beta_{k,i,t} A_{i,t} \mathbf{H}_t^{-1} \mathbf{G}_{i,t}\right).$$

VI. Colophon

We use `R` (R Core Team, 2023) to generate this project's results. We report the packages with their package version in Table IA-8. All packages are shared across co-authors, with results being finally produced on a single machine. Some scripts make use of a cluster (indicated in the replication code). Thus, we include package versions used by the cluster in a separate column. Note that the base R versions, indicated by the package *base*, differ between the local machine and the cluster.

Table IA-8: Colophon.
This table shows the R packages and their respective versions used throughout the project. Local packages' versions are in the second column. In the third column, we report the package version used on the cluster. Citations are provided in the last column.

Package	Local	Cluster	Citation
base	4.3.2	4.1.0	R Core Team (2023)
datasets	4.3.2	4.1.0	R Core Team (2023)
DBI	1.2.1	1.1.3	R Special Interest Group on Databases (R-SIG-DB) et al. (2024)
dbplyr	2.4.0		Wickham et al. (2023b)
devtools	2.4.5		Wickham et al. (2022)
dplyr	1.1.4	1.1.0	Wickham et al. (2023a)
forcats	1.0.0		Wickham (2023a)
frenchdata	0.2.0		Areal (2021)
furrr	0.3.1		Vaughan and Dancho (2022)
ggplot2	3.4.4	3.4.1	Wickham (2016)
ggpubr	0.6.0		Kassambara (2023)
gmm	1.8		Chausse (2010)
googledrive	2.1.1		D'Agostino McGowan and Bryan (2023)
graphics	4.3.2	4.1.0	R Core Team (2023)
grDevices	4.3.2	4.1.0	R Core Team (2023)
janitor	2.2.0		Firke (2023)
jsonlite	1.8.8		Ooms (2014)
lfe	2.9-0		Gaure (2013)
lmtest	0.9-40		Zeileis and Hothorn (2002)
lubridate	1.9.3	1.9.2	Grolemund and Wickham (2011)
MASS	7.3-60.0.1		Venables and Ripley (2002)
methods	4.3.2	4.1.0	R Core Team (2023)
multidplyr	0.1.3		Wickham (2023b)
purrr	1.0.2	1.0.1	Wickham and Henry (2023)
RcppRoll	0.3.0		Ushey (2018)
readr	2.1.5	2.1.4	Wickham et al. (2024a)
readxl	1.4.3		Wickham and Bryan (2023)
renv	1.0.3		Ushey and Wickham (2023)
RPostgres	1.4.6		Wickham et al. (2023c)
RSQLite	2.3.5	2.3.0	Müller et al. (2024)
sandwich	3.1-0		Zeileis et al. (2020)
scales	1.3.0		Wickham et al. (2023d)
slider	0.3.1		Vaughan (2023)
stargazer	5.2.3		Hlavac (2022)
stats	4.3.2	4.1.0	R Core Team (2023)
stringr	1.5.1	1.5.0	Wickham (2023c)
texreg	1.39.3		Leifeld (2013)
tibble	3.2.1	3.1.8	Müller and Wickham (2023)
tidyfinance	0.2.0		Scheuch et al. (2023)
tidyquant	1.0.7		Dancho and Vaughan (2023)
tidyr	1.3.1	1.3.0	Wickham et al. (2024b)
tidyverse	2.0.0	2.0.0	Wickham et al. (2019)
tikzDevice	0.12.6		Sharpsteen and Bracken (2023)
utils	4.3.2	4.1.0	R Core Team (2023)
xtable	1.8-4		Dahl et al. (2019)
zoo	1.8-12		Zeileis and Grothendieck (2005)

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