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. We consider the effects of greenness demand on bond yields in Section IV. Then, we show the effect of demand shocks on investor wealth in absolute terms in Section V. In Section VI.1, we study the real effects of (firm-level) greenness demand. Finally, we provide a colophon of all packages we use in Section VII.

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	30,815,253
Q1 2012	MF	PIMCO Total Return Fund	21,429,878
Q4 2022	MF	Vanguard Total Bond Market Index Fund	34,772,693
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	1,982,784,173

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).

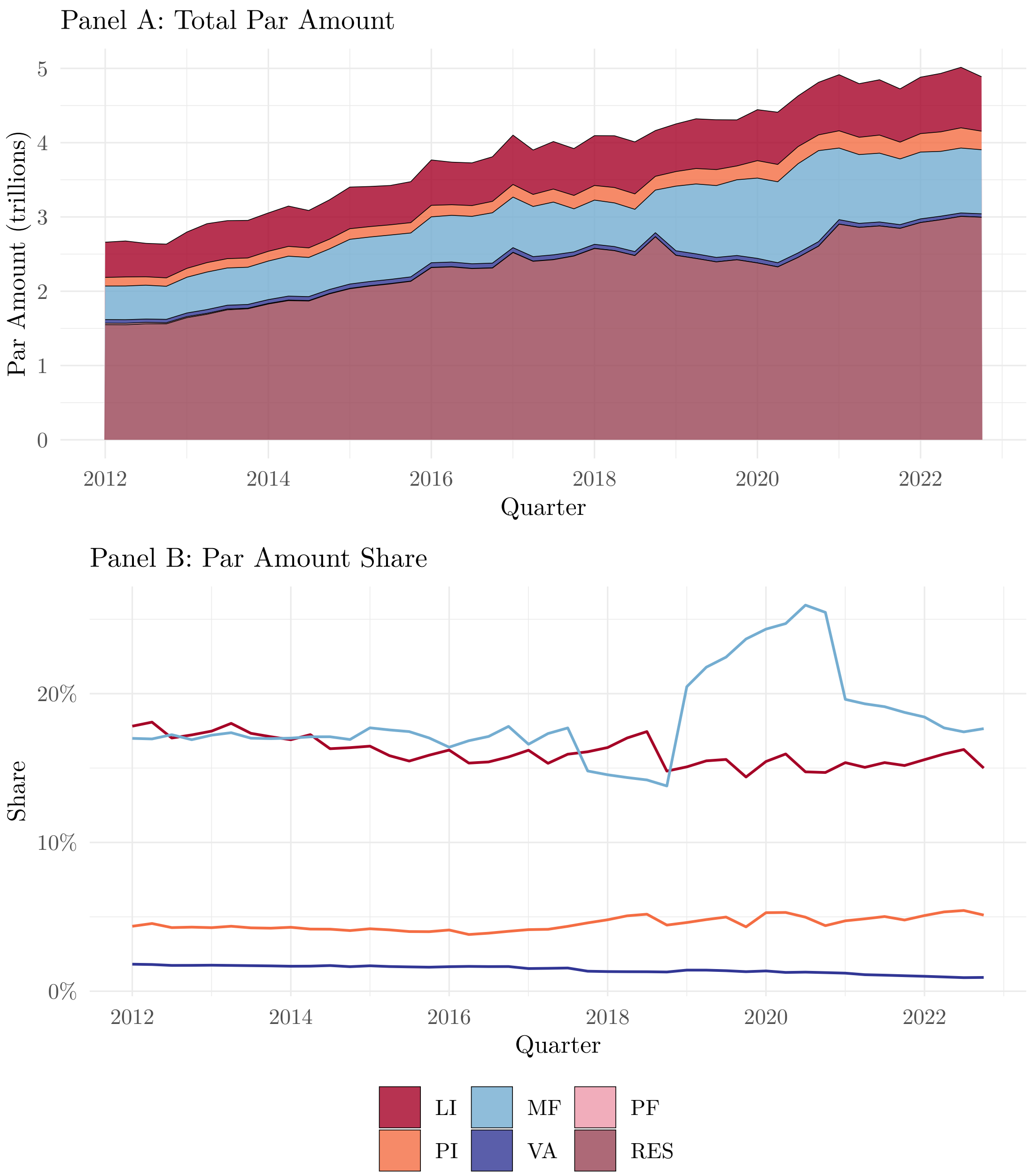


Figure IA-2: Average Bond Characteristics over Time.
This figure shows the development of the par amount-weighted averages for the respective asset characteristics of each investor type. We abbreviate life insurers (LI), property, casualty, and health insurers (PI), mutual funds (MF), and variable annuity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

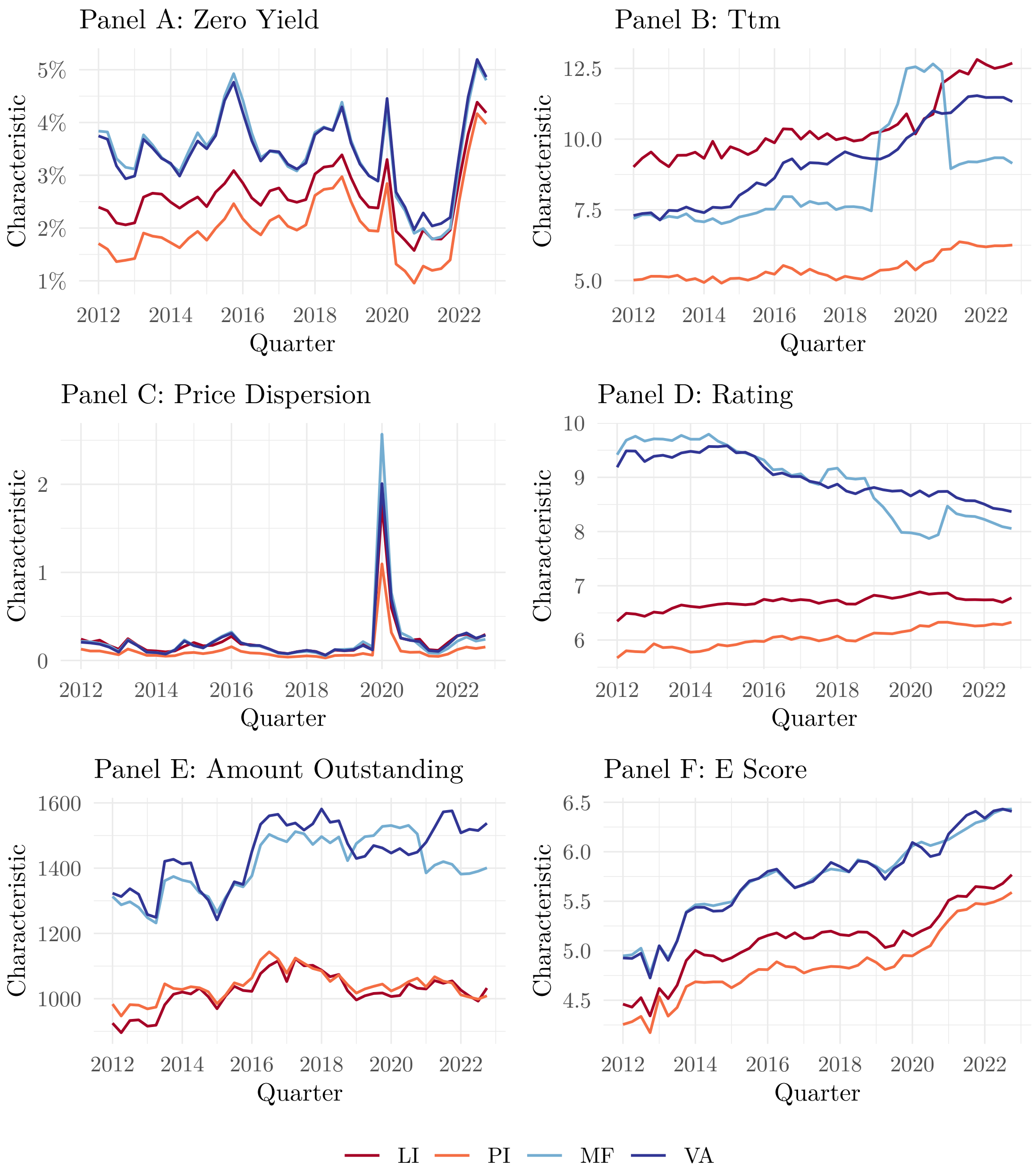
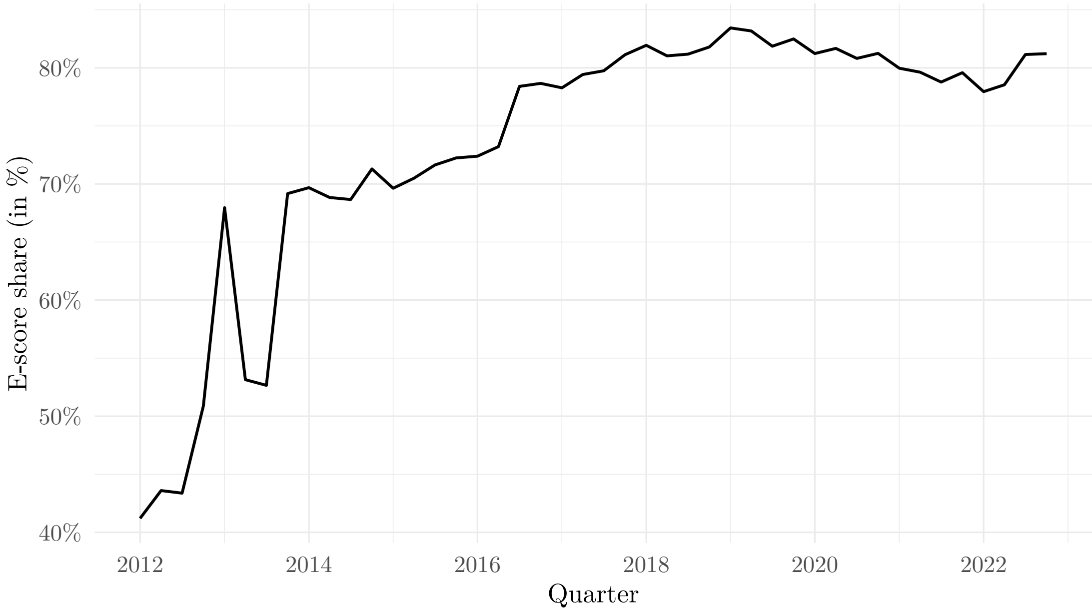


Figure IA-3: E-score Coverage.
This figure shows the share of bonds in our sample with an E-score.



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.

Table IA-2: Demand Curves of Institutional Investors

This table shows the results of quarterly regressions of the demand coefficients on investor-type fixed effects. 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	0.168***	−0.258***	−0.072***	−0.315***	−0.008***	0.031***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
PI	0.135***	−0.369***	−0.112***	−0.331***	0.0005	0.043***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
MF	0.245***	−0.328***	−0.156***	0.024***	0.015***	0.024***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.0005)	(0.001)
VA	0.217***	−0.303***	−0.198***	−0.002	0.005***	0.019***
	(0.003)	(0.005)	(0.002)	(0.003)	(0.001)	(0.002)
PF	0.080***	−0.274***	−0.169***	−0.013	−0.009***	−0.076***
	(0.009)	(0.014)	(0.006)	(0.009)	(0.003)	(0.005)
RES	0.161***	−0.724***	−0.032	0.497***	−0.007	0.045
	(0.052)	(0.080)	(0.033)	(0.051)	(0.019)	(0.028)
log(AUM)	−0.011***	0.040***	−0.028***	0.008***	−0.003***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.001)
Active Share	0.006***	−0.015***	−0.007***	0.045***	−0.003***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.001)
Turnover	0.008***	0.018***	−0.0002	−0.001	−0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.0005)
Observations	154,749	154,749	154,749	154,749	154,749	154,749
Adjusted R^2	0.024	0.018	0.044	0.233	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.

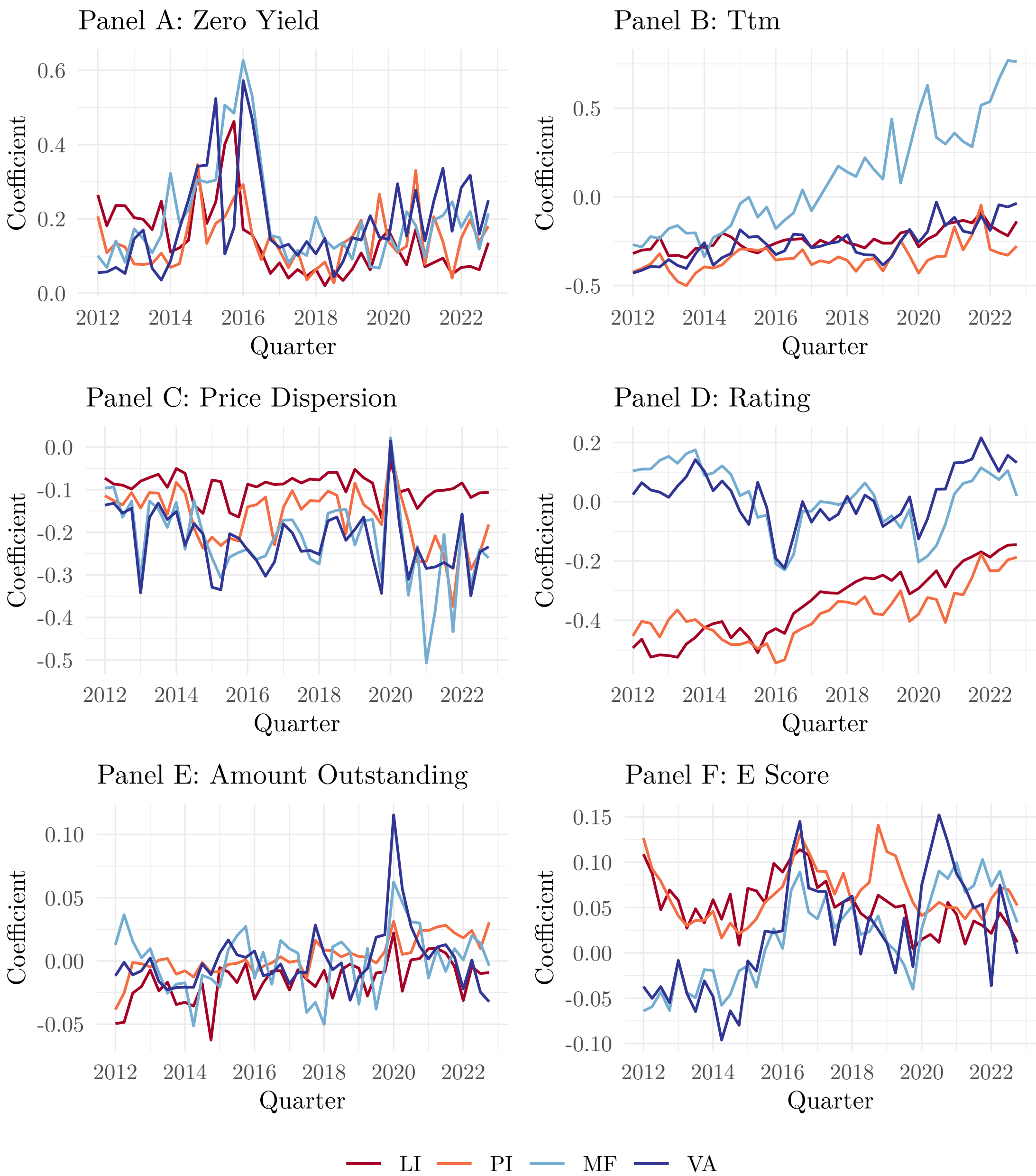


Figure IA-5: Demand Coefficients over Time (Arithmetic Average).
This figure shows the development of the average demand coefficients for the respective asset characteristics of each investor type. We abbreviate life insurers (LI), property, casualty, and health insurers (PI), mutual funds (MF), and 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.

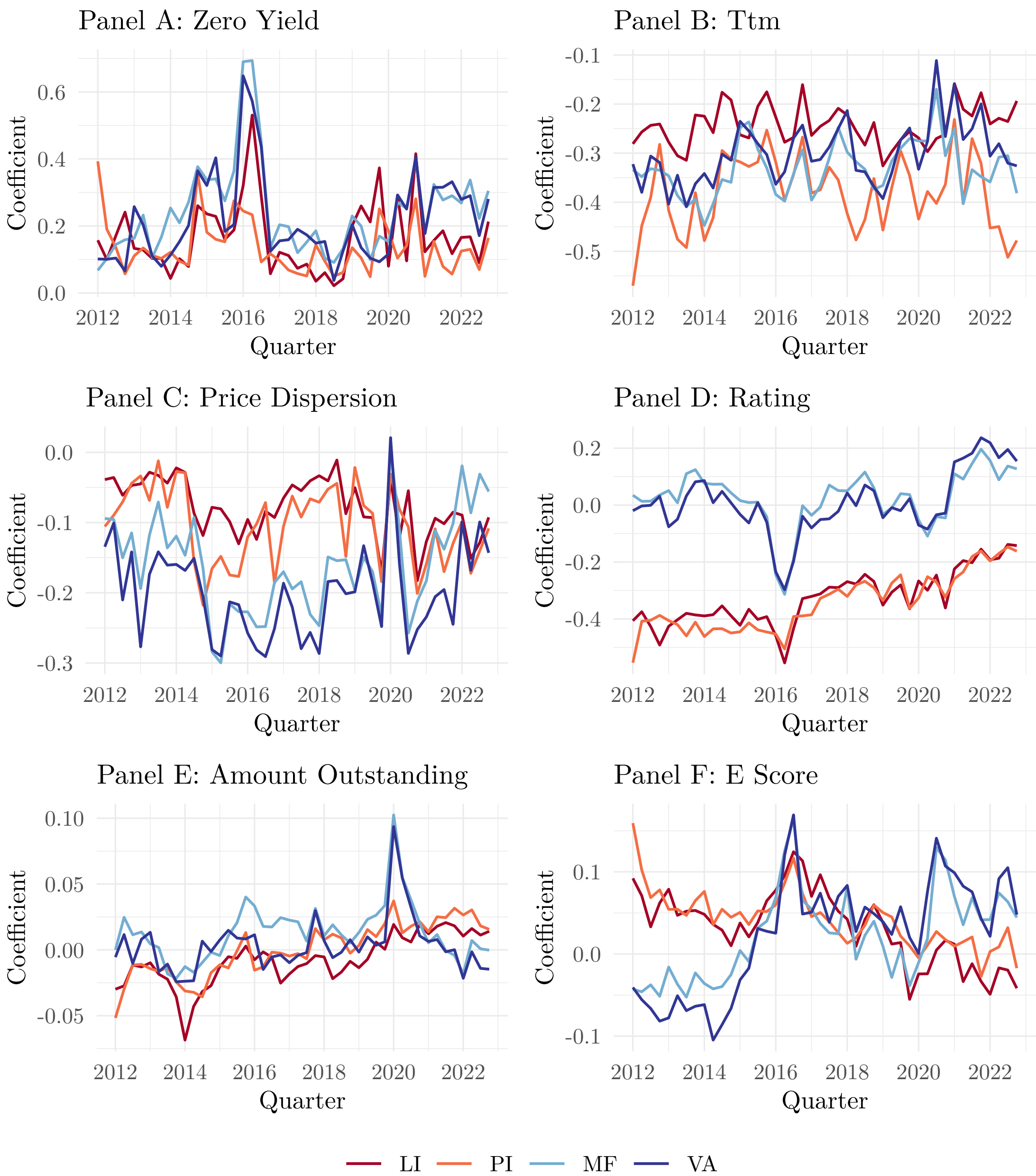


Figure IA-6: Average Demand.

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.

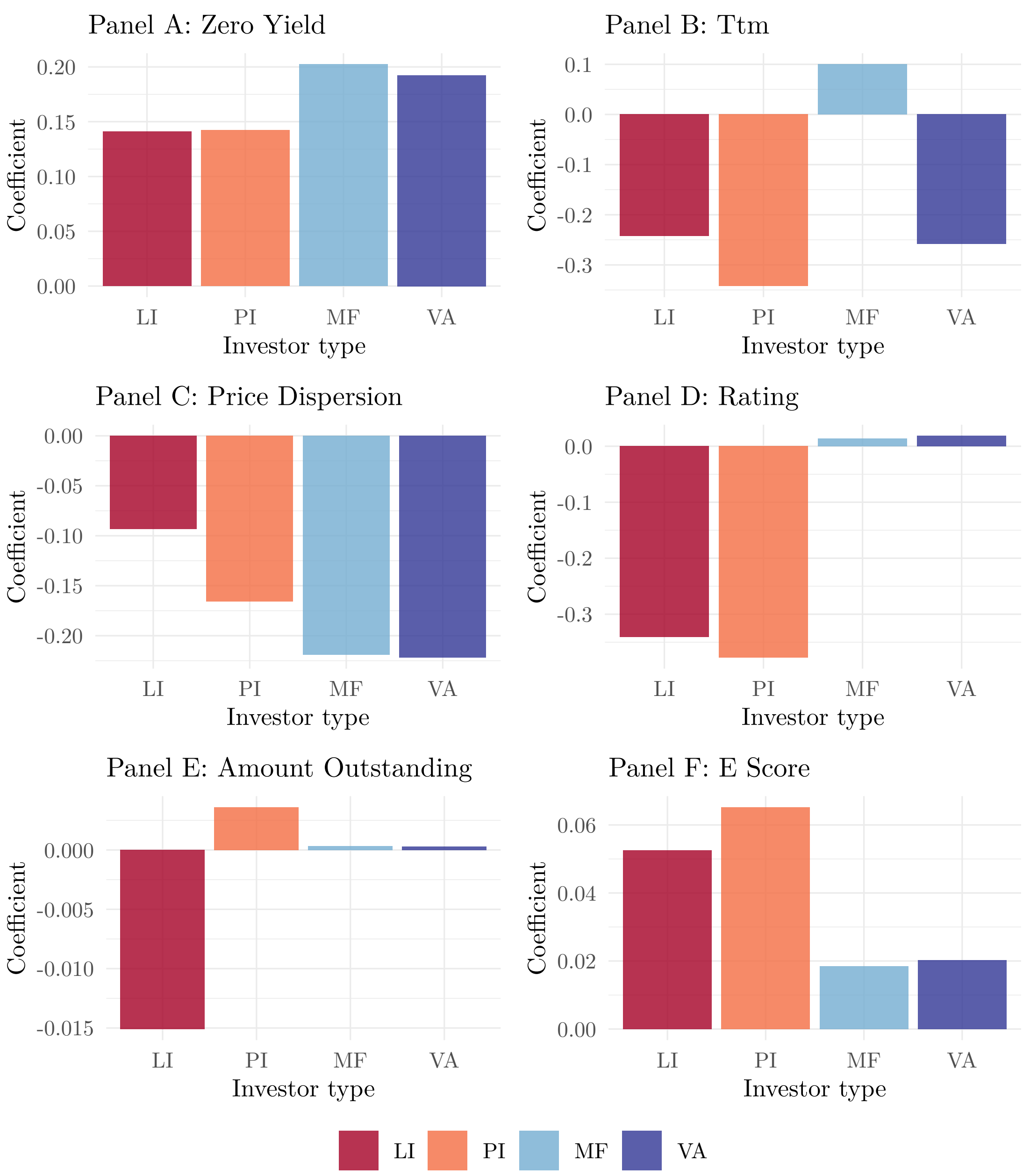
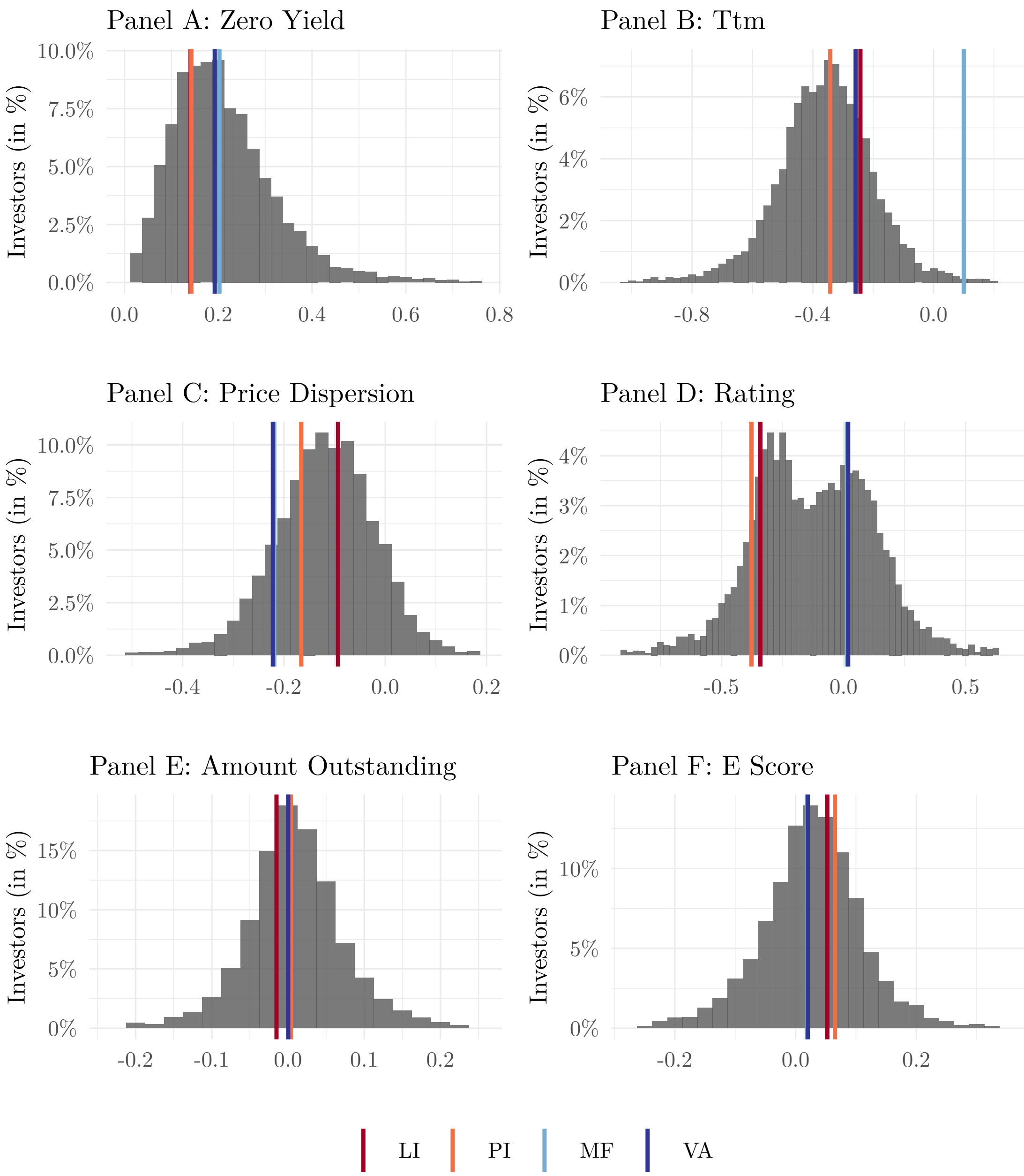


Figure IA-7: Histogram of Demand.
This figure shows histograms of the investor-level averages of demand coefficients of the respective asset characteristics. The colored vertical lines represent the time-series averages of the value-weighted demand coefficients of the investor type. We abbreviate life 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.



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 (12), enables us to find the equilibrium price. Therefore, we rewrite market clearing (12) 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

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

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. Greenness-induced Bond Yield Changes

Table IA-3: Impact of Environmental Preferences on Bond Yields

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

		Counterfactual		
	Actual	MF, VA	LI, PI, PF	All
E-score	−11.507***	−6.048	2.755	8.249*
	(3.698)	(3.835)	(4.207)	(4.312)
Time to Maturity	29.241***	28.504***	29.218***	28.498***
	(5.612)	(5.625)	(5.600)	(5.632)
Price Dispersion	61.290***	61.596***	61.854***	62.159***
	(6.271)	(6.250)	(6.334)	(6.313)
Rating	130.604***	130.160***	131.580***	131.147***
	(12.281)	(12.211)	(12.434)	(12.358)
Amt. Outstanding	8.451***	7.892***	7.707**	7.154**
	(2.782)	(2.816)	(2.893)	(2.931)
Observations	175,297	175,297	175,297	175,297
Adjusted R^2	0.439	0.428	0.429	0.423

V. Demand Shocks' Wealth Impact

Table IA-4: 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 (sub-type 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	0.20	0.33	0.17	0.04
Brown	−0.46	−0.40	−0.75	−0.68

Panel B: COP21 - Absolute Effect

Type	LI	PI	MF	VA
Green	664.30	223.09	77.27	−112.12
Brown	−1,328.92	−539.27	−1,219.13	−705.36

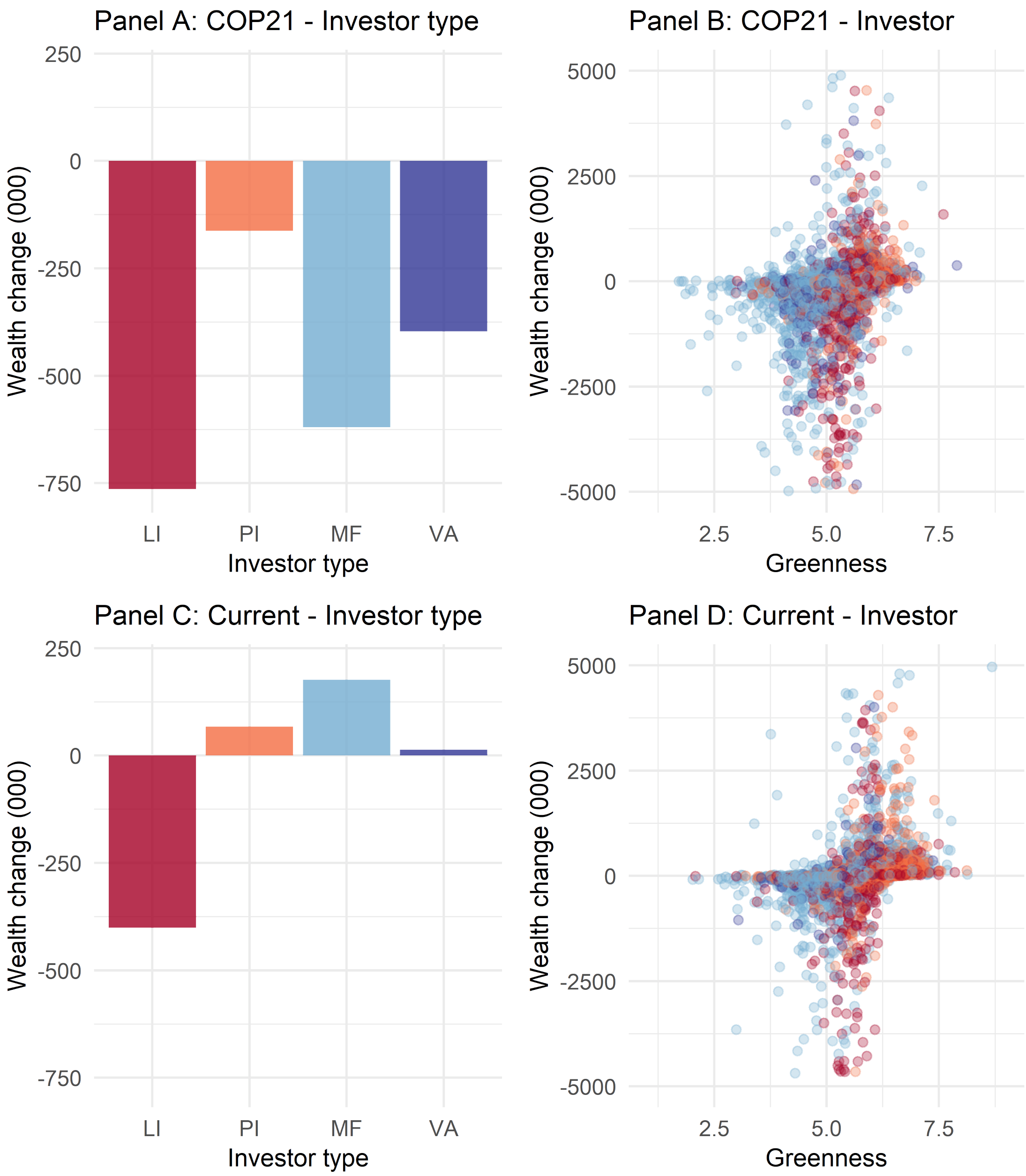
Panel C: Current - Relative Effect

Type	LI	PI	MF	VA
Green	0.26	0.33	0.30	0.27
Brown	−0.30	−0.15	−0.43	−0.43

Panel D: Current - Absolute Effect

Type	LI	PI	MF	VA
Green	146.65	376.57	1172.56	333.49
Brown	−623.71	−235.01	−406.99	−174.98

Figure IA-8: 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).



VI. Real Effects

VI.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 to a yield impact to account for differing maturities. Lastly, we calculate the paramount-weighted average of the bond-level yield impact to aggregate this measure on a firm level.

Table IA-5: 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, the dependent variable is the environmental performance in one year. In Panel B, the dependent variable is the environmental performance change over the succeeding year and the independent variable E-score is measured as a first-difference as well. 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 parenthesis are clustered at the industry level. We indicate significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

Panel A: Levels

	All	Green	Brown
Firm-$\overline{\text{GD}}_{y-1}$	-0.042^{*}	-0.082^{***}	-0.008
	(0.025)	(0.031)	(0.041)
E-score$_{y-1}$	0.913^{***}	0.915^{***}	0.859^{***}
	(0.011)	(0.021)	(0.021)
Num. obs.	4,202	2,149	2,053
Adj. R^2	0.869	0.718	0.618

Panel B: Changes

	All	Green	Brown
Firm-$\overline{\text{GD}}_{y-1}$	-0.032	-0.087^{**}	0.018
	(0.024)	(0.035)	(0.032)
ΔE-score$_{y-1}$	-0.059^{***}	-0.047^{*}	-0.023
	(0.020)	(0.024)	(0.035)
Num. obs.	4,075	2,107	1,968
Adj. R^2	0.004	0.006	0.002

Table IA-6: 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 a four-quarter window. In the second column, the dependent variable is a dummy variable indicating whether a firm issued bonds in a four-quarter window. 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 parenthesis. We indicate significance at the 10%, 5%, and 1% level by *, **, and ***, respectively.

	log(Amt.$_{t:t+3}$+1)	Amt.$_{t:t+3}$> 0
E-score$_{t-1}$	0.152***	0.010***
	(0.022)	(0.002)
Firm-$\overline{\text{GD}}_{t-4:t-1}$ × E-score$_{t-1}$	−0.026***	−0.002***
	(0.010)	(0.001)
Num. obs.	21,095	21,095
Adj. R^2	0.103	0.091

VI.2. 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 parenthesis 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$_{y-1}$	0.187***	0.013***
	(0.027)	(0.002)
$\overline{\text{GD}}_{y-1}\times$ E-score$_{y-1}$	0.017	0.001
	(0.013)	(0.001)
Num. obs.	12,410	12,410
Adj. R^2	0.050	0.044

VI.3. Derivations

Derivation of Equation (IA-3)**:** Our demand system, outlined in Section 5.1, along with market clearing (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 (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 $\mathbf{x}_{k,t}$:

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

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

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

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

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

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

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

VII. 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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