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GREEN TILTS

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ABSTRACT

We estimate financial institutions' portfolio tilts that relate to stocks' environmental, social, and governance (ESG) characteristics. We find ESG-related tilts totaling 6% of the investment industry's assets under management in 2021. ESG tilts are significant at both the extensive margin (which stocks are held) and the intensive margin (weights on stocks held). The latter tilts are larger. Institutions divest from brown stocks more by reducing positions than by eliminating them. The industry tilts increasingly toward green stocks, due to only the largest institutions. Other institutions and households tilt increasingly toward brown stocks. UNPRI signatories tilt greener; banks tilt browner.

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1. Introduction

“Investing based on environmental, social, and governance (ESG) criteria has exploded in popularity, reaching \$35 trillion in global assets under management (AUM) in 2020, according to Bloomberg Intelligence.” Sentences like this introduce countless papers on ESG investing. Do such figures accurately reflect the amount of ESG investing? How much do institutions’ portfolio choices relate to companies’ ESG characteristics? How have these ESG-related portfolio tilts changed over time? Which investors tilt green, and which ones make the offsetting brown tilts? These are the questions we pursue.

As in our opening example, a common approach to measuring ESG investing is to sum the AUM of institutions that include ESG in their stated investment policies. This approach is simple and transparent but has limitations. Most importantly, it does not consider the degree to which such institutions have actually modified their portfolios in ways related to assets’ ESG characteristics. For example, an institution may tilt its portfolio toward assets with favorable ESG characteristics, i.e., “green” assets, and away from unfavorable “brown” assets, but those tilts might be very modest, typifying a practice known as “greenwashing.” The total AUM of such institutions surely overstates their ESG-related investing.

Another limitation of the usual approach works in the other direction: Institutions not declaring an ESG policy could nevertheless be making portfolio decisions related to ESG characteristics. The reason is that such characteristics can enter not only for reasons related to social responsibility but also for financial reasons, which are less likely to appear in stated ESG policies. For example, an institution could overweight green stocks because it sees them as underpriced, or because it aims to hedge against climate risk.

Our approach neither sums AUM nor screens by investment policies. Instead, we estimate ESG-related portions of institutions’ portfolio weights. We focus on equity portfolios, using holdings from 13F filings. For each institution, we begin by estimating how every stock’s ESG characteristics relate to the stock’s weight in the institution’s portfolio, controlling for the stock’s other characteristics. Combining these estimates across stocks then gives an institution-level measure of ESG-related tilt. Finally, we aggregate those tilts across institutions to estimate the total ESG-related portfolio tilt in the investment industry.

We find that the total dollar ESG-related tilt is about 6% of the industry’s AUM in equity investments in 2021. By this measure, there is much less ESG investing than commonly reported. For example, 76% of our sample’s AUM belongs to institutions that have signed the United Nations’ Principles for Responsible Investment (UNPRI).

We incorporate various dimensions of ESG-related tilts. For example, we consider both the extensive margin (i.e., which stocks are held) and the intensive margin (i.e., weights on stocks held). We find significant ESG effects at both margins, though the intensive-margin effects are two to three times larger than the extensive-margin effects. We also allow a stock’s E, S, and G characteristics to relate separately to an institution’s portfolio weights. We find each of those three dimensions contributes about equally to aggregate ESG-related tilts.

Allowing E, S, and G characteristics to enter separately is a key virtue of our approach. For example, one institution might care about G but not S, while another institution cares about S but not G. If a stock’s E, S, and G characteristics are combined into a composite ESG score, the latter could rate two stocks equally, but one stock could be high G and low S while the other is low G and high S. The above two institutions would differ in how they tilt their weights on the two stocks, but those tilts would not be explained by the stocks’ composite scores. We take companies’ E, S, and G characteristics from ratings provided by MSCI, a leading provider. MSCI also provides a composite ESG score for each company. If we restrict our estimation to this composite rather than the E, S, and G components, we find that over 40% of ESG-related tilts are missed.

We also measure the extent to which ESG tilts are green or brown. Given the multiple dimensions of ESG, any of them can be used to measure greenness. For each one, such as E or the composite score, we compute an institution’s net tilt toward green stocks, which we term “GMB” tilt (green minus brown). Aggregating GMB tilts across all 13F institutions gives the industry’s GMB tilt. Since 2012, the beginning of our sample, the industry has become increasingly green, exhibiting a consistently positive and rising GMB tilt. In contrast, the aggregate portfolio of non-13F investors has become browner, exhibiting a negative and decreasing GMB tilt. We also find that the rise in GMB tilt of 13F institutions occurs primarily via the intensive margin, i.e., increasingly overweighting green stocks and underweighting brown stocks. For example, divestment from brown stocks, a long-standing theme, occurs largely at the intensive margin, meaning that most of this divestment involves reducing positions rather than eliminating them. All of these findings are remarkably robust to whether we measure greenness by E, S, G, or the composite score.

ESG investing varies greatly across 13F-filing institutions. In particular, the industry’s increasing greenness noted above is driven by the largest institutions. For example, when we rank institutions by AUM and separate them at the 33rd and 66th percentiles, we find that only the top third exhibits a positive and rising GMB tilt. The GMB tilts of both the middle and bottom thirds resemble those of the non-13F investors: negative and decreasing over time, meaning brown and increasingly so. At least that is the pattern when using

three of the four greenness scales (S, G, and composite score). When greenness is defined with respect to E, all three AUM segments have consistently positive GMB tilts, but only the largest institutions exhibit a rising GMB tilt. Although the largest institutions account for the industry’s increasing greenness, their total ESG-related tilts constitute a smaller fraction of their AUM, as compared to the other 13F institutions.

As noted earlier, we do not use institutions’ stated ESG policies to estimate ESG-related tilts. We do ask, however, whether those policies relate to our estimated tilts. In particular, we ask whether institutions that have signed the UNPRI have larger GMB tilts. Indeed, they do; we find that UNPRI signatories are significantly greener. Not only do we see that result strongly within the cross-section of institutions, but we also find that a given institution becomes greener after becoming a UNPRI signatory.

We also consider an institution’s ESG tilt in the context of all its portfolio tilts. Taking as given that the market portfolio contains no tilts of any kind, any non-market portfolio contains non-zero tilts. For an institution less inclined to tilt its portfolio for any reason, ESG or otherwise, a given ESG tilt is more economically significant in the context of that institution’s investing. That is, the ESG tilt represents a greater disruption of what the institution would otherwise do, given its investing style or mandate. To measure an institution’s total tilts arising from all reasons, i.e., the deviations of its portfolio weights from market weights, we use the active share measure of Cremers and Petajisto (2009). We divide our ESG tilt measures by active share, so as to gauge ESG tilts from the above perspective. We find that, on average, ESG tilts are one quarter as large as total portfolio tilts at the end of our sample. ESG tilt is positively correlated with active share, consistent with the notion that institutions less likely to tilt for all reasons are less likely to tilt due to ESG.

ESG investing is distinct from index investing, i.e., holding the market portfolio. ESG preferences affect market portfolio weights, but we do not include those effects as part of ESG investing. The basic rationale follows Pástor, Stambaugh, and Taylor (2021): When all investors care equally about ESG, they all hold the market portfolio, because their preferences are fully reflected in the market portfolio’s weights via equilibrium prices. There is then only index investing and no ESG investing.¹ The latter arises only when ESG preferences differ across investors. The above study, to simplify its theory, precludes reasons other than ESG for why investors deviate from the market portfolio. We allow other reasons, to increase realism given our empirical focus, but we maintain the same concept of ESG investing by

¹To say there is no ESG investing in that setting seems reasonable. The standard CAPM is another setting in which investors all hold the market portfolio. Presumably one would not describe that setting as having some amount of “low-beta” investing simply because the model implies low-beta stocks have lower expected returns, and so higher market weights.

controlling for market weights when estimating tilts.

This paper contributes to the large literature that studies the composition of institutional portfolios. This literature documents various institutional investors' preference for large and liquid stocks (e.g., Falkenstein (1996), Gompers and Metrick (2001), Bennett et al. (2003), and Ferreira and Matos (2008)). Institutions' portfolio holdings are also related to stock characteristics such as the book-to-market ratio, prior-year return, and various risk measures.² We estimate institutions' ESG-related portfolio tilts while controlling for the tilt-relevant non-ESG stock characteristics identified by prior work.

We are not the first to examine institutions' portfolio tilts with respect to stocks' ESG characteristics. For example, Ferreira and Matos (2008) document institutions' preference for firms with good governance. Bolton and Kacperczyk (2021) find that institutions underweight firms with high scope-1 carbon emission intensity. Atta-Darkua et al. (2022) find that institutions that join climate-related investor initiatives increase their holdings of firms with low carbon emissions. Starks, Venkat, and Zhu (2023) find that institutions with longer investment horizons tilt their portfolios more towards firms with high ESG scores. Gibson, Krueger, and Mitali (2021) relate institutions' portfolio-level environmental and social scores to performance. Nofsinger, Sulaeman, and Varma (2019) find that institutions underweight stocks with negative environmental and social indicators. Hong and Kostovetsky (2012) find that Democratic-leaning fund managers allocate less to the stocks of firms viewed as socially irresponsible. Choi, Gao, and Jiang (2020a) show that institutions reduced the carbon exposures of their portfolios between 2001 and 2015.

Like these studies, we find that institutions' portfolios tilt green, and increasingly so. However, our approach to measuring ESG-related portfolio tilts is fundamentally different. We do not analyze portfolio-level ESG characteristics because they reflect also stocks' non-ESG characteristics such as size and book-to-market, which are correlated with ESG characteristics. By controlling for non-ESG characteristics, our approach separates ESG tilts from investment styles such as large-cap growth. Our approach has two additional advantages. First, it measures the extensive- and intensive-margin components of ESG tilts, yielding new insights. For example, divestment from brown stocks occurs largely at the intensive margin; intensive-margin (but not extensive-margin) divestment grows substantially over time; and the upward trend in the aggregate green tilt occurs entirely at the intensive margin. Second, instead of analyzing one ESG characteristic (e.g., carbon emissions) at a time, our approach

²See, for example, Falkenstein (1996), Gompers and Metrick (2001), Edelen, Ince, and Kadlec (2016), DeVault, Sias, and Starks (2019), Kojien and Yogo (2019), and Lettau, Ludvigson, and Manoel (2021). Aggregating across institutions, Lewellen (2011) shows that their total holdings closely resemble those of the market portfolio.

uses all of the E, S, and G characteristics simultaneously. Moreover, these characteristics enter separately, capturing the fact that different institutions care about different dimensions of ESG, and to different degrees. We find that the aggregate E-, S-, and G-related tilts have similar magnitudes and time-series patterns, which is surprising because governance is a long-standing concern and environment is often viewed as the focal dimension of ESG.

Existing studies find mixed evidence on whether UNPRI signatories engage in ESG-related behavior, raising concerns about greenwashing (Gibson et al. (2022), Liang, Sun, and Teo (2022), and Kim and Yoon (2023)). In contrast, we find that after institutions become UNPRI signatories, their ESG tilts tend to become greener.

Prior evidence on ESG-related trading by retail investors is also mixed. On the one hand, Choi, Gao, and Jiang (2020b) find that retail investors, but not institutions, respond to abnormally warm temperatures by selling stocks of carbon-intensive firms. Li, Watts, and Zhu (2023) find that retail investors' trades respond to a broader set of ESG news events. On the other hand, Moss, Naughton, and Wang (2021) find that retail investors' buy and sell decisions do not respond to ESG disclosures. Instead of analyzing responses to news or disclosures, we focus on ESG-related portfolio tilts. We find that the portfolios of non-13F investors, most of whom are retail investors, tilt brown, and increasingly so.

Our study is also related to the literature exploring the links between institutional ownership, including the ownership by responsible institutions, and various aspects of corporate social responsibility.³ Our focus on institutions' ESG tilts provides a different and complementary perspective on judging institutional responsibility. Finally, our study is related to the literature on the price impact of demand shocks associated with ESG investing.⁴

The remainder of the paper is organized as follows. Section 2 presents our definitions of ESG-related portfolio tilts. Section 3 explains our estimation procedure. Section 4 presents our evidence on the cross-sectional and time-series patterns of ESG tilts. Section 5 concludes.

2. ESG-related portfolio tilts

To quantify the amount of ESG investing, we measure the extent to which investors tilt their portfolios in relation to stocks' ESG characteristics. We denote the set of all stocks'

³See, for example, Chen, Dong, and Lin (2020), Choi et al. (2023), Dyck et al. (2019), Gantchev, Giannetti, and Li (2022), Heath et al. (2021), Hwang, Titman, and Wang (2022), Ilhan et al. (2020), and Li and Raghunandan (2021).

⁴See, for example, Koijen, Richmond, and Yogo (2022), Noh and Oh (2021), and van der Beck (2022).

ESG characteristics by \mathcal{G} . Each stock has multiple ESG characteristics. We denote neutral values of the same characteristics by \mathcal{G}_0 . Specifically, \mathcal{G}_0 is the counterpart of \mathcal{G} in which each stock’s value of each ESG characteristic is replaced by the market portfolio’s value of the same characteristic. Let w_{in} denote investor i ’s portfolio weight on stock n . For any given investor-stock pair, we define the investor’s ESG-related portfolio tilt in this stock as

$$\Delta_{in} = \text{E}[w_{in}|\mathcal{G}, \mathcal{C}] - \text{E}[w_{in}|\mathcal{G}_0, \mathcal{C}], \quad (1)$$

where E denotes a conditional expectation and \mathcal{C} is the set of stocks’ non-ESG stock characteristics. Δ_{in} is the part of w_{in} attributable to the difference between \mathcal{G} and \mathcal{G}_0 , holding constant the non-ESG characteristics. Holding \mathcal{C} constant is important because the ESG and non-ESG characteristics can be correlated. For example, Pástor, Stambaugh, and Taylor (2022) show that stocks with lower book-to-market ratios tend to have higher environmental ratings (i.e., growth stocks tend to be greener than value stocks). By including a stock’s book-to-market ratio among the non-ESG characteristics, we control for this ratio in estimating the relation between \mathcal{G} and portfolio weights. We conduct our analysis at a given point in time, t , but we suppress the variables’ dependence on t , for simplicity.

The above definition of Δ_{in} , a difference in conditional expectations, has a familiar analogue in regression analysis. A common way to quantify an independent variable’s contribution to the dependent variable is to compare fitted values (estimated conditional expectations) for two values of the independent variable, such as the latter’s actual value and its sample average. One could, for example, follow that procedure and estimate Δ_{in} by just regressing, across stocks, w_{in} on stock n ’s ESG and non-ESG characteristics. We avoid that simple regression approach for two reasons. First, how an investor weights a stock depends on its attractiveness relative to other stocks in the investor’s portfolio, and that comparison involves the other stocks’ characteristics as well. Second, we include portfolio choices made at the extensive margin, not just the intensive, as there are often many stocks for which $w_{in} = 0$. That feature of the data is poorly suited for the simple regression.

2.1. Extensive- and intensive-margin tilts

The conditional expectations entering the value of Δ_{in} in equation (1) can be written as $\text{E}[w_{in}|\cdot] = \text{Prob}\{w_{in} > 0|\cdot\} \times \text{E}\{w_{in}|w_{in} > 0, \cdot\}$. Therefore, \mathcal{G} relates to w_{in} through two channels: via the probability that investor i holds stock n and via the amount invested in the stock if held. To quantify both of these channels, for any set of ESG characteristics $\tilde{\mathcal{G}}$,

we denote

$$\pi(\tilde{\mathcal{G}}) \equiv \text{Prob}\{w_{in} > 0 | \tilde{\mathcal{G}}, \mathcal{C}\} \quad (2)$$

$$w^+(\tilde{\mathcal{G}}) \equiv \text{E}\{w_{in} | w_{in} > 0; \tilde{\mathcal{G}}, \mathcal{C}\}. \quad (3)$$

We apply these formulas for two different values of $\tilde{\mathcal{G}}$: the observed values, \mathcal{G} , and the neutral values, \mathcal{G}_0 . We can thus rewrite equation (1) as $\Delta_{in} = \pi(\mathcal{G})w^+(\mathcal{G}) - \pi(\mathcal{G}_0)w^+(\mathcal{G}_0)$. We can then split Δ_{in} into two components,

$$\Delta_{in} = \Delta_{in}^{ext} + \Delta_{in}^{int}, \quad (4)$$

representing the extensive- and intensive-margin tilts, respectively. These components are

$$\Delta_{in}^{ext} = w^+(\mathcal{G}_0) \{\pi(\mathcal{G}) - \pi(\mathcal{G}_0)\} \quad (5)$$

$$\Delta_{in}^{int} = \pi(\mathcal{G}) \{w^+(\mathcal{G}) - w^+(\mathcal{G}_0)\}. \quad (6)$$

The extensive-margin tilt, Δ_{in}^{ext} , is computed by varying the probability of holding the stock, without changing the expected portfolio weight conditional on holding the stock. This tilt provides an answer to the question: how much of investor i 's portfolio weight in stock n is attributable to the relation between the stock's ESG characteristics and the probability of holding the stock?

The intensive-margin tilt, Δ_{in}^{int} , is computed by varying the expected portfolio weight conditional on holding the stock, without changing the probability of holding the stock. This tilt provides an answer to the question: how much of investor i 's portfolio weight in stock n relates to the stock's ESG characteristics, conditional on holding the stock?

Note that Δ_{in} is defined for all stocks n , including stocks not actually held by investor i . For stocks not held, $\Delta_{in} < 0$ suggests that the exclusion is related to \mathcal{G} , while $\Delta_{in} > 0$ suggests that the investor would be shorting the stock absent ESG considerations.

2.2. Investor-level tilts

For any investor i , we compute the investor's ESG-related portfolio tilt by adding up the absolute values of the investor's portfolio tilts with respect to each of the N stocks:

$$T_i = \frac{1}{2} \sum_{n=1}^N |\Delta_{in}|. \quad (7)$$

This definition parallels that of the ESG tilt in Pástor, Stambaugh, and Taylor (2021), except that here Δ_{in} allows deviations from market weights to depend on more than just stocks'

ESG characteristics. The division by two ensures that we avoid double-counting: for each stock the investor overweights because of \mathcal{G} , the investor must underweight one or more other stocks. Put differently, $\sum_{n=1}^N \Delta_{in} = 0$ for all i , which follows from equation (1), so any positive Δ_{in} 's must be balanced by negative ones.

We similarly compute investor-level intensive- and extensive-margin tilts:

$$T_i^{int} = \frac{1}{2} \sum_{n=1}^N |\Delta_{in}^{int}| \quad (8)$$

$$T_i^{ext} = \frac{1}{2} \sum_{n=1}^N |\Delta_{in}^{ext}|. \quad (9)$$

Note that, in general, $T_i \neq T_i^{int} + T_i^{ext}$. While Δ_{in} can be decomposed cleanly into Δ_{in}^{int} and Δ_{in}^{ext} (see equation (4)), decomposing $|\Delta_{in}|$ is less straightforward. In particular, $|\Delta_{in}| = |\Delta_{in}^{int} + \Delta_{in}^{ext}| \leq |\Delta_{in}^{int}| + |\Delta_{in}^{ext}|$, and the inequality is strict if and only if Δ_{in}^{int} and Δ_{in}^{ext} have opposite signs. It follows immediately that $T_i \leq T_i^{int} + T_i^{ext}$.

2.3. Aggregate tilts

For any given set of investors, we can compute the aggregate tilt as an asset-weighted average tilt across investors:

$$T = \frac{1}{\sum_i A_i} \sum_i A_i T_i, \quad (10)$$

where A_i is the dollar value of investor i 's assets and $\sum_i A_i$ is the total value of assets across investors. T measures the fraction of total investor assets that is “tilted.”

We compute aggregate intensive- and extensive-margin tilts analogously:

$$T^{int} = \frac{1}{\sum_i A_i} \sum_i A_i T_i^{int} \quad (11)$$

$$T^{ext} = \frac{1}{\sum_i A_i} \sum_i A_i T_i^{ext}. \quad (12)$$

2.4. Green and brown tilts

The tilt measures presented so far capture all ESG-related portfolio tilts, regardless of their direction. Two investors with the same value of T_i could in principle be using ESG characteristics in opposite ways, one tilting toward and the other away from stocks with high values

of these characteristics. Next, we design directional tilt measures that separate “green” investment behavior from “brown.” Green behavior tilts toward green stocks and away from brown stocks, whereas brown behavior tilts in the opposite direction.

To define directional tilt measures, we need to designate stocks as green and brown. That is not straightforward when there are multiple ESG characteristics, because stocks with high values of one ESG characteristic could have low values of another. For any given ESG characteristic, however, such as a composite ESG rating or an E score, we can define greenness in terms of that characteristic. Let g_n denote stock n ’s value of that characteristic and g_0 denote the characteristic’s neutral value, which is the capitalization-weighted average of g_n across stocks. We can then classify the stock as green if $g_n \geq g_0$ and brown if $g_n < g_0$. In other words, we label a stock as green if it is greener than the market portfolio and brown if it is browner than the market portfolio.

For each $\{i, n\}$ pair, we classify the tilt into one of four categories. Consequently, each Δ_{in} from equation (1) takes one of the following four values (the other three are zero):

$$\Delta_{in}^{OG} : \quad \text{when } \Delta_{in} > 0 \text{ and } g_n \geq g_0 : \text{ Overweight Green stocks (green tilt)} \quad (13)$$

$$\Delta_{in}^{UB} : \quad \text{when } \Delta_{in} < 0 \text{ and } g_n < g_0 : \text{ Underweight Brown stocks (green tilt)} \quad (14)$$

$$\Delta_{in}^{OB} : \quad \text{when } \Delta_{in} > 0 \text{ and } g_n < g_0 : \text{ Overweight Brown stocks (brown tilt)} \quad (15)$$

$$\Delta_{in}^{UG} : \quad \text{when } \Delta_{in} < 0 \text{ and } g_n \geq g_0 : \text{ Underweight Green stocks (brown tilt)}. \quad (16)$$

There are two types of “green tilts,” which reflect green investment behavior, and two types of “brown tilts,” which reflect brown investment behavior. An investor can tilt green by either overweighting green stocks or underweighting brown stocks. An investor can tilt brown by either overweighting brown stocks or underweighting green stocks.

Aggregating the signed tilts across stocks to the investor level, we define

$$T_i^{OG} = \sum_{n=1}^N \Delta_{in}^{OG}, \quad T_i^{UB} = - \sum_{n=1}^N \Delta_{in}^{UB}, \quad T_i^{OB} = \sum_{n=1}^N \Delta_{in}^{OB}, \quad T_i^{UG} = - \sum_{n=1}^N \Delta_{in}^{UG}. \quad (17)$$

We put minus signs in front of two of the sums to ensure that all four tilts are nonnegative. For a given investor i , all four tilts can be strictly positive—the investor can be overweighting some green stocks while underweighting others, and similarly for brown stocks.

To quantify a given investor’s overall green and brown behaviors, we combine the above tilts to measure the investor’s total green tilt (T_i^G) and total brown tilt (T_i^B):

$$T_i^G = T_i^{OG} + T_i^{UB} \geq 0 \quad (18)$$

$$T_i^B = T_i^{OB} + T_i^{UG} \geq 0. \quad (19)$$

We also compute the investor's green-minus-brown tilt as

$$T_i^{GMB} = T_i^G - T_i^B. \quad (20)$$

$T_i^{GMB} > 0$ indicates that the investor's behavior is green overall, whereas $T_i^{GMB} < 0$ indicates net brown behavior. For comparison, note that the unsigned tilt from equation (7) equals

$$T_i = \frac{1}{2}(T_i^{OG} + T_i^{UB} + T_i^{OB} + T_i^{UG}) \quad (21)$$

$$= \frac{1}{2}(T_i^G + T_i^B). \quad (22)$$

The value of T_i thus represents the average of the green and brown tilts T_i^G and T_i^B , whereas T_i^{GMB} represents their difference.

We also decompose the green and brown tilts into their extensive- and intensive-margin components $T_i^{G,ext}$, $T_i^{G,int}$, $T_i^{B,ext}$, $T_i^{B,int}$, $T_i^{GMB,ext}$, and $T_i^{GMB,int}$. To compute those, we first decompose the Δ_{in} 's in equations (13) through (16) into their components as in equation (4), and then we aggregate those components to the investor level as in equations (8) and (9). Finally, we compute asset-weighted averages across investors, analogous to equations (10) through (12), yielding the aggregate tilt measures T^G , T^B , and T^{GMB} , as well as their components $T^{G,ext}$, $T^{G,int}$, $T^{B,ext}$, $T^{B,int}$, $T^{GMB,ext}$, and $T^{GMB,int}$. Note that if the aggregates are computed across all investors, then the green and brown tilts are always equal:

$$T^G = T^B, \quad (23)$$

as we prove in the Appendix. Given that the green and brown tilts fully offset each other, the value of T^{GMB} computed across all investors is zero. Nonetheless, T^{GMB} can be nonzero when computed across important subsets of investors, as we show later.

3. Estimating portfolio tilts

To compute the various portfolio tilts defined in Section 2, we need to estimate two quantities: π and w^+ from equations (2) and (3), respectively. With those estimates in hand, we can compute the components of Δ_{in} in equations (5) and (6), which yield Δ_{in} in equation (4). We can then aggregate the Δ_{in} estimates into all other tilts defined in Section 2.

Estimating π and w^+ requires a model for portfolio weights. In Section 3.1, we describe our econometric model for the extensive margin of portfolio weights, which yields an estimate of π . In Section 3.2, we present our model for the intensive margin, which yields an estimate

of w^+ . Finally, in Section 3.3, we describe how we adjust our estimates for potential bias and compute their standard errors.

We arrange the elements of \mathcal{G} into an $N \times K_1$ matrix G of the N stocks' ESG characteristics. We also arrange the elements of \mathcal{C} into an $N \times K_2$ matrix C of non-ESG characteristics, which include stocks' market capitalization weights. We define $X \equiv [\iota \ G \ C]$, where ι is an N -vector of ones, so that X is an $N \times K$ matrix, where $K = 1 + K_1 + K_2$. Let x_{nj} denote the (n, j) element of X , and X_n its n th row. We ensure that all elements of X are non-negative (by using cross-sectional percentiles of raw characteristics, as we explain later).

3.1. Extensive margin

Our model of the extensive margin gives the value of

$$\pi_{in} \equiv \text{Prob}\{w_{in} > 0 | X\}. \quad (24)$$

We assume that π_{in} for each investor-stock pair is given by an investor-specific logit model:

$$\pi_{in} = \frac{e^{X_n a_i}}{1 + e^{X_n a_i}}. \quad (25)$$

We estimate the model in equation (25) for a given investor i by running a logistic regression across all stocks with non-missing data; as a result, the number of observations is the same for all investors. The dependent variable is an indicator $1_{w_{in} > 0}$, which is equal to one if stock n is held by investor i and zero otherwise. We estimate the coefficients a_i by maximum likelihood and denote the model's fitted value by $\hat{\pi}_{in}$. The estimated probabilities $\hat{\pi}_{in}$ are always between 0 and 1, by construction. Another desirable property of the logit model is that the average estimated probability is equal to the actual proportion of stocks held, given that X includes a vector of ones. In other words, letting L_i denote the number of stocks held by investor i , the average value of $\hat{\pi}_{in}$ across n is equal to L_i/N .

3.2. Intensive margin

Our model of the intensive margin gives the value of

$$w_{in}^+ \equiv \text{E}\{w_{in} | w_{in} > 0, X, \pi_i\}. \quad (26)$$

The expectation in equation (26) conditions on the full set of probabilities $\pi_i \equiv [\pi_{i1} \cdots \pi_{iN}]'$ and the full matrix X , because an investor's expected weight on a given stock can depend on what other stocks, and characteristics thereof, the investor could hold as well.

We model w_{in}^+ as a restricted linear function of stock n 's characteristics, after scaling it by the stock's market portfolio weight, w_{mn} . Specifically, we assume that

$$\frac{w_{in}^+}{w_{mn}} = \sum_{j=1}^K c_{ij} x_{nj}, \quad n = 1, \dots, N, \quad (27)$$

so that w_{in}^+ is linear in the K values of $w_{mn}x_{nj}$. If stock n is held, its expected weight could in principle depend not only on the stock's own value of $w_{mn}x_{nj}$ but also on the values of that quantity for other stocks the investor may hold. Recognizing that potential dependence, we allow c_{ij} to depend on the portfolio's expected sum of $w_{mn}x_{nj}$ across stocks. We also restrict the expected portfolio weights to add up to one:

$$\sum_{n=1}^N \pi_{in} w_{in}^+ = 1, \quad (28)$$

as long as π_i has at least one positive element. As we show in the Appendix, we can then estimate w_{in}^+/w_{mn} by the fitted values from the regression

$$\frac{w_{in}}{w_{mn}} = \sum_{j=1}^K b_{ij} \tilde{x}_{inj} + e_{in}, \quad n = 1, \dots, N, \quad (29)$$

where the slope coefficients sum to one, $\sum_{j=1}^K b_{ij} = 1$, and the j -th independent variable is

$$\tilde{x}_{inj} = \frac{x_{nj}}{\sum_{n=1}^N \pi_{in} w_{mn} x_{nj}}. \quad (30)$$

This regression is estimated for each investor i across all stocks held by the investor.

To derive the regression model in equation (29), we assume that for each stock n held by investor i , the actual portfolio weight w_{in} obeys

$$w_{in} = w_{in}^+ + \epsilon_{in}, \quad (31)$$

where ϵ_{in} has zero mean conditional on X . The latter assumption merits discussion, given alternative treatments such as Kojien and Yogo (2019). Following their argument, note that ϵ_{in} includes effects on w_{in} of the stock's characteristics that our model omits. Let ζ_n denote such a characteristic. If ζ_n is related to demands for stock n by a substantial mass of investors, then ζ_n can affect the stock's price, p_n , making ϵ_{in} correlated with p_n . Because X includes variables that contain p_n , such as the market weight w_{mn} , the assumption that $E[\epsilon_{in}|X] = 0$ then fails.

While the above scenario of non-zero correlation between ϵ_{in} and p_n is possible, it does not even imply a sign for the correlation. In particular, let $\bar{\lambda}\zeta_n$ denote the effect of ζ_n

on p_n , and let the contribution of ζ_n to w_{in} be $\lambda_i \zeta_n$. The correlation between ϵ_{in} and p_n is positive (negative) if λ_i and $\bar{\lambda}$ have the same (opposite) sign. Consider an actively managed institution. (For a passive institution, we are presumably not omitting a relevant ζ_n .) Suppose ζ_n reflects positive noise-trader sentiment injecting a positive component, $\bar{\lambda} \zeta_n$, into the equilibrium p_n . On one hand, an active manager with sufficient skill to recognize that effect underweights the stock, giving the institution's λ_i the opposite sign of $\bar{\lambda}$. That opposite sign occurs even if the institution and others with similar skill exert negative pressure on p_n in the process of underweighting the stock. The decision to underweight the stock is made with full knowledge of the accompanying p_n , whatever the forces determining that equilibrium price. On the other hand, an active manager with less skill can be infected with the same positive sentiment as the noise traders, giving that institution's λ_i the same sign as $\bar{\lambda}$. Because even the sign of any correlation between ϵ_{in} and p_n is ambiguous, we adopt $E[\epsilon_{in}|X] = 0$ as a reasonable simplification. Also motivating this simplification is that we do not focus on the relation between w_{in} and the price-related variables in X .

3.3 Bias adjustment and standard errors

The coefficients in equations (25) and (29) are consistently estimated, and thus so are the values of Δ_{in} and the resulting tilts defined in Section 2. The finite-sample properties of those estimates are not evident, however. We therefore conduct bootstrap simulations to adjust for any potential biases in our estimated tilts and to obtain standard errors.

For example, to de-bias the raw estimates of T_i , which we denote by T_i^{raw} , we simulate many samples of portfolio weights, which we denote by \tilde{w}_{in} , by resampling the residuals from the extensive- and intensive-margin regressions estimated on the sample of observed weights, w_{in} . For each simulated sample \tilde{w}_{in} , we estimate the extensive- and intensive-margin regressions on that sample, obtaining an estimate of the investor-level tilt, which we denote by \tilde{T}_i . We estimate the bias in T_i^{raw} as $TBias_i = \bar{\tilde{T}}_i - T_i^{raw}$, where $\bar{\tilde{T}}_i$ is the average value of \tilde{T}_i across simulations. Our bias-adjusted estimate of T_i is $T_i^{raw} - TBias_i$. The details of the bootstrap procedure are in the Appendix.

An important by-product of this procedure is the standard error of T_i , which we obtain from the standard deviation of the \tilde{T}_i 's across simulations. Again, the details are in the Appendix. All of the standard errors reported in the paper are bootstrapped.

4. Empirical results

In this section, we use the econometric framework described in Section 3 to estimate the various ESG-related tilts introduced in Section 2. We detect and analyze various patterns in ESG tilts, both across time and across institutions.

4.1. Data

We estimate the model using quarterly panel data on institutional investment managers that file Form 13F with the Securities and Exchange Commission. An institution is required to file this form if its holdings of U.S. stocks exceed \$100 million. Here, “institution” refers to an investment company such as Vanguard, not its individual funds. Most sample institutions are investment advisors, but the sample also includes banks, insurance companies, pension funds, and endowments. It also includes non-U.S. institutions’ holdings of U.S. stocks.

We obtain the 13F holdings data from Thomson/Refinitiv. From these data, we compute institutions’ quarterly portfolio weights w_{in} among the subset of “covered” stocks, meaning stocks with non-missing ESG and non-ESG characteristics. There are roughly 2,000 covered stocks throughout our sample period. In 2021, covered stocks account for 81% of the combined market capitalization of all CRSP stocks.⁵ We define an institution’s AUM to be its combined dollar holdings of covered stocks.

We exclude institutions with less than \$100 million in total 13F holdings (covered and uncovered), less than 50% of their total 13F dollar holdings in covered stocks, and, to allow sufficient precision in the intensive model, fewer than 30 covered stocks held. These filters drop institutions that together account for just 3% of covered stocks’ total market capitalization in 2021.

The number of institutions in our sample ranges from 1,731 in 2012 to 3,086 in 2021. Institutions’ combined AUM increases from \$9.7 trillion to \$31.3 trillion during that period. The institutions hold between 65% and 71% of covered stocks’ combined market capitalization during our sample period.

Our measures of ESG characteristics are from Pástor, Stambaugh, and Taylor (2022). We use data from MSCI, the world’s largest provider of ESG ratings data (Eccles and Stroehle, 2018). The MSCI data have the advantages of being widely used in industry, covering a

⁵We study stocks with CRSP share codes of 10, 11, 12, or 18.

large number of companies and years, providing granular industry-unadjusted measures, and having low noise relative to other ESG data providers.⁶ Our sample begins in 2012q4, when MSCI greatly expanded its coverage.

We compute environmental greenness as in Pástor, Stambaugh, and Taylor (2022), interacting the MSCI variables “Environmental Pillar Score” and “Environmental Pillar Weight.”⁷ We compute social and governance greenness the same way, replacing MSCI’s E variables with their S and G counterparts. In some analysis we use a composite ESG score equal to MSCI’s Weighted Average Key Issue score. This composite score equals the sum of our E, S, and G greenness measures plus a constant. These greenness measures are not industry-adjusted. In most of our analysis, stock n ’s ESG characteristics are represented by a 3×1 vector containing the stock’s cross-sectional percentiles of E, S, and G greenness. In some of our analysis, there is only one ESG characteristic per stock, namely, the stock’s percentile of its composite ESG score.

We use cross-sectional percentiles also to compute \mathcal{G}_0 , which contains the values of the ESG characteristics for the market portfolio. For each ESG characteristic, we compute its value-weighted average across all covered stocks, then we set the corresponding element of \mathcal{G}_0 to that average’s percentile in the cross section of stocks.

In \mathcal{C} , the set of non-ESG stock characteristics, we include seven variables that are commonly used in portfolio construction: market capitalization, book-to-market ratio, profitability, investment, dividends-to-book ratio, market beta, and the stock’s return during the past 12 months, excluding the most recent month. All seven variables are motivated by evidence from prior work cited earlier. For example, Kojien and Yogo (2019) use essentially the same variables, except for the last one, which is motivated by Gompers and Metrick (2001), among others. Rather than including the raw variables in \mathcal{C} , we include their cross-sectional percentiles. All variables are computed from CRSP and Compustat data. Their precise definitions are in the Appendix. In the intensive model, \mathcal{C} also includes w_{mn} , the stock’s weight in the market portfolio of covered stocks, as dictated by the model. The intensive

⁶As of May 2021, the MSCI ESG Ratings data are used by more than 1,700 clients, including pension funds, asset managers, consultants, advisers, banks, and insurers (<https://www.msci.com/our-solutions/esg-investing>). MSCI covers more firms than other ESG raters, such as Asset4, KLD, RobescoSAM, Sustainalytics, and Vigeo Eiris (Berg et al., 2022). Berg et al. (2022) find that MSCI’s ESG scores are the least noisy among the eight ESG data vendors they consider. MSCI generates its ratings based on a variety of sources and updates those ratings at least annually.

⁷Environmental greenness equals $-(10 - E_score_{i,t-1}) \times E_weight_{i,t-1}/100$. E_score is “Environmental Pillar Score,” a number between zero and 10 measuring a company’s resilience to long-term environmental risks. E_weight is “Environmental Pillar Weight,” a number between zero and 100 measuring the importance of E relative to S and G in the company’s industry. As Pástor, Stambaugh, and Taylor (2022) explain, interacting pillar scores and weights in this way is important for producing a meaningful measure of greenness.

model thus includes two different measures related to stock size.

4.2. The industry’s ESG-related tilts

The solid line in Panel A of Figure 1 displays quarterly estimates of T from equation (10) computed across all sample 13F institutions, i.e., the ESG-related tilt for the total industry. The series begins in 2012 at 7.0%, drops as much as 2% mid-sample, and ends in 2021 at 5.8%. In other words, in 2021, the dollar amount of ESG-related effects in each institution’s stock holdings, summed across institutions, is almost 6% of the industry’s total AUM.

Recall that our estimation approach controls for numerous non-ESG stock characteristics. If we rerun our approach without including those controls, the estimate of T is substantially larger, attributing too much to ESG effects. In 2021, for example, that alternative estimate is 7.8%, more than a third too high. This result underscores the importance of controlling for non-ESG characteristics when computing ESG-related tilts.

Panel A of Figure 1 also displays estimates of the industry’s tilts at the intensive and extensive margins, defined in equations (11) and (12). The extensive-margin tilt is typically around 2%, while the intensive-margin tilt is two to three times higher.

We also estimate tilts related separately to E, S, and G. For example, we estimate E tilts by changing only the E scores to a neutral value while keeping the S and G scores unchanged. Specifically, we reestimate our model using an alternative version of Δ_{in} , denoted Δ_{in}^E , in which \mathcal{G}_0 replaces stocks’ actual E scores by the market’s E score while keeping stocks’ actual S and G scores. To compute institution- and industry-level E tilts, we aggregate Δ_{in}^E the same way we aggregate Δ_{in} to compute total ESG tilts. Panel B of Figure 1 displays the industry’s separate E, S, and G tilts. The three tilts are remarkably similar, with each fluctuating modestly around 4% throughout the sample period.

Even though the separate E, S, and G tilts are similar in magnitude, the industry’s ESG-related tilt is not adequately captured by a single ESG composite. In fact, reestimating our model with \mathcal{G} containing only the composite ESG measure, instead of the three E, S, and G scores, gives a substantially smaller estimate of T . In 2021, for example, our estimate of T that allows the three ESG dimensions to matter individually is 1.7 times the estimate that combines those dimensions into a composite score. In essence, when totaled across institutions, the effects of E, S, and G are similar, but institutions differ with respect to the relative importance of each dimension.

As explained earlier, we conduct bootstrap simulations to incorporate finite sample properties of our estimates. Table 1 reports fourth-quarter values, year by year, of the tilts plotted in Figure 1, along with bootstrapped standard errors. In general, the standard errors for industry-level tilt measures are small. For example, the standard errors for the overall tilt measure T are at most 0.003, while the estimates of T are typically at least 20 times larger. The 5th and 95th percentiles of the bootstrap distributions are generally close to the estimated tilts minus/plus twice the standard errors. A key reason behind the low standard errors of industry-level tilts is diversification of estimation error across institutions. Institution-level tilts have larger standard errors, but they are nevertheless often statistically significant. The Appendix reports the tilt estimates and standard errors for the 100 institutions with the largest values of covered AUM in our sample.

Our 6% headline number for the aggregate ESG tilt rests on a variety of modeling choices. As discussed earlier, this number would increase if we were to leave out controls for non-ESG characteristics, and it would decrease if we were to replace the E, S, and G scores with the ESG composite. In addition, the number might decrease if we were to include more non-ESG characteristics beyond the seven already included, and it might increase if we were to disaggregate the holdings of mutual-fund companies or include ESG ratings from additional providers. The number is also conditional on the functional forms of our extensive- and intensive-margin models. While we find our modeling choices reasonable, we encourage the reader to view the magnitudes of our results with the customary dose of caution.

4.3. ESG tilts and active share

Many discussions of ESG investing note its increasing popularity. Therefore, one might be puzzled when seeing no upward trend in the investment industry’s ESG-related tilt displayed in Panel A of Figure 1. If anything the pattern is opposite, with the largest estimates of T occurring at the beginning of the sample period.

When considering this seeming puzzle, it is useful to note that ESG investing is not the U.S. investment industry’s only trend. Other trends are important in this context. First, the market share of indexing, relative to active management, has been steadily growing. For example, among equity mutual funds and ETFs, the market share of index funds almost doubled between 2012 and 2021.⁸ Second, the typical actively managed fund has become more diversified over time, holding more stocks and weighting stocks more in line with

⁸The Investment Company Institute’s *2022 Investment Company Fact Book* reports (p. 30) that index funds’ ownership of the U.S. stock market increased from 8% to 16%, while active fund’s ownership share dropped from 19% to 14%.

benchmarks (e.g., Pástor, Stambaugh, and Taylor, 2020). In other words, active management has been both losing market share and becoming less active, continuing the trends noted by Stambaugh (2014). These trends combine to produce a downward trend in the industry’s overall portfolio tilts relative to passive benchmarks.

Given this downward trend in portfolio tilts generally, it is less surprising that ESG-related tilts have not increased. We suggest gauging ESG-related tilts from a perspective that acknowledges this decline in tilts overall. As a simple measure of an institution’s tilts made for any reasons, we use active share, defined by Cremers and Petajisto (2009) as

$$\text{Active Share}_i = \frac{1}{2} \sum_{n=1}^N |w_{in} - w_{mn}|. \quad (32)$$

Taking the market index as the portfolio having no tilt, active share reflects an institution’s net tilt due to all sources. Panel A of Figure 2 displays the AUM-weighted average of active share for the institutions in our sample. Consistent with a decline in tilts generally, this series exhibits a steady downward trend, falling from 0.43 to 0.33 between 2012 and 2021.

To take overall tilts into account, we divide each institution’s ESG tilt by the institution’s concurrent active share. We aggregate those ratios to the industry level, again taking an AUM-weighted average, and plot them in Figure 3 in the same format as previously in Figure 1. In contrast to Figure 1, almost all of the series in Figure 3 trend upward, especially since 2016, with 2019 being a peak. Only the extensive-margin tilt trends downward, as it does in Figure 1 also. This exception notwithstanding, we see that accounting for active share presents a different picture of ESG investing’s importance over time. Even though the industry’s ESG-related tilts do not represent a growing fraction of AUM, they do represent a growing fraction of all portfolio tilts.

Active share varies greatly across institutions. Panel B of Figure 2 plots time series of cross-sectional percentiles in active share. We see that the 5th percentile hovers around 0.3 throughout the sample period, while the 95th percentile is consistently near the maximum value of 1.0. Given this dispersion in active share, the reasoning that motivates the above industry-level perspective should also manifest at the institution level. That is, an institution less inclined to tilt for any reason should be less likely to tilt for ESG-related reasons.

To explore this hypothesis, we regress institution-level ESG-related tilt, T_i , on institution-level active share. We also include the institution’s AUM in the regression to allow for the negative tradeoff funds are likely to face between AUM and tilts of any kind (e.g., Pástor, Stambaugh, and Taylor, 2020). We run the regression, in logs, with and without fixed effects for time or institution. Table 2 reports the results. Consistent with the cross-sectional

hypothesis, active share consistently enters very strongly (t -statistics between 13 and 43), with a coefficient between 0.9 and 1.2. Given that we run the regression in logs, a coefficient not far from unity suggests that dividing T_i by active share, as we do, comes reasonably close to capturing active share’s role in providing a perspective on ESG-related tilt. We also see that the AUM coefficient is significantly negative, as expected, especially when isolating the cross-sectional relation by including time fixed effects. Much of the variation in AUM is cross-sectional, so there is less power to isolate an AUM relation over time by including institution fixed effects, but a negative relation nevertheless appears when including both time and institution fixed effects. Larger institutions have smaller ESG-related tilts, even controlling for active share.

To further illustrate how active share helps in interpreting ESG-related tilts, we compare two of the largest institutions, BlackRock and Fidelity. Panel A of Figure 4 shows each institution’s estimated ESG-related tilt, T_i . Based on this plot, one might infer that Fidelity was especially ESG-conscious from 2012 through 2015, substantially more so than BlackRock, and that Fidelity then became less ESG-conscious in subsequent years, when its ESG-related tilts were roughly similar to BlackRock’s. A different narrative emerges when the tilts are divided by each institution’s active share. We then infer from Panel B of Figure 4 that the institutions had similar degrees of ESG concerns prior to 2016, after which BlackRock became increasingly ESG-conscious, unlike Fidelity. Of course the reason active share reshapes the story is that Fidelity is oriented more toward active funds while BlackRock has a larger presence in indexing, so BlackRock has a lower active share. Thus, as compared to Fidelity, a given ESG-related tilt represents a larger relative portfolio displacement from BlackRock’s perspective, because its portfolio tilts made for any reason are generally more modest than Fidelity’s. In fact, by 2021, BlackRock’s ESG-related tilt was more than 50% as large as its portfolio tilts arising from all sources (active share). This heightened ESG emphasis is consistent with BlackRock’s public statements in recent years (e.g., Fink, 2021).

4.4. Green and brown tilts

For any given univariate dimension of ESG, such as E or the composite ESG score, we can apply the classifications in (13) through (16) and compute the various green-versus-brown tilts defined thereafter in Section 2. For example, by taking AUM-weighted averages of T_i^G and T_i^B defined via equations (17) through (19), we can compute the industry’s green tilt, T^G , and its brown tilt, T^B . In doing so, we first divide each institution-level tilt by the institution’s concurrent active share, so as to continue to provide the perspective discussed above. For ease of exposition, we refer to each resulting quantity simply as “tilt,” rather

than “tilt divided by active share.”

Figure 5 plots time series of the investment industry’s green tilt (Panel A) and brown tilt (Panel B). Each panel displays these tilts computed using four alternative scales to classify greenness: E, S, G, and the composite ESG score. There are three main findings. First, the green tilt always exceeds the brown tilt, indicating that the industry as a whole tilts green throughout the sample period. Second, the industry’s green tilt trends upward, whereas its brown tilt is fairly constant, implying that the industry is becoming increasingly green. Third, all of these patterns are strikingly similar across the four greenness measures.

If 13F-filing institutions tilt green, then other investors must tilt brown (see equation (23)). We illustrate this point in Figure 6. Our sample institutions’ positive and increasing green-minus-brown (GMB) tilt is plotted as the solid line in each of the four panels, with each panel based on one of the four greenness measures. The dashed line in each panel plots the GMB tilt of non-13F filers, taken collectively as one quasi-institution. Non-13F filers include households and institutions below the \$100 million filing threshold for Form 13F. This segment of stockholders has tilted brown and increasingly so, balancing the green tilt of the 13F-filing institutions.

Recall from Section 2 that we can also compute green and brown tilts at both the intensive and extensive margins. Panels A and B of Figure 7 reveal that the rise in the industry’s green tilt occurs primarily via the intensive margin, that is, by increasing the weights on green stocks held and decreasing the weights on brown stocks held. The extensive green tilt (holding more green stocks and fewer brown stocks) is substantially smaller, especially in the later years. For the brown tilts, in Panels C and D, the intensive margin is again more important than the extensive, with both tilts exhibiting flat behavior over time.

Some of the most vocal dialogue surrounding ESG investing calls for institutions to divest from brown stocks.⁹ Such divestment is the component of green tilt that we denote as underweighting brown. In this context, divestment includes both avoidance of brown stocks and reduction of existing positions. Figure 8 shows that divestment at the intensive margin (Panel A) is consistently larger than divestment at the extensive margin (Panel B). Unlike the extensive margin, the intensive one rises substantially over time, increasing threefold between 2012 and 2021. In other words, most brown-stock divestment is partial, reducing brown stocks’ weights, as opposed to total divestment that eliminates holdings.

⁹For example, in 2020, the world’s largest asset manager, BlackRock, announced that it would exit investments in thermal coal producers, and the world’s largest sovereign wealth fund, that of Norway, fully divested from oil and gas explorers and producers.

The relatively low amount of total divestment may seem surprising, given the attention garnered by divestment advocacy. To dig deeper, we consider the number of brown stocks totally divested. Specifically, across all stocks n that are brown on a given dimension, say E, we sum an institution’s negative values of $\Delta_{in}^{\pi} = \pi_{in}(\mathcal{G}) - \pi_{in}(\mathcal{G}_0^E)$, where \mathcal{G}_0^E is the same as \mathcal{G} except that all the E scores are replaced by the market’s E score. The resulting total gives the expected number of brown stocks whose total divestment (i.e., not being held) we can relate to the stocks’ having brown E scores. The AUM-weighted average of this value across institutions is plotted as the solid line in Figure 9, which contains a panel for each of the four greenness measures. For greenness measured by the composite ESG score (Panel A), we see that the number of divested brown stocks (per institution) rises substantially over time, from around 5 stocks in 2012 to over 20 stocks in 2019, then dropping to about 10 stocks in 2021. Similar patterns, just with lower peaks, occur when greenness is measured using E or S scores (Panels B and C). For governance (Panel D), we see somewhat the opposite pattern, starting at around 10 stocks divested in the early years and then declining thereafter. In general, though, we see that total divestment rises over time in terms of numbers of stocks (Figure 9) but not in terms of portfolio tilts (Figure 8). Evidently the relatively few stocks totally divested account for small fractions of AUM in even the later years.

Summing the positive values of Δ_{in}^{π} across brown stocks n gives the expected number of brown stocks added by the institution. The AUM-weighted average of this value across institutions is plotted as the dashed line in Figure 9. Prior to 2017, the addition of a few stocks, generally fewer than five, relates to the stocks’ having brown E, S, or composite ESG scores (Panels A through C). In subsequent years, the expected number of such stocks added drops to nearly zero. For stocks with brown G scores (Panel D), we find few additions throughout the sample period. Intuitively, institutions have dropped more brown stocks (a green behavior) than they have added (a brown behavior).

4.5. Which institutions are greener?

Institutions filing 13F statements differ from each other in numerous respects, especially institution size. Recall from Table 2 that larger institutions tend to have smaller ESG-related tilts. As we show next, however, those tilts tend to be green, enough so to account for the positive and increasing GMB tilt of the entire industry shown in Figure 6.

In Figure 10 we plot the AUM-weighted average GMB tilt separately for large, medium, and small institutions, grouped by AUM terciles. For each of the four greenness measures, large institutions exhibit positive and increasing GMB tilts. In other words, large institutions

are green, and increasingly so over time. In contrast, the GMB tilts of medium and small institutions are negative and decreasing when greenness is based on S or G. When based on E, their GMB tilts are consistently positive but larger in the earlier years. Their GMB tilts based on the composite ESG score are positive in the early years, consistent with the early green E tilt, but negative and decreasing in later years, consistent with the increasingly brown S and G tilts. In essence, the industry’s positive and increasing GMB tilt owes to just the largest institutions.

In fact, the number of green-tilting institutions is generally about the same as those tilting brown. The top row of plots in Figure 11 displays the fractions of institutions with positive and negative estimated GMB tilts. For all four greenness measures, we see about as many green institutions as brown, consistently over the sample period. The bottom row of plots in Figure 11 shows the fractions of the industry’s total AUM held by green institutions versus brown. There we see a rather different story, with much more AUM held by green-tilting institutions than by brown. Particularly striking are the small fractions of AUM held by institutions exhibiting a statistically significant brown tilt, compared to the substantial fractions of AUM held by significantly green institutions, especially in the later years.

We also explore whether characteristics other than AUM relate to an institution’s GMB tilt. First, we entertain differences across types of institutions, as classified by prior studies including Bushee (2001) and Bushee, Carter, and Gerakos (2014). Following those studies, we classify institutions as (i) investment advisors, (ii) banks, (iii) insurance companies, or (iv) pensions/endowments.¹⁰ By both institution count and AUM, the bulk of sample institutions are investment advisors, with banks a distant second. Second, we consider whether an institution has signed the UNPRI. We download the list of signatories and signature dates from the UNPRI website. We merge these data with our sample by using institution name and combining fuzzy matching, manual checks, and web searches.

Table 3 reports the estimates from panel regressions of institutions’ GMB tilts on a number of explanatory variables that include institution-type and UNPRI dummies as well as the institution’s active share and log AUM. We also include a time trend, by itself and interacted with log AUM. Across the columns, we show specifications with no fixed effects, with time fixed effects, and with institution fixed effects. Results including both fixed effects are in the Appendix; they are very similar to the results based on institution fixed effects only. When including fixed effects, we omit explanatory variables as appropriate (e.g., no

¹⁰We are grateful to Brian Bushee for providing these data on his website. Following Bushee et al. (2014), we combine the categories Investment Company and Independent Investment Advisor into a single category; we combine Public Pension Funds and University and Foundation Endowments into a single category; and we omit institutions classified as Miscellaneous.

institution-type dummies when including institution fixed effects).

A number of significant relations appear in Table 3. With either no fixed effects or time fixed effects, AUM exhibits a strongly significant positive relation to greenness. Since the time trend is constructed to equal zero in 2021, the result indicates that larger institutions are greener at the end of the sample period. The positive coefficient on the interaction term indicates that the relation between AUM and greenness strengthens over time. These results are robust across greenness measures, with just two exceptions (the AUM coefficient when greenness is measured by E and the interaction-term coefficient when greenness is measured by G). Estimates in the first column imply that increasing AUM from its 33rd percentile to its 67th percentile is associated with a 2.3 percentage point (pp) increase in GMB tilt in 2021 and a 1.8 pp decrease in GMB tilt in 2012.¹¹ These relations, including their reversal over time, are consistent with the patterns in Figure 10.

UNPRI signatories have significantly greener tilts. This relation holds not just across institutions (i.e., in specifications with time fixed effects) but also over time within institutions (i.e., in specifications with institution fixed effects). The latter result indicates that an institution becomes greener after becoming a UNPRI signatory. Statistical significance is high in all columns except the last two. Those exceptions aside, UNPRI signatories' GMB tilts are higher by a sizable 3.4–5.4 pp. The regressions' low R^2 values, however, suggest that UNPRI status is far from a perfect indicator of whether an institution is green or brown.

GMB tilt also differs significantly across institution types, at least when greenness is measured by the ESG composite or S. Specifically, F-tests reject equality of tilts across the four institution types. Depending on the specification, banks' GMB tilts are 7.4–13.2 pp lower than those of insurance companies (the omitted type). Banks are also significantly browner than both investment advisors and pensions/endowments ($p < 0.012$). When greenness is instead measured by E or G, banks again appear browner than the other institution types, but the differences are typically insignificant. According to most specifications, insurance companies are the greenest institution type.

Table 4 explores whether these patterns in GMB tilt are driven by its green or brown leg. We estimate similar panel regressions replacing the dependent variable T_i^{GMB} with either T_i^G or T_i^B .¹² We see that the positive relation between AUM and greenness is driven by brown tilts, not green tilts. Therefore, at the end of our sample period, larger institutions

¹¹The difference in $\log(\text{AUM})$ between the two percentiles is 1.43. Note that 0.023 equals 1.43×0.0158 , and -0.018 equals $1.43 \times [0.0158 - 0.36 \times 0.0788]$, where -0.36 is the value of Trend in 2012.

¹²Table 4 reports results from regressions without fixed effects. Results with fixed effects are in the Appendix. Results with time fixed effects are very similar to those reported in Table 4.

are less brown, not more green. Both legs, however, contribute to the widening gap in GMB tilts between large and small institutions. The roles of time trends, UNPRI status, and institution type are similarly strong, but opposite in sign, for green and brown tilts. Finally, active share has a very strong, positive relation to both green and brown tilts. The GMB tilt, however, exhibits a weaker relation with active share, as the positive effects in the green and brown legs offset each other (Table 3). This result reinforces the importance of evaluating ESG-related tilts in relation to active share.

5. Conclusion

The total amount of ESG investing is substantial but much smaller than the aggregate AUM of institutions that proclaim to invest in line with ESG-related principles. Our estimates indicate that the total amount of ESG-related tilts in institutional equity portfolios is about 6% of the institutions' total equity AUM. This fraction has been fairly steady throughout our sample from 2012 to 2021. However, institutions' portfolio tilts in general, as measured by active share, have declined over this period. When divided by active share, the typical institution's ESG tilt has grown from 14% to almost 25% over the last five years, indicating that ESG tilts are one fourth as large as total portfolio tilts at the end of our sample.

Our approach to estimating ESG tilts has several advantages. First, it isolates tilts toward stocks' ESG characteristics after controlling for non-ESG characteristics. This is valuable because the two sets of characteristics are correlated. For example, an institution may hold Tesla's stock because it views Tesla as environmentally friendly or because it likes holding large-cap growth stocks. Our approach separates the two motives. Second, our approach allows the three dimensions of ESG to enter separately, recognizing, for example, that investors may assess Tesla's environmental virtues separately from Tesla's treatment of its employees. We find that using only a composite ESG score misses over 40% of the tilts associated with the E, S, and G characteristics. We also find that each of those three dimensions contributes about equally to ESG-related tilts. Third, our approach breaks down ESG tilts into components capturing the extensive and intensive margins. We find significant ESG tilts at both margins, but the intensive-margin tilts are two to three times larger.

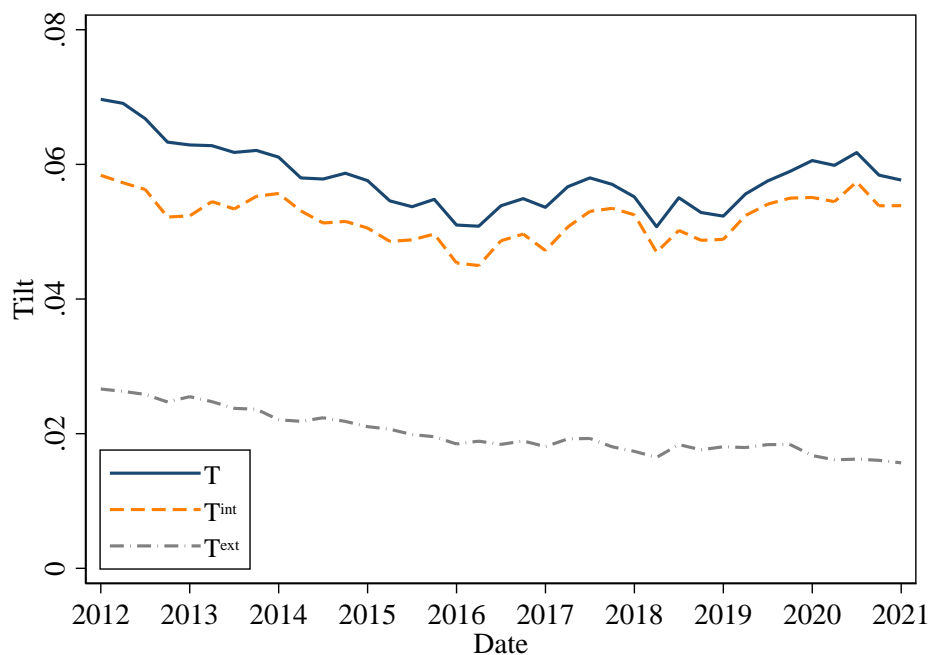
Our approach also allows us to separate green tilts from brown. We find that institutions as a whole tilt more green than brown, and increasingly so. The rise in the aggregate net green tilt occurs mostly at the intensive margin. For example, institutions divest from brown stocks mostly by reducing positions rather than eliminating them. In contrast to 13F institutions, other institutions and households tilt more brown than green, and increasingly

so. Our results are similar for four different ESG-related measures of greenness.

We find that greenness varies strongly across institutions. Larger institutions are significantly greener. In fact, the aforementioned steady rise in the investment industry's aggregate net green tilt is fully driven by the largest third of institutions. Those institutions are green and increasingly so, whereas smaller institutions are increasingly brown. Interestingly, UN-PRI signatories are also significantly greener. This is true not only across institutions but also over time, indicating that a given institution becomes greener after becoming a signatory. Finally, the least green institution type is banks.

Our study opens many avenues for future research. We focus here on aggregate and institution-level tilts, but we are also exploring stock-level tilts and their determinants. Interesting questions about institutions remain as well: Why are larger institutions greener? Why are insurance companies greener than banks? Why do institutions utilize the intensive margin more than the extensive? Are institutions' tilts greener in Europe than in the U.S.? Do institutions substitute voting green for tilting green, or are those actions complementary?

Panel A: Total, intensive, and extensive ESG tilts



Panel B: E tilt, S tilt, and G tilt

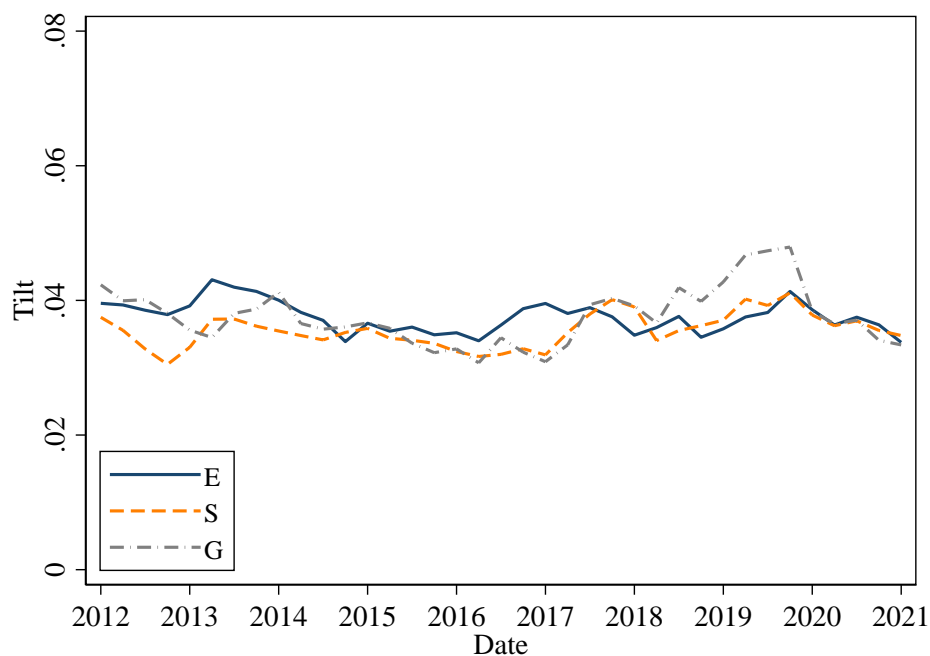
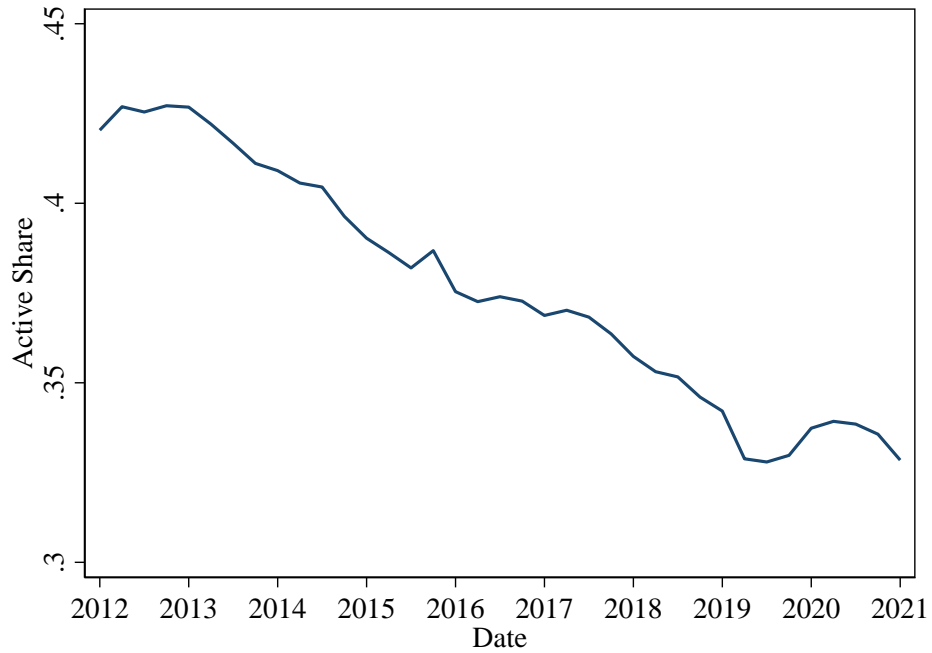


Figure 1. ESG-related tilts. Panel A plots the aggregate ESG-related tilt (T) and its decomposition into intensive and extensive tilts, T^{int} and T^{ext} , respectively. Panel B plots tilts for each ESG component: E, S, and G. Tilts are expressed as a fraction of institutions' aggregate AUM. Tick marks are at the fourth quarter of each year.

Panel A: AUM-weighted average



Panel B: Percentiles

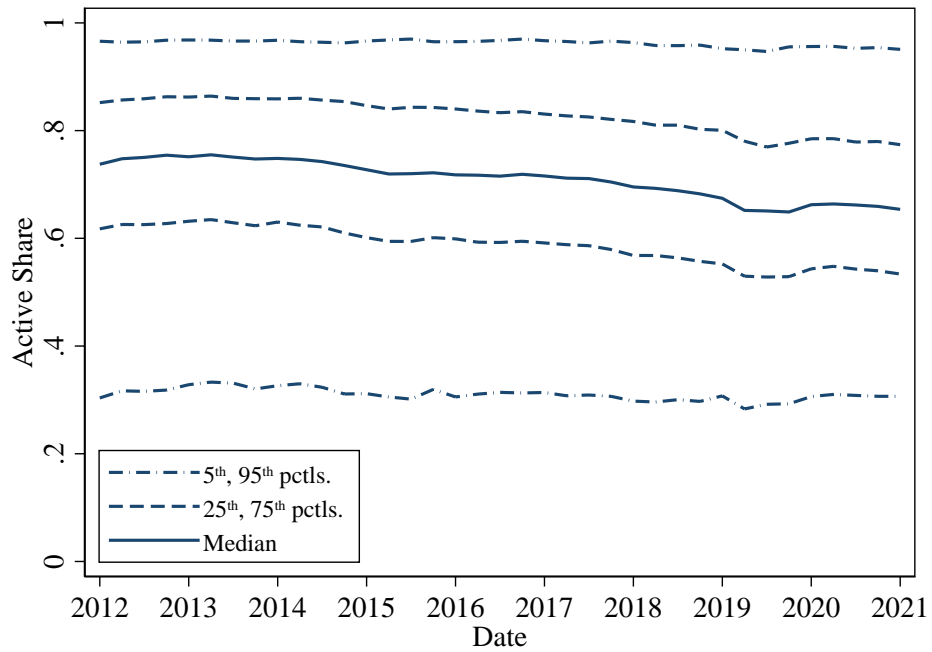
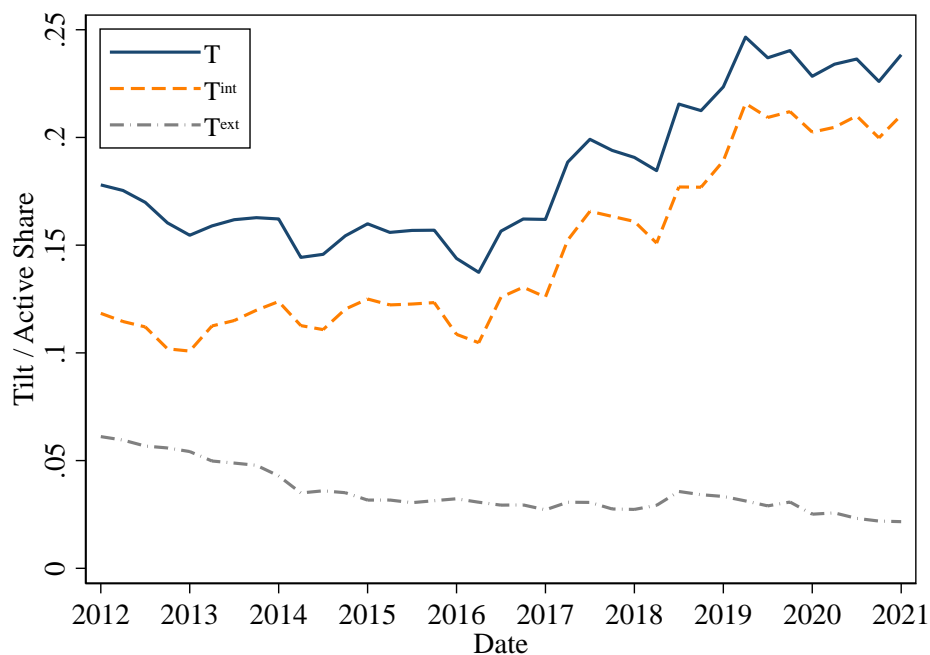


Figure 2. Active share. Panel A plots the AUM-weighted average of institutions' Active Share. Panel B plots the cross-sectional percentiles of Active Share.

Panel A: Total, intensive, and extensive ESG tilts



Panel B: E tilt, S tilt, and G tilt

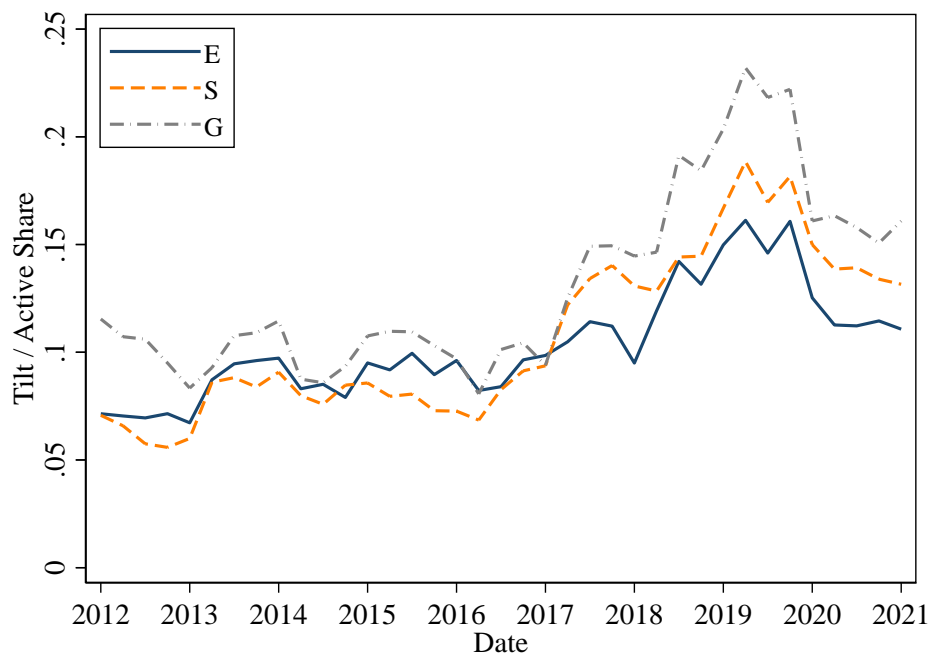
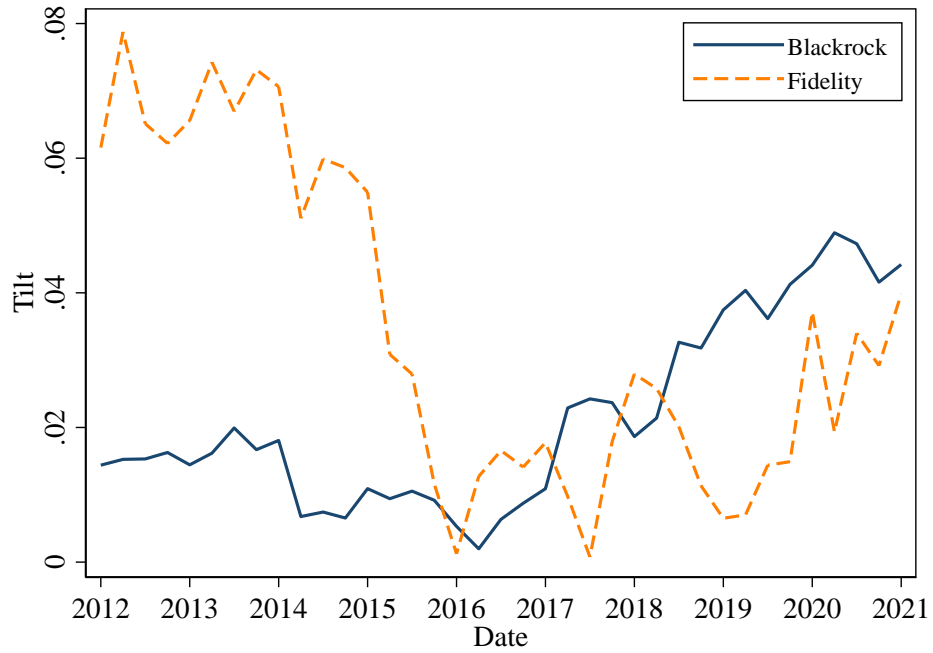


Figure 3. ESG-related tilts relative to active share. Tilts in both panels are the same as in Figure 1, but here we divide each institution's tilt by its active share and then plot the AUM-weighted average of the resulting quantities.

Panel A: Raw tilts



Panel B: Tilts divided by Active Share

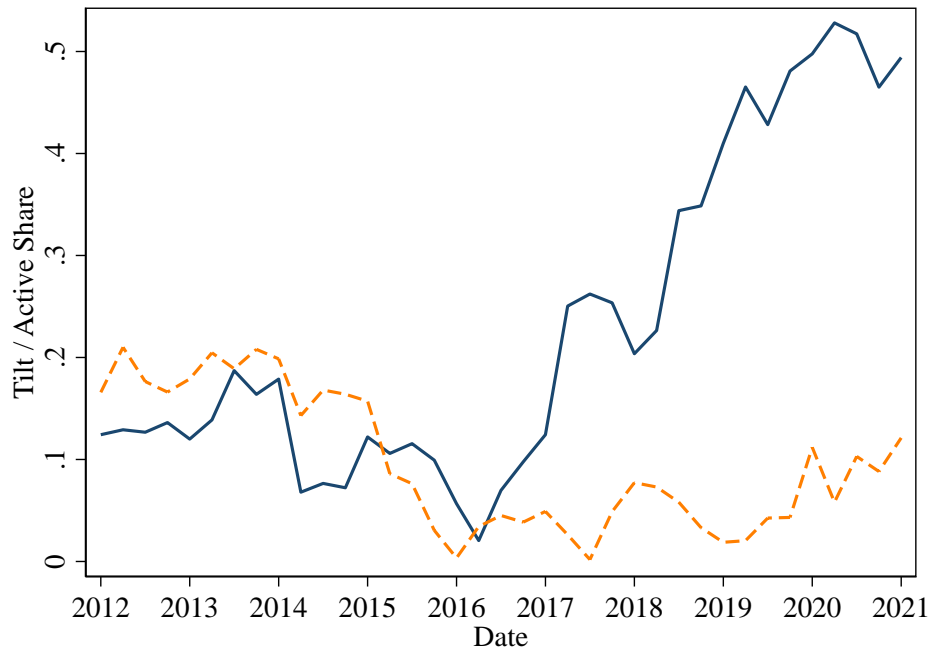


Figure 4. Tilts relative to active share. Panel A plots the time series of T_i , the ESG-related tilt, for BlackRock and Fidelity. Panel B plots each institution's ratio of T_i to active share.

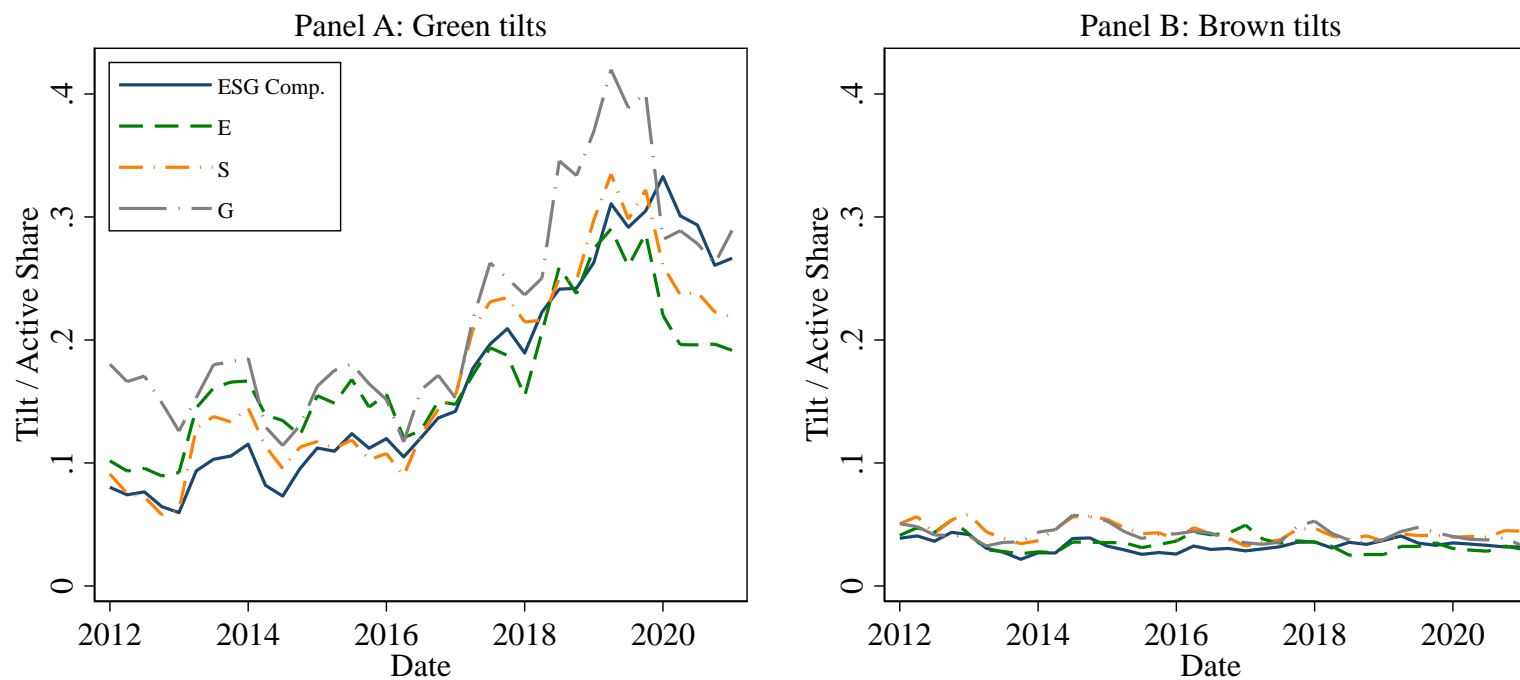


Figure 5. Green and brown tilts. The green and brown tilts for the ESG composite are from the model specification with a single ESG characteristic per stock. The other three pairs of tilts are from the specification with three ESG characteristics per stock. We divide each institution's tilt by its active share, and we plot the AUM-weighted average of the resulting quantities.

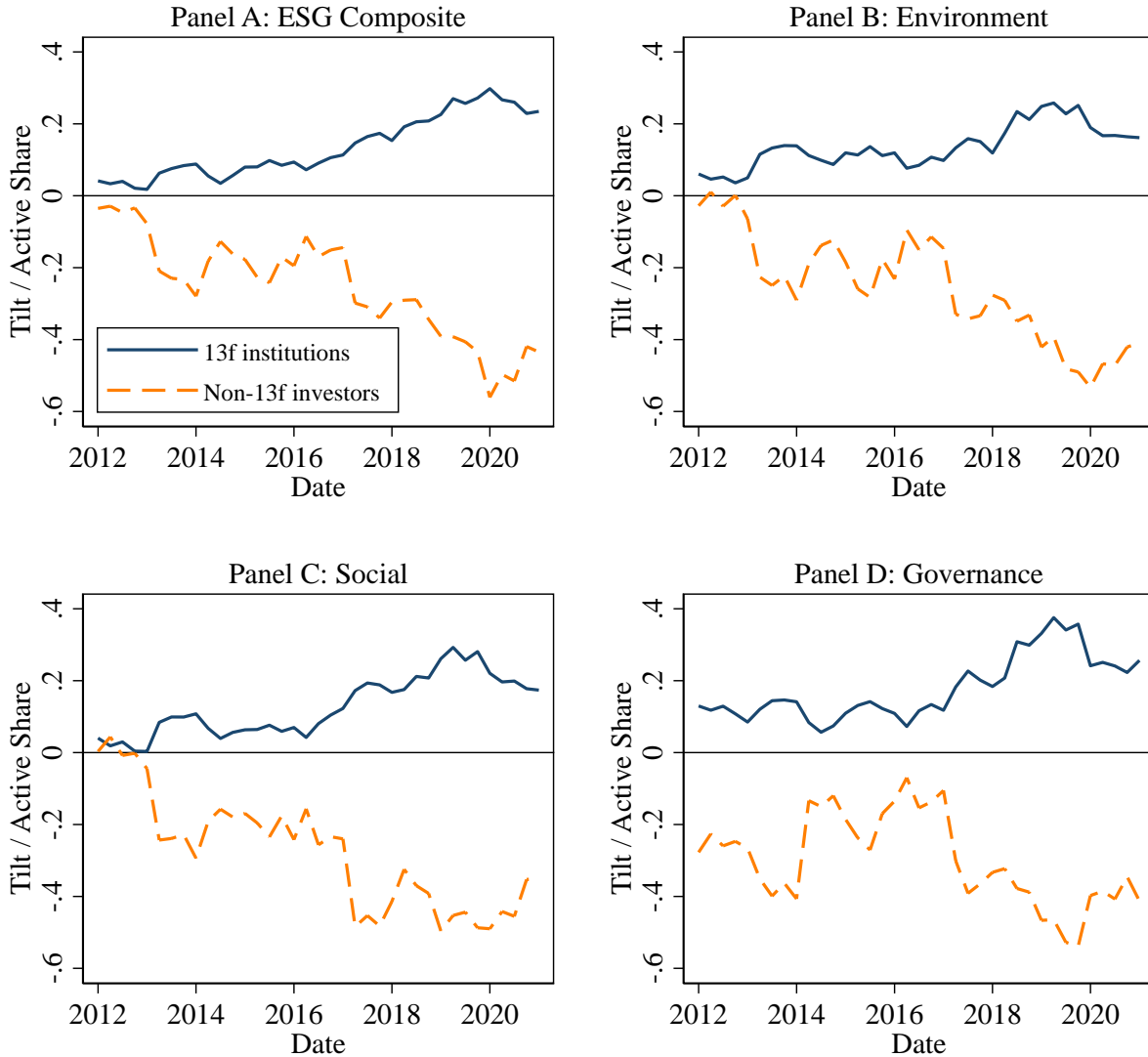


Figure 6. GMB tilts of 13F filers and non-filers. The solid line shows the AUM-weighted average of tilt divided by active share across sample 13F institutions. The dashed line shows the same quantity for non-13F investors, which we treat as a single quasi-institution whose dollar holding of each stock equals the stock’s market capitalization minus the combined holding of the stock by 13F institutions’ (including those not in our sample). In Panel A, \mathcal{G} contains just the composite ESG score, so tilts are computed from the model specification with a single ESG characteristic per stock. In Panels B through D, g_n is a stock’s E, S, or G component, and tilts are computed from the specification with \mathcal{G} containing three ESG characteristics per stock.

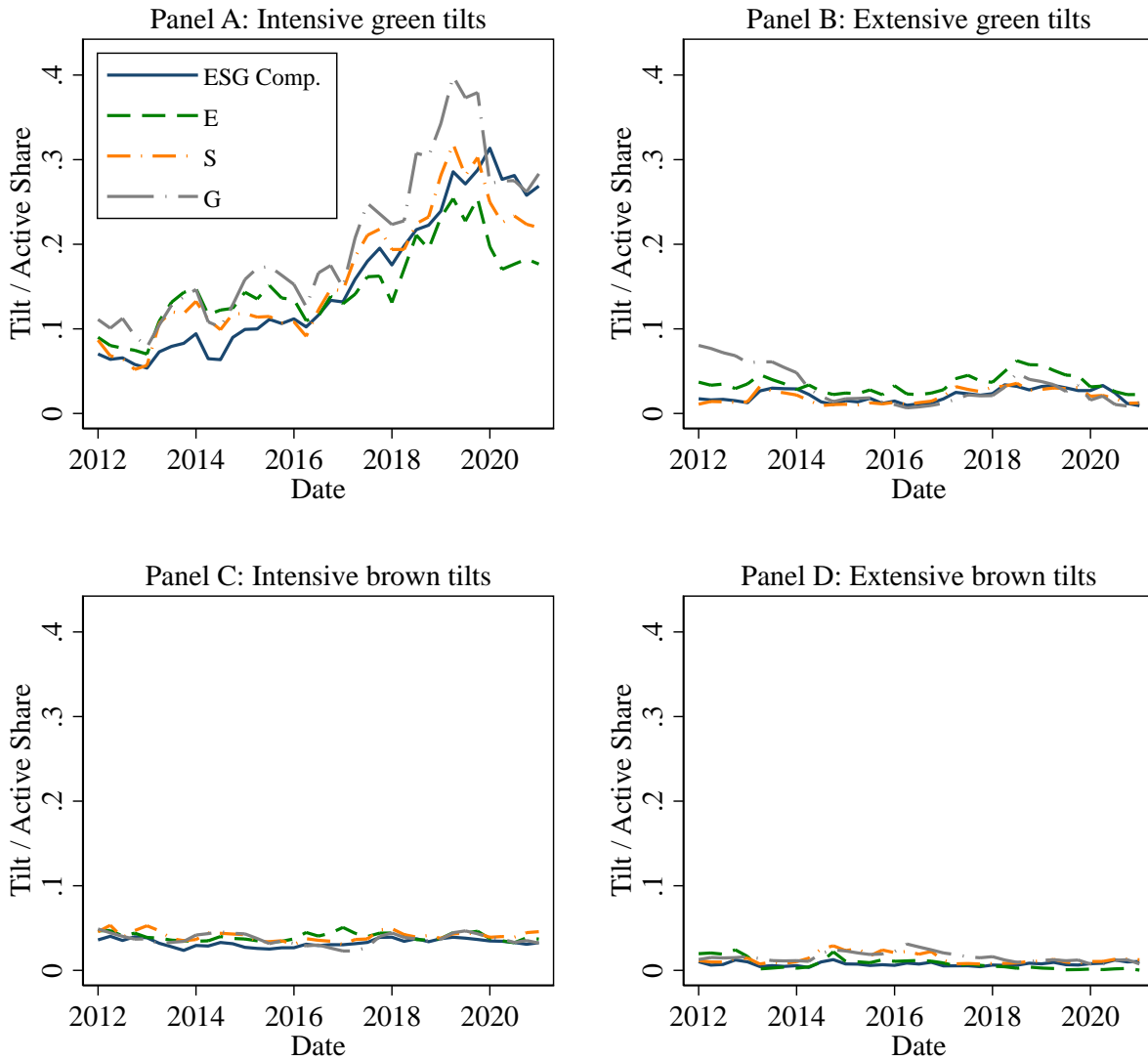


Figure 7. Components of green and brown tilts. Tilts using the ESG composite are from the model specification with a single ESG characteristic per stock, and other tilts are from the specification with three ESG characteristics per stock. We divide each institution's tilt by its active share and plot the AUM-weighted average of the resulting quantities.

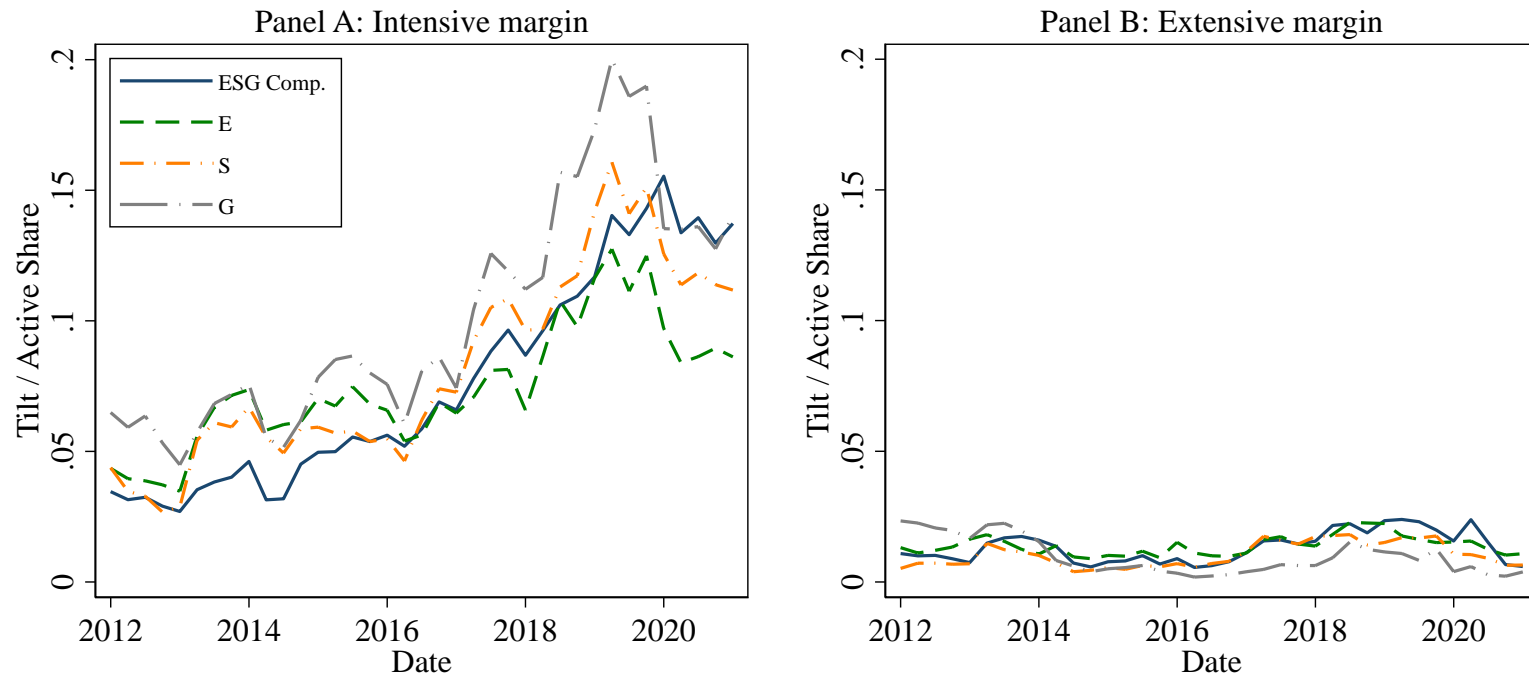


Figure 8. Divestment from brown stocks. Divestment from brown stocks, which is a component of green tilt, can be done on either the extensive margin (full divestment) or intensive margin (partial divestment). We show both. Panel A shows the component of intensive green tilts (from Panel A of Figure 7) coming from under-weighting brown stocks. Panel B shows the component of the extensive green tilts (shown in Panel B of Figure 7) coming from under-weighting brown stocks. Tilts using the ESG composite are from the model specification with a single ESG characteristic per stock, and other tilts are from the specification with three ESG characteristics per stock. We divide each institution's tilt by its active share and plot the AUM-weighted average of the resulting quantities.

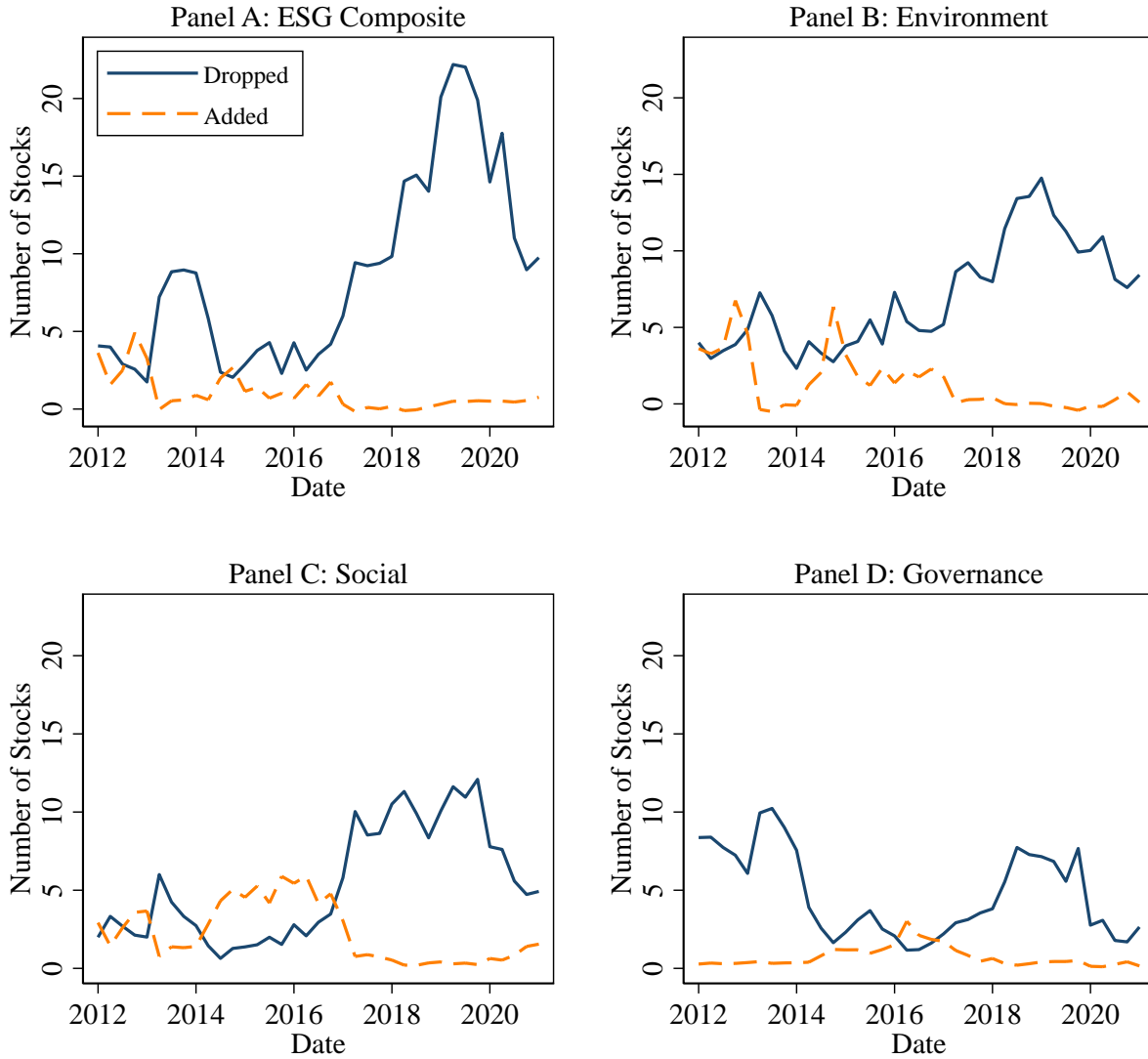


Figure 9. Number of brown stocks added and dropped. This figure shows the AUM-weighted average of institutions' expected number of brown stocks added and dropped. For example, on the Environment dimension, define $\Delta_{in}^{\pi} = \pi_{in}(\mathcal{G}) - \pi_{in}(\mathcal{G}_0^E)$, where \mathcal{G}_0^E equals \mathcal{G} except for the E characteristic, which is set to the market's value of the characteristic. Institution i 's expected number of brown stocks added (dropped) equals the sum across all brown stocks n of Δ_{in}^{π} conditional on Δ_{in}^{π} being positive (negative). Tilts using the ESG composite are from the model specification with a single ESG characteristic per stock, and other tilts are from the specification with three ESG characteristics per stock.

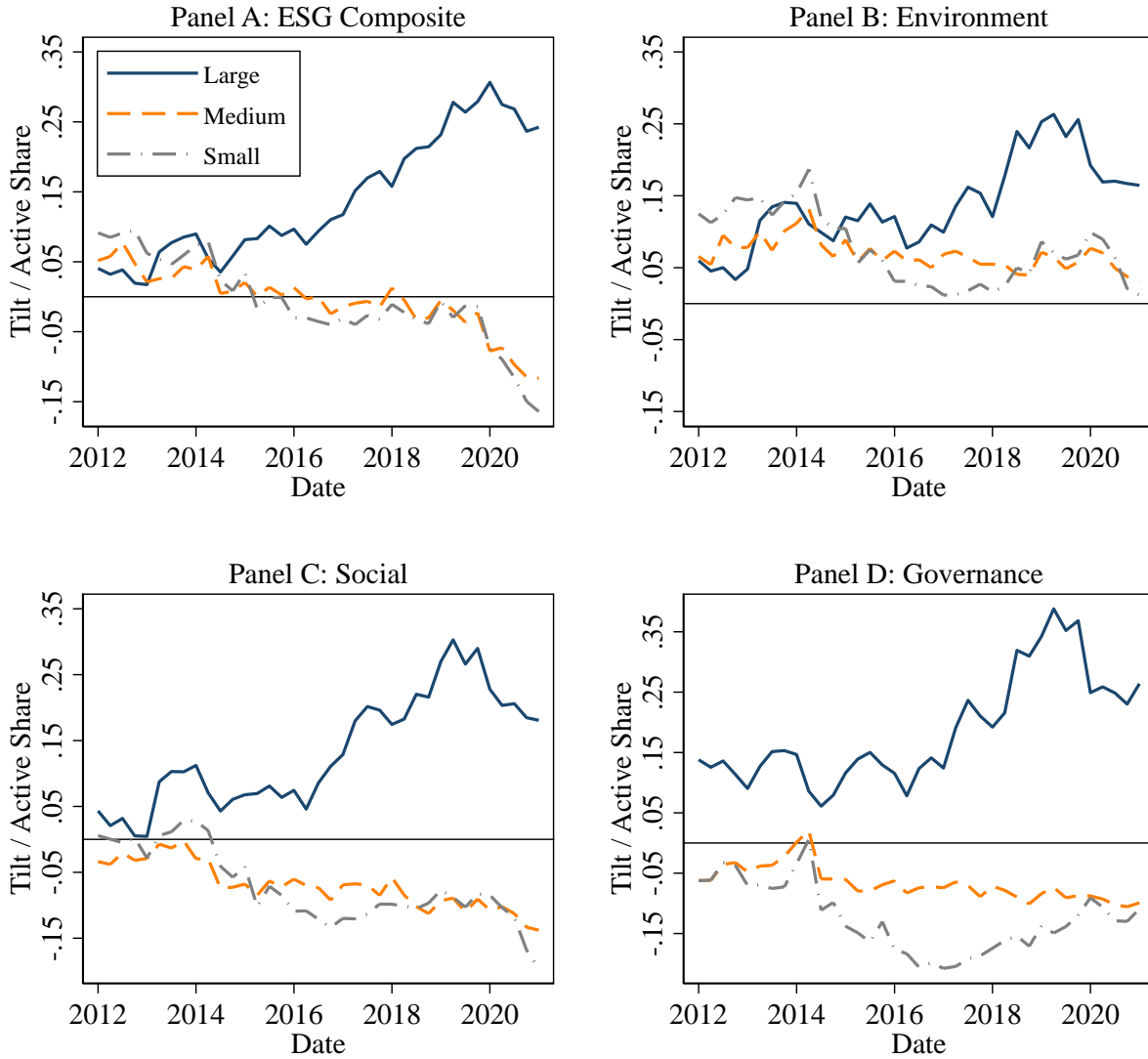


Figure 10. Institution size and greenness. This figure compares GMB tilts across subsamples formed on institution size. Each line shows the AUM-weighted average of GMB tilt divided by active share within a subsample of institutions. In Panel A, \mathcal{G} contains only the composite ESG score, and tilts are computed from the specification with a single ESG characteristic per stock. In Panels B through D, g_n is a stock's E, S, or G component, and tilts are from the specification with \mathcal{G} containing three ESG characteristics per stock. Large, Medium, and Small institutions are those with AUM in the top, middle, and bottom quarterly tercile, respectively.

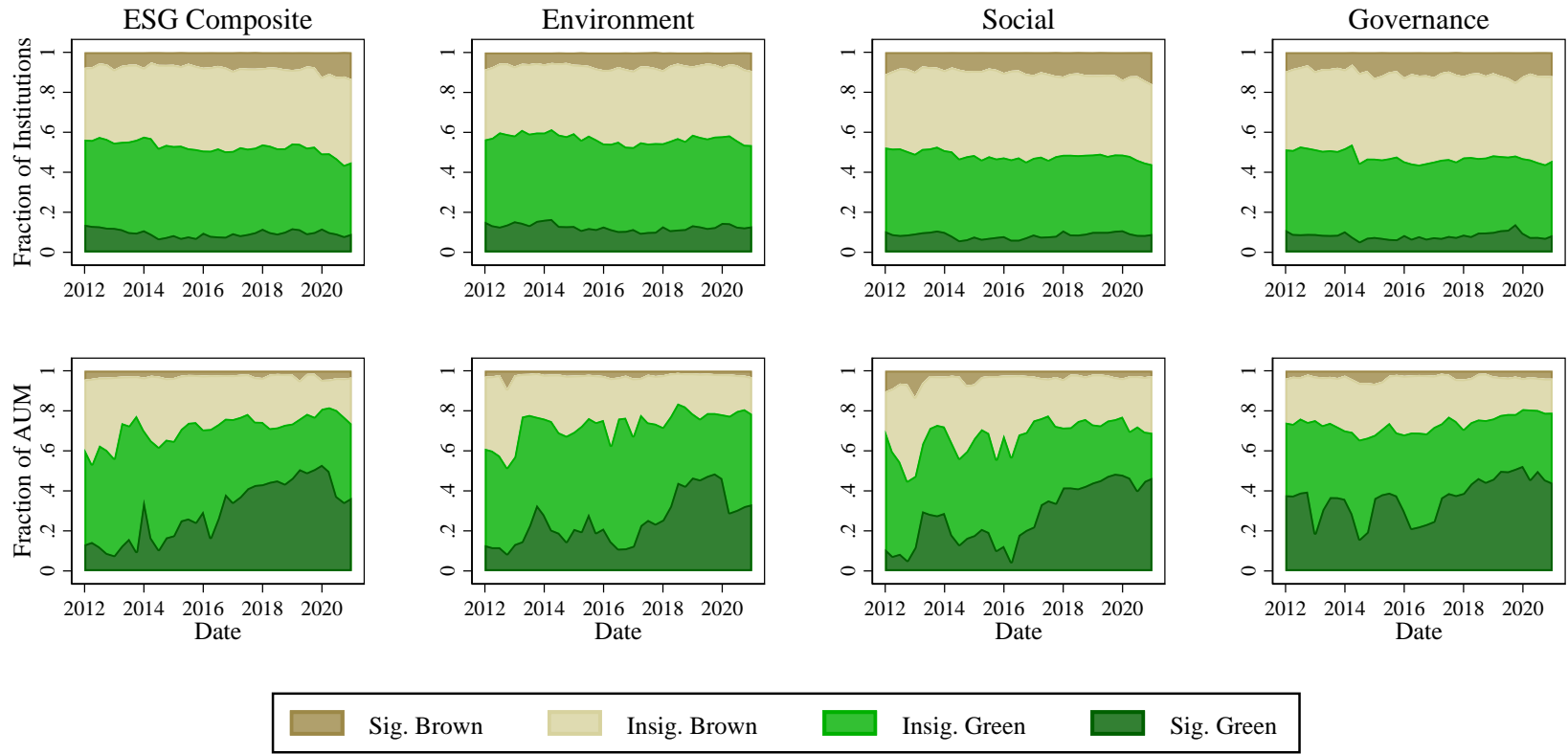


Figure 11. Fraction of institutions green vs. brown. The top row shows the fraction of institutions that are significantly brown at the 5% confidence level, insignificantly brown at the 5% confidence level, and similarly for green. The bottom row shows the fraction of sample covered AUM belonging to institutions that are significantly brown at the 5% level, and so on. Column headers indicate the greenness measure.

Table 1
Aggregate tilts

This table shows estimated aggregate tilts from each year's fourth quarter. Bootstrapped standard errors are in parentheses. Tilts are expressed as a fraction of institutions' aggregate covered AUM.

Year	T	T^{int}	T^{ext}	T^{Env}	T^{Soc}	T^{Gov}
2012	0.070 (0.002)	0.058 (0.002)	0.027 (0.001)	0.040 (0.002)	0.037 (0.002)	0.042 (0.002)
2013	0.063 (0.002)	0.052 (0.002)	0.026 (0.001)	0.039 (0.002)	0.033 (0.002)	0.036 (0.002)
2014	0.061 (0.002)	0.056 (0.002)	0.022 (0.001)	0.040 (0.002)	0.035 (0.002)	0.041 (0.002)
2015	0.058 (0.002)	0.051 (0.002)	0.021 (0.001)	0.037 (0.002)	0.036 (0.002)	0.037 (0.002)
2016	0.051 (0.002)	0.045 (0.002)	0.018 (0.001)	0.035 (0.002)	0.032 (0.002)	0.033 (0.002)
2017	0.054 (0.002)	0.047 (0.002)	0.018 (0.001)	0.040 (0.002)	0.032 (0.002)	0.031 (0.002)
2018	0.055 (0.002)	0.053 (0.002)	0.017 (0.001)	0.035 (0.002)	0.039 (0.002)	0.039 (0.002)
2019	0.052 (0.002)	0.049 (0.002)	0.018 (0.001)	0.036 (0.002)	0.037 (0.002)	0.043 (0.002)
2020	0.061 (0.002)	0.055 (0.002)	0.017 (0.001)	0.039 (0.002)	0.038 (0.002)	0.038 (0.002)
2021	0.058 (0.003)	0.054 (0.002)	0.016 (0.002)	0.034 (0.002)	0.035 (0.002)	0.033 (0.002)

Table 2
ESG-related tilt, active share, and institution size

This table contains results from panel regressions with the dependent variable equal to the log of the institution's ESG-related tilt, T_{it} . AUM is divided by the total market capitalization of all covered stocks. All regressions use 80,023 institution \times quarter observations from 2012q4–2021q4. The bottom rows indicate the fixed effects (FEs) included. Robust t -statistics clustered by institution are in parentheses. We tabulate the regression R^2 as well as the R^2 from a regression on FEs only.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(Active share)	1.198 (43.05)	1.217 (43.35)	0.902 (14.15)				1.043 (34.34)	1.057 (34.16)	0.870 (13.14)
log(AUM)				-0.176 (-22.18)	-0.181 (-22.59)	-0.0838 (-5.00)	-0.0935 (-15.13)	-0.0902 (-14.09)	-0.0323 (-1.96)
R^2	0.196	0.200	0.528	0.089	0.091	0.523	0.217	0.219	0.528
R^2 (FEs only)	N/A	0.001	0.522	N/A	0.001	0.522	N/A	0.001	0.522
Time FEs	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Institution FEs	No	No	Yes	No	No	Yes	No	No	Yes

Table 3: Which institutions are greener?

This table contains results from panel regressions with the dependent variable equal to the institution’s GMB tilt, T_i^{GMB} . The greenness measure is noted in the column headers. All regressions use the 79,647 institution \times quarter observations from 2012q4–2021q4. AUM is divided by the total market capitalization of all covered stocks. Trend equals the observation’s quarter minus 2021q4, divided by 100, so Trend is increasing over time, zero at the end of the sample, and negative in preceding quarters. We compute active share as in Cremers and Petajisto (2009). 1(UNPRI) is an indicator for whether the institution signed the UNPRI on or before the given quarter. We drop the institution-type indicators from specifications with institution FEs given their small within-institution variation. Insurance is the excluded institution-type dummy, so coefficients on included institution-type dummies measure effects relative to insurance companies. Robust t -statistics clustered by institution are in parentheses. The regression R^2 as well as the R^2 from a regression with fixed effects only are shown at the bottom. The last row contains the p -value that tests whether the coefficients are equal across the four institution-type dummies (Insurance, Inv. advisor, Bank, and Pension/endowment).

	No Fixed Effects				Time Fixed Effects				Institution Fixed Effects			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	0.0158 (5.84)	-0.00166 (-0.54)	0.0202 (6.08)	0.0153 (5.46)	0.0152 (5.55)	-0.000152 (-0.05)	0.0206 (6.13)	0.0173 (6.05)	0.00338 (0.52)	-0.0179 (-2.35)	0.0122 (1.54)	-0.00528 (-0.79)
log(AUM) \times trend	0.0788 (6.83)	0.0322 (2.41)	0.0514 (3.85)	-0.000989 (-0.09)	0.0758 (6.50)	0.0395 (2.92)	0.0531 (3.93)	0.00867 (0.75)	0.0651 (4.99)	0.0263 (1.85)	0.0494 (3.32)	-0.00524 (-0.42)
Trend	0.598 (5.15)	0.199 (1.47)	0.387 (2.88)	-0.0665 (-0.57)					0.449 (3.59)	0.0849 (0.61)	0.368 (2.56)	-0.109 (-0.87)
Active share	-0.0243 (-1.36)	-0.0459 (-2.03)	-0.00409 (-0.18)	-0.0880 (-4.26)	-0.0231 (-1.29)	-0.0445 (-1.97)	-0.00316 (-0.14)	-0.0866 (-4.19)	-0.0656 (-1.40)	-0.149 (-2.72)	-0.0264 (-0.47)	-0.0863 (-1.79)
1(UNPRI)	0.0475 (4.38)	0.0543 (4.59)	0.0523 (4.28)	0.0357 (3.44)	0.0478 (4.41)	0.0527 (4.46)	0.0516 (4.23)	0.0338 (3.26)	0.0364 (2.30)	0.0461 (2.51)	0.0286 (1.75)	0.00465 (0.28)
1(Inv. advisor)	-0.0338 (-2.07)	-0.0149 (-0.67)	-0.00459 (-0.17)	-0.0310 (-1.21)	-0.0341 (-2.09)	-0.0149 (-0.67)	-0.00469 (-0.17)	-0.0310 (-1.21)				
1(Bank)	-0.0738 (-3.49)	-0.0302 (-1.20)	-0.132 (-3.86)	-0.0601 (-2.09)	-0.0739 (-3.50)	-0.0301 (-1.20)	-0.132 (-3.85)	-0.0601 (-2.09)				
1(Pension/endowment)	-0.0289 (-1.54)	-0.0314 (-1.15)	0.0185 (0.62)	-0.0149 (-0.54)	-0.0286 (-1.52)	-0.0312 (-1.14)	0.0186 (0.63)	-0.0148 (-0.53)				
R^2	0.013	0.004	0.018	0.015	0.015	0.006	0.019	0.018	0.442	0.461	0.500	0.432
R^2 (FEs only)	N/A	N/A	N/A	N/A	0.008	0.003	0.004	0.003	0.438	0.459	0.498	0.432
p (Inst. types equal)	0.005	0.506	0.000	0.081	0.005	0.513	0.000	0.081	N/A	N/A	N/A	N/A

Table 4: Green and brown tilts

This table shows results from panel regressions with dependent variable equal to the institution's green tilt (T_i^G , columns 1–4) or brown tilt (T_i^B , columns 5–8). There are no fixed effects. Remaining details are the same as in Table 3.

	Green Tilts				Brown Tilts			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	0.00167 (1.18)	-0.00552 (-2.84)	0.00239 (1.35)	0.00357 (2.60)	-0.0142 (-7.90)	-0.00387 (-2.24)	-0.0178 (-8.17)	-0.0118 (-6.08)
log(AUM) \times trend	0.0332 (5.04)	0.0224 (2.53)	0.0186 (2.48)	0.00559 (0.95)	-0.0456 (-6.42)	-0.00986 (-1.38)	-0.0327 (-3.96)	0.00656 (0.86)
Trend	0.275 (4.13)	0.160 (1.78)	0.185 (2.39)	0.0593 (0.98)	-0.323 (-4.52)	-0.0394 (-0.54)	-0.202 (-2.45)	0.126 (1.62)
Active share	0.0805 (8.07)	0.119 (8.52)	0.118 (9.62)	0.0741 (7.36)	0.105 (9.32)	0.164 (12.55)	0.122 (7.94)	0.162 (11.55)
1(UNPRI)	0.0258 (3.62)	0.0275 (3.44)	0.0183 (2.36)	0.0107 (1.88)	-0.0218 (-3.76)	-0.0268 (-4.53)	-0.0340 (-4.99)	-0.0249 (-3.87)
1(Inv. advisor)	-0.0107 (-1.00)	-0.00452 (-0.26)	0.00576 (0.53)	-0.0188 (-1.46)	0.0231 (2.93)	0.0104 (1.13)	0.0104 (0.50)	0.0122 (0.72)
1(Bank)	-0.0190 (-1.63)	-0.0156 (-0.83)	-0.0304 (-2.51)	-0.0308 (-2.19)	0.0547 (4.26)	0.0146 (1.26)	0.102 (3.87)	0.0294 (1.53)
1(Pension/endowment)	-0.0173 (-1.55)	-0.0175 (-0.90)	0.00871 (0.68)	-0.0184 (-1.28)	0.0115 (1.15)	0.0139 (1.07)	-0.00979 (-0.46)	-0.00352 (-0.19)
R^2	0.015	0.019	0.019	0.008	0.029	0.028	0.035	0.038
p (Inst. types equal)	0.233	0.402	0.000	0.134	0.000	0.599	0.000	0.102

REFERENCES

- Atta-Darkua, Vaska, Simon Glossner, Philipp Krueger, and Pedro Matos, 2023, Decarbonizing institutional investor portfolios: Helping to green the planet or just greening your portfolio? Working paper.
- Bennett, James A., Richard W. Sias, and Laura T. Starks, 2003, Greener pastures and the impact of dynamic institutional preferences, *Review of Financial Studies* 16, 1203–1238.
- Berg, Florian, Julian F. Koelbel, and Roberto Rigobon, 2022, Aggregate confusion: The divergence of ESG ratings, *Review of Finance* 26, 1315–1344.
- Berg, Florian, Julian F. Koelbel, Anna Pavlova, and Roberto Rigobon, 2022, ESG confusion and stock returns: Tackling the problem of noise, Working paper, MIT.
- Bolton, Patrick, and Marcin Kacperczyk, 2021, Do investors care about carbon risk? *Journal of Financial Economics* 142, 517–549.
- Bushee, Brian J., 2001, Do institutional investors prefer nearterm earnings over longrun value? *Contemporary Accounting Research*, 18, 207–246.
- Bushee, Brian J., Mary Ellen Carter, and Joseph Gerakos, 2014, Institutional investor preferences for corporate governance mechanisms, *Journal of Management Accounting Research* 26, 123–149.
- Chen, Tao, Hui Dong, and Chen Lin, 2020, Institutional shareholders and corporate social responsibility, *Journal of Financial Economics* 135, 483–504.
- Choi, Darwin, Zhenyu Gao, and Wenxi Jiang, 2020a, Measuring the carbon exposure of institutional investors, *Journal of Alternative Investments* 23, 8–11.
- Choi, Darwin, Zhenyu Gao, and Wenxi Jiang, 2020b, Attention to global warming, *Review of Financial Studies* 33, 1112–1145.
- Choi, Darwin, Zhenyu Gao, Wenxi Jiang, and Hulai Zhang, 2023, Carbon stock devaluation. Working paper.
- Cremers, Martijn, and Antti Petajisto, 2009, How active is your fund manager? A new measure that predicts performance, *Review of Financial Studies* 22, 3329–3365.
- DeVault, Luke, Richard Sias, and Laura Starks, 2019, Sentiment metrics and investor demand, *Journal of Finance* 74, 985–1024.
- Dyck, Alexander, Karl V. Lins, Lukas Roth, and Hannes F. Wagner, 2019, Do institutional investors drive corporate social responsibility? International evidence, *Journal of Financial Economics* 131, 693–714.
- Eccles, Robert G., and Judith C. Strohle, 2018, Exploring social origins in the construction

- of ESG measures, Working paper, University of Oxford.
- Edelen, Roger M., Ozgur S. Ince, and Gregory B. Kadlec, 2016, Institutional investors and stock return anomalies, *Journal of Financial Economics* 119, 472–488.
- Falkenstein, Eric G., 1996, Preferences for stock characteristics as revealed by mutual fund portfolio holdings, *Journal of Finance* 51, 111–135.
- Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.
- Ferreira, Miguel A., and Pedro Matos, 2008, The colors of investors’ money: The role of institutional investors around the world, *Journal of Financial Economics* 88, 499–533.
- Fink, Larry, 2021, BlackRock CEO’s annual letter to shareholders. <https://www.blackrock.com/corporate/investor-relations/larry-fink-chairmans-letter>.
- Gantchev, Nickolay, Mariassunta Giannetti, and Rachel Li, 2022, Does money talk? Divestitures and corporate environmental and social policies, *Review of Finance* 26, 1469–1508.
- Gibson Brandon, Rajna, Simon Glossner, Philipp Krueger, Pedro Matos, and Tom Steffen, 2022, Do responsible investors invest responsibly? *Review of Finance* 26, 1389–1432.
- Gibson Brandon, Rajna, Philipp Krueger, and Shema F Mitali, 2021, The sustainability footprint of institutional investors: ESG driven price pressure and performance, Working paper.
- Gompers, Paul A, and Andrew Metrick, 2001, Institutional investors and equity prices, *Quarterly Journal of Economics* 116, 229–259.
- Heath, Davidson, Daniele Macciocchi, Roni Michaely, and Matthew C. Ringgenberg, 2021, Does socially responsible investing change firm behavior? Working Paper.
- Hong, Harrison, and Leonard Kostovetsky, 2012, Red and blue investing: Values and finance, *Journal of Financial Economics* 103, 1–19.
- Hwang, Chuan Yang, Sheridan Titman, and Ying Wang, 2022, Investor tastes, corporate behavior, and stock returns: An analysis of corporate social responsibility, *Management Science* 68, 7131–7152.
- Ilhan, Emirhan, Philipp Krueger, Zacharias Sautner, and Laura T. Starks, 2020, Climate risk disclosure and institutional investors, Working Paper.
- Investment Company Institute, 2022, *Investment Company Fact Book*, Washington, DC.
- Kim, Soohun, and Aaron Yoon, 2023, Analyzing active fund managers’ commitment to ESG: Evidence from the United Nations Principles for Responsible Investment, *Management Science* 69, 741–758.

- Koijen, Ralph S.J., and Motohiro Yogo, 2019, A demand system approach to asset pricing, *Journal of Political Economy* 127, 1475–1515.
- Koijen, Ralph S.J., Robert J. Richmond, and Motohiro Yogo, 2020, Which investors matter for equity valuations and expected returns? Working paper.
- Lettau, Martin, Sydney C. Ludvigson, and Paulo Manoel, 2021, Characteristics of mutual fund portfolios: Where are the value funds? Working paper.
- Lewellen, Jonathan, 2011, Institutional investors and the limits of arbitrage, *Journal of Financial Economics* 102, 62–80.
- Li, Qianqian, Edward M. Watts, and Christina Zhu, 2023, Retail investors and ESG news, Working paper.
- Li, Xi, and Aneesh Raghunandan, 2021, Institutional ownership and workplace misconduct: Evidence from federal labor law violations, Working paper.
- Liang, Hao, Lin Sun, and Melvyn Teo, 2022, Responsible hedge funds, *Review of Finance* 26, 1585–1633.
- Moss, Austin, James P. Naughton, and Clare Wang, 2020, The irrelevance of ESG disclosure to retail investors: Evidence from Robinhood, Working paper.
- Nofsinger, John R., Johan Sulaeman, and Abhishek Varma, 2019, Institutional investors and corporate social responsibility, *Journal of Corporate Finance* 58, 700–725.
- Noh, Don, and Sangmin S. Oh, 2020, Measuring institutional pressure for greenness: A demand system approach, Working paper.
- Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2020, Fund tradeoffs, *Journal of Financial Economics* 138, 614–634.
- Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2021, Sustainable investing in equilibrium, *Journal of Financial Economics* 142, 550–571.
- Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2022, Dissecting green returns, *Journal of Financial Economics* 146, 403–424.
- Stambaugh, Robert F., 2014, Presidential address: Investment noise and trends, *Journal of Finance* 69, 1415–1453.
- Starks, Laura T., Parth Venkat, and Qifei Zhu, 2023, Corporate ESG profiles and investor horizons, Working paper.
- van der Beck, Philippe, 2022, Flow-driven ESG returns, Working paper.

Appendix

A.1. Green and brown tilts net to zero across all investors

In this section, we prove the statement in equation (23), namely, that the green and brown tilts aggregated across all investors are always equal: $T^G = T^B$.

For each investor i , define $\phi_i = A_i/A$, where $A = \sum_j A_j$ is total AUM across all investors. Each stock n 's market portfolio weight is given by $w_{mn} = M_n/M$, where M_n is stock n 's market capitalization and $M = \sum_j M_j$ is total market capitalization across all stocks. Note that $A = M$. Also note that $w_{in} = M_{in}/A_i$, where M_{in} is the dollar amount of stock n held by investor i . Therefore, for each stock n ,

$$\sum_i \phi_i w_{in} = \sum_i \frac{A_i}{A} \frac{M_{in}}{A_i} = \sum_i \frac{M_{in}}{A} = \sum_i \frac{M_{in}}{M} = \frac{M_n}{M} = w_{mn}, \quad (\text{A.1})$$

with the sums taken across all investors. Taking conditional expectations of both sides of equation (A.1), we obtain

$$\sum_i \phi_i \mathbb{E}\{w_{in} | \mathcal{G}, \mathcal{C}\} = \sum_i \phi_i \mathbb{E}\{w_{in} | \mathcal{G}_0, \mathcal{C}\} = w_{mn}, \quad (\text{A.2})$$

treating the ϕ_i 's as known and noting that w_{mn} is included in \mathcal{C} . Recalling the definition of Δ_{in} from equation (1), equation (A.2) immediately implies that

$$\sum_i \phi_i \Delta_{in} = 0 \quad (\text{A.3})$$

for all n . That is, each stock's AUM-weighted tilt is zero. Let \mathcal{S}_G denote the set of all green stocks. For any green stock n , note from the definitions in equations (13) through (16) that $\Delta_{in} = \Delta_{in}^{OG} + \Delta_{in}^{UG}$. Summing both sides of equation (A.3) across all green stocks, using the definitions in (17), we obtain

$$\begin{aligned} 0 &= \sum_{n \in \mathcal{S}_G} \left(\sum_i \phi_i \Delta_{in} \right) = \sum_i \phi_i \sum_{n \in \mathcal{S}_G} \Delta_{in} = \sum_i \phi_i \sum_{n \in \mathcal{S}_G} (\Delta_{in}^{OG} + \Delta_{in}^{UG}) = \sum_i \phi_i (T_i^{OG} - T_i^{UG}) \\ &= T^{OG} - T^{UG}, \end{aligned}$$

implying

$$T^{OG} = T^{UG}, \quad (\text{A.4})$$

where $T^{OG} = \sum_i \phi_i T_i^{OG}$ and $T^{UG} = \sum_i \phi_i T_i^{UG}$ are the aggregate overweight-green and underweight-green tilts, respectively. Analogously, summing equations (A.3) across all brown stocks, we obtain

$$T^{OB} = T^{UB}, \quad (\text{A.5})$$

where $T^{OB} = \sum_i \phi_i T_i^{OB}$ and $T^{UB} = \sum_i \phi_i T_i^{UB}$. We thus obtain the desired equation (23):

$$T^G = T^B, \quad (\text{A.6})$$

where $T^G = \sum_i \phi_i T_i^G$ and $T^B = \sum_i \phi_i T_i^B$ are the aggregate green and brown tilts, respectively. The last step follows from recognizing that $T^G = T^{OG} + T^{UB}$ and $T^B = T^{OB} + T^{UG}$, based on equations (18) and (19). \square

A.2. Estimating the intensive-margin model

This section extends the discussion from Section 3.2 by providing a detailed justification for the regression model in equation (29). We begin by specifying two desired properties of our model for the intensive margin. First, for simplicity, w_{in}^+/w_{mn} is given by a restricted linear function of stock n 's characteristics:

$$\frac{w_{in}^+}{w_{mn}} = \sum_{j=1}^K c_{ij} x_{nj}, \quad n = 1, \dots, N. \quad (\text{A.7})$$

That is, w_{in}^+ is linear in the K values of $w_{mn} x_{nj}$. If a given stock n is held, its expected weight could in principle depend not only on the stock's own value of $w_{mn} x_{nj}$ but also on the values of that quantity for other stocks the investor may hold. Recognizing that potential dependence, we allow c_{ij} to depend on the portfolio's expected sum across stocks of $w_{mn} x_{nj}$ (i.e., $\pi_i' h_j$, where h_j denotes the $N \times 1$ vector whose n -th element is $w_{mn} x_{nj}$). Second, for any π_i having at least one positive element, expected unconditional weights, which we denote by \bar{w}_{in} , always sum to one:

$$\sum_{n=1}^N \bar{w}_{in} = \sum_{n=1}^N \pi_{in} w_{in}^+ = 1. \quad (\text{A.8})$$

Given these two properties, it can be readily verified that c_{ij} must be proportional to the reciprocal of $\sum_{n=1}^N \pi_{in} w_{mn} x_{nj}$. That is,

$$c_{ij} = b_{ij} / \sum_{n=1}^N \pi_{in} w_{mn} x_{nj}, \quad j = 1, \dots, K, \quad (\text{A.9})$$

where b_{ij} does not depend on X or π_i . In addition, it must be that

$$\sum_{j=1}^K b_{ij} = 1. \quad (\text{A.10})$$

Substituting the right-hand side of equation (A.9) into equation (A.7) gives

$$\frac{w_{in}^+}{w_{mn}} = \sum_{j=1}^K b_{ij} \left(\frac{x_{nj}}{\sum_{n=1}^N \pi_{in} w_{mn} x_{nj}} \right). \quad (\text{A.11})$$

For each stock held by the investor, the actual weight w_{in} obeys

$$w_{in} = w_{in}^+ + \epsilon_{in}, \quad (\text{A.12})$$

where ϵ_{in} has zero mean conditional on X . Combining equations (A.11) and (A.12) gives the following regression model for the stocks held:

$$\frac{w_{in}}{w_{mn}} = \sum_{j=1}^K b_{ij} \tilde{x}_{n,j} + e_{in}, \quad (\text{A.13})$$

where the j -th independent variable is

$$\tilde{x}_{nj} = \frac{x_{nj}}{\sum_{n=1}^N \pi_{in} w_{mn} x_{nj}}. \quad (\text{A.14})$$

The quantity $e_{in} \equiv \epsilon_{in}/w_{mn}$ satisfies the property required of a regression disturbance, i.e., that it has zero expectation conditional on the \tilde{x}_{nj} s, because the n -th row of X includes w_{mn} (as noted earlier). The regression coefficients in (A.13) must obey the restriction in equation (A.10). To incorporate this restriction, we can substitute for b_{ik} the quantity $1 - \sum_{j \neq k} b_{ij}$, for any k , without loss of generality. For notational convenience, let $k = 1$, in which case substituting for b_{i1} gives the unrestricted regression

$$y_{in} = \sum_{j=1}^{K-1} \gamma_{ij} z_{nj} + e_{in}, \quad (\text{A.15})$$

where

$$y_{in} = w_{in}/w_{mn} - \tilde{x}_{n1}, \quad (\text{A.16})$$

$$z_{nj} = \tilde{x}_{n,j+1} - \tilde{x}_{n1}, \quad (\text{A.17})$$

$$\gamma_{ij} = b_{i,j+1}, \quad \text{and} \quad (\text{A.18})$$

$$1 - \sum_{j=1}^{K-1} \gamma_{ij} = b_{i1}. \quad (\text{A.19})$$

We estimate the regression in (A.15) using the set of stocks held by the investor. To do so, we must first construct the underlying values of $\tilde{x}_{n,j}$, which depend on π_i via equation (A.14). For that purpose we set $\pi_i = \hat{\pi}_i$, the estimate of π_i from our model of the extensive margin. We estimate the γ_{ij} 's by least squares, and we use those estimates to obtain the corresponding estimates of the b_{ij} 's via equations (A.18) and (A.19). Finally, we plug those estimates into equation (A.11) to obtain expected weights for all assets, $n = 1, \dots, N$.

The resulting values of w_{in}^+ contain some estimation error. This error is causing about 6% of investor-stock observations of w_{in}^+ to be negative and less than 1% of them to exceed 1. We remove these implausible values by truncating w_{in}^+ to $[0,1]$. After this truncation,

the expected unconditional weights, \bar{w}_{in} , no longer sum to 1. We restore that property by rescaling w_{in}^+ . Specifically, we divide $w_{in}^+(\mathcal{G})$ and $w_{in}^+(\mathcal{G}_0)$ by the investor-specific sums of $\bar{w}_{in}(\mathcal{G})$ and $\bar{w}_{in}(\mathcal{G}_0)$, respectively. After this adjustment, $\bar{w}_{in}(\mathcal{G})$ and $\bar{w}_{in}(\mathcal{G}_0)$ both sum to 1 for every investor. As a result, the sum of our estimated values of Δ_{in} across stocks is zero for each investor, as it is for the population values of Δ_{in} . In addition, we truncate T_i^{int} , T_i^{ext} and their green and brown components to be less than 1. This truncation affects only around 0.5% of institutions that represent less than 0.1% of covered AUM in 2021. In 2021, the other tilts (T_i , T_i^G , T_i^B , T_i^{GMB}) never exceed 1.

A.3. Bias adjustment and standard errors

This section describes the bootstrap procedure that we use to de-bias the raw estimates of T_i and obtain their standard errors, extending the discussion from Section 3.3. We use the same procedure to de-bias all other quantities of interest (T_i^{ext} , T_i^{int} , T^{ext} , T^{int} , T_i^G , T_i^B , T_i^{GMB} , $T_i^{GMB,ext}$, $T_i^{GMB,int}$, etc.) and obtain their standard errors.

Let S denote the set of stocks with non-missing data (i.e., “covered” stocks), and let N denote the number of stocks in this set. Let K_i denote the number of covered stocks held by institution i . The bootstrap algorithm proceeds as follows, for each institution i :

1. Estimate the extensive- and intensive-margin regression models using the actual data (observed portfolio weights w_{in} and characteristics X).
 - (a) For each covered stock, let $\hat{\pi}_{in}$ denote the estimated probability that institution i holds stock n , for all $n \in S$.
 - (b) Let e_i denote the $K_i \times 1$ vector of estimated residuals from the intensive-margin regression (equation (A.13)). Since this regression has no intercept, the mean of e_i is not necessarily zero. We de-mean e_i at the institution level to be consistent with the model’s assumption that $\epsilon_{in} = e_{in} w_{mn}$ has zero mean conditional on X .
 - (c) Let \hat{b}_i denote the intensive-margin model’s estimated coefficient vector.
2. Motivated by the heteroskedasticity observed in the data, we allow the volatility of e_{in} to depend on stock n ’s market capitalization, M_n , in an institution-specific manner. Specifically, we assume the volatility of e_{in} is proportional to $M_n^{\gamma_i}$. We estimate γ_i as the coefficient on $\log(M_n)$ from an institution-specific regression of $\log(|e_{in}|)$ on $\log(M_n)$.¹³ Let $\delta_{in} \equiv e_{in}/M_n^{\gamma_i}$ denote the volatility-adjusted value of e_{in} , up to a constant of proportionality. Let δ_i denote the vector of δ_{in} .
3. Compute the actual value of T_i from equation (7). Label this value T_i^{raw} .

¹³In 2021, the mean and median of estimated γ_i are -0.280 and -0.295 , respectively. Estimated γ_i is negative for 95-99% of institutions and significantly negative at the 5% level for 75-90% of institutions.

4. Compute a simulated value of \tilde{T}_i by using the following steps:

- (a) Simulate which stocks are held, \tilde{I}_{in} , as follows. For each of the N covered stocks in S , draw a uniform $[0,1]$ random variable and set the indicator $\tilde{I}_{in} = 1$ if this random variable is below $\hat{\pi}_{in}$ and $\tilde{I}_{in} = 0$ otherwise. Let L_i denote the number of stocks with $\tilde{I}_{in} = 1$, which is the number of stocks held in the simulated sample. We require $L_i \geq 30$ stocks, just like in the actual data; if this condition is not met, we repeat this step until the condition is met.
- (b) With this new sample of size N , estimate the extensive-margin model while replacing the actual I_{in} with the simulated \tilde{I}_{in} . Denote the fitted values as $\tilde{\pi}_{in}$.
- (c) Simulate weights among the stocks held, \tilde{w}_{in} , as follows. For each of the L_i stocks that are held, compute w_{in}^+/w_{mn} from equation (A.11) while using the estimates of \hat{b}_i and $\hat{\pi}_{in}$ from step 1. Following equations (A.11) and (A.13), compute a draw of \tilde{w}_{in}/w_{mn} by adding to w_{in}^+/w_{mn} a random draw of e . To compute this random draw of e , multiply $M_n^{\gamma_i}$ by a random draw (with replacement) of an element of δ_i . This multiplication performs a heteroskedasticity adjustment to e .
- (d) With this new sample of size L_i , estimate the intensive-margin model as in equations (A.11) to (A.19), replacing π_{in} with $\tilde{\pi}_{in}$ and w_{in} with \tilde{w}_{in} . Denote the new intensive-margin model coefficients by \tilde{b}_{ij} . Substitute \tilde{b}_{ij} and $\tilde{\pi}_{in}$ into equation (A.11) to obtain \tilde{w}_{in}^+ , also denoted $\tilde{w}^+[\mathcal{G}, \tilde{\pi}_i(\mathcal{G})]$. Similarly, compute $\tilde{w}^+[\mathcal{G}_0, \tilde{\pi}_i(\mathcal{G}_0)]$.
- (e) Replacing variables with their tilde counterparts, compute $\tilde{\Delta}_{in}$ in equation (1).
- (f) Compute \tilde{T}_i from equation (7), substituting $\tilde{\Delta}_{in}$ for Δ_{in} .

5. Repeat step 4 for a total of $NSim$ trials.

6. Compute $TBias_i = \tilde{\tilde{T}}_i - T_i^{raw}$, where $\tilde{\tilde{T}}_i$ is the average value of \tilde{T}_i across the $NSim$ trials. $TBias_i$ is the estimated bias in T_i^{raw} .

7. Compute our final bias-adjusted estimate of T_i :

$$\hat{T}_i = T_i^{raw} - TBias_i. \quad (\text{A.20})$$

8. Compute the standard error of \hat{T}_i as follows. Let V_T denote the variance of \tilde{T}_i across the $NSim$ trials. The standard error of \hat{T}_i is $[V_T + V_T/NSim]^{1/2}$. We need to add $V_T/NSim$ because $TBias_i$, an average across $NSim$ trials, is itself estimated with error. The variance of the $TBias_i$ estimate is $V_T/NSim$.

9. We compute a 95% confidence interval for T_i as follows.

- (a) The lower end of this interval equals $\hat{T}_i - \text{Gap}_{2.5}$, where $\text{Gap}_{2.5} = \tilde{\tilde{T}}_i - \tilde{T}_i^{2.5}$ is the gap between the mean and the 2.5th percentile of \tilde{T}_i across simulated trials.
- (b) The higher end of this interval equals $\hat{T}_i + \text{Gap}_{97.5}$, where $\text{Gap}_{97.5} = \tilde{T}_i^{97.5} - \tilde{\tilde{T}}_i$ is the gap between the 97.5th percentile and the mean of \tilde{T}_i across simulated trials.

A.4. Additional data details

The non-ESG stock characteristics, C , are computed as follows. BE/ME is the book-to-market ratio. Book equity equals stockholder equity plus TXDITC (imputing zero if missing) minus BVPS, where stockholder equity equals SEQ if available, otherwise CEQ+PSTK, otherwise AT-LT. BVPS equals PSTKRV if available, otherwise PSTKL, PSTK, or zero. Profitability equals profits divided by end-of-year book equity, where profits equals revenues (REVT) minus COGS minus SG&A (XSGA, imputing zero if missing) minus interest expense (XINT, imputing zero if missing). Profitability is missing if book equity is negative. Investment is the year-over-year fraction change in book assets. These variable definitions follow Fama and French (2015). Dividends/BE is dividends (DVT) divided by end-of-year book equity, replacing DVT with zero if negative. All ratios are from the most recent fiscal year end, and we lag all ratios by six months so investors can observe them. Market cap, computed from CRSP, is observed one month before the beginning of the given time period. We estimate market betas from rolling stock-level time-series regressions of excess stock returns on excess market returns, using the past 60 months of data and requiring at least 24 months of data. Return[-11,-1] is the stock's return during the past 12 months, excluding the most recent one. Note that the most recent month is month zero, i.e., the current month, because holdings are measured at the end of the month.

A.5. Additional results

Table A.1
Tilts of Largest 100 Institutions in 2021q4

	Institution Name	AUM	AS	Tilt				Tilt / Active Share				GMB Tilt / Active Share			
				ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
1	VANGUARD GROUP, INC.	3724	0.070	0.017	0.006	0.013	0.016	0.239	0.088	0.184	0.229	0.433	0.228	0.392	0.476
				(0.023)	(0.013)	(0.006)	(0.009)	(0.332)	(0.189)	(0.087)	(0.132)	(0.552)	(0.345)	(0.191)	(0.230)
2	BLACKROCK INC	3230	0.089	0.044	0.018	0.027	0.041	0.494	0.199	0.299	0.455	0.788	0.399	0.602	0.889
				(0.007)	(0.007)	(0.007)	(0.007)	(0.079)	(0.075)	(0.077)	(0.073)	(0.132)	(0.152)	(0.155)	(0.142)
3	STATE STR CORPORATION	1848	0.098	0.032	0.011	0.008	0.032	0.323	0.114	0.078	0.324	0.293	0.227	0.158	0.627
				(0.003)	(0.004)	(0.004)	(0.003)	(0.035)	(0.040)	(0.038)	(0.035)	(0.072)	(0.079)	(0.077)	(0.067)
4	FIDELITY MGMT & RESEARCH CO	1036	0.329	0.040	0.017	0.029	0.010	0.121	0.050	0.087	0.031	-0.021	0.116	-0.176	0.076
				(0.013)	(0.014)	(0.015)	(0.011)	(0.040)	(0.042)	(0.047)	(0.033)	(0.088)	(0.102)	(0.097)	(0.080)
5	T. ROWE PRICE ASSOCIATES, INC.	912	0.413	0.030	0.014	0.011	0.031	0.072	0.033	0.026	0.075	-0.053	-0.088	-0.080	0.149
				(0.013)	(0.014)	(0.012)	(0.015)	(0.030)	(0.034)	(0.030)	(0.037)	(0.076)	(0.091)	(0.086)	(0.079)
6	GEODE CAPITAL MGMT, L.L.C.	727	0.060	0.017	0.012	0.007	0.016	0.288	0.195	0.123	0.273	0.480	0.385	0.245	0.529
				(0.002)	(0.002)	(0.002)	(0.002)	(0.036)	(0.040)	(0.036)	(0.036)	(0.069)	(0.079)	(0.073)	(0.069)
7	CAPITAL WORLD INVESTORS	520	0.535	0.016	0.010	-0.023	0.028	0.029	0.019	-0.043	0.053	-0.003	0.068	-0.020	0.119
				(0.023)	(0.026)	(0.021)	(0.025)	(0.042)	(0.048)	(0.038)	(0.047)	(0.111)	(0.127)	(0.130)	(0.113)
8	WELLINGTON MANAGEMENT CO, LLP	512	0.470	0.006	-0.003	0.019	-0.003	0.012	-0.007	0.040	-0.006	-0.022	-0.006	-0.089	-0.020
				(0.016)	(0.015)	(0.020)	(0.015)	(0.034)	(0.031)	(0.043)	(0.032)	(0.100)	(0.105)	(0.102)	(0.107)
9	NORTHERN TRUST CORP	499	0.082	0.024	0.014	0.013	0.023	0.297	0.173	0.153	0.283	0.506	0.345	0.307	0.549
				(0.004)	(0.004)	(0.004)	(0.003)	(0.044)	(0.054)	(0.050)	(0.042)	(0.074)	(0.106)	(0.099)	(0.082)
10	JPMORGAN CHASE & COMPANY	496	0.334	0.002	0.005	0.012	0.004	0.006	0.016	0.036	0.012	0.114	0.059	0.085	0.056
				(0.013)	(0.015)	(0.013)	(0.013)	(0.038)	(0.044)	(0.040)	(0.038)	(0.098)	(0.115)	(0.099)	(0.106)
11	MELLON BANK NA	430	0.124	0.030	0.012	0.018	0.028	0.239	0.100	0.142	0.228	0.382	0.199	0.284	0.441
				(0.005)	(0.006)	(0.006)	(0.005)	(0.042)	(0.048)	(0.046)	(0.042)	(0.079)	(0.095)	(0.092)	(0.081)
12	MSDW & COMPANY	414	0.239	0.027	-0.001	0.014	0.024	0.112	-0.003	0.058	0.100	-0.183	0.037	-0.123	-0.195
				(0.009)	(0.007)	(0.009)	(0.010)	(0.036)	(0.029)	(0.038)	(0.041)	(0.082)	(0.091)	(0.087)	(0.082)
13	CAPITAL INTL INVESTORS	388	0.575	-0.002	0.019	-0.008	-0.029	-0.004	0.032	-0.014	-0.051	-0.051	-0.118	-0.006	-0.035
				(0.026)	(0.028)	(0.024)	(0.024)	(0.045)	(0.049)	(0.042)	(0.042)	(0.138)	(0.141)	(0.150)	(0.144)
14	AMVESCAP PLC LONDON	355	0.274	0.022	0.012	0.035	0.004	0.081	0.045	0.127	0.014	0.209	0.117	0.254	0.065
				(0.011)	(0.011)	(0.015)	(0.009)	(0.040)	(0.042)	(0.053)	(0.033)	(0.083)	(0.111)	(0.109)	(0.095)
15	CAPITAL RESEARCH GBL INVESTORS	347	0.575	0.050	0.014	0.025	0.060	0.087	0.024	0.043	0.105	0.140	0.102	0.131	0.220
				(0.038)	(0.033)	(0.037)	(0.038)	(0.066)	(0.058)	(0.064)	(0.066)	(0.156)	(0.162)	(0.176)	(0.148)
16	BERKSHIRE HATHAWAY INC.	322	0.876	0.165	0.148	0.121	0.027	0.189	0.170	0.138	0.031	0.399	0.262	0.322	0.146
				(0.066)	(0.079)	(0.057)	(0.045)	(0.075)	(0.090)	(0.065)	(0.052)	(0.189)	(0.202)	(0.229)	(0.183)
17	CHARLES SCHWAB INVT MGMT, INC.	277	0.172	0.024	0.015	0.018	0.022	0.140	0.088	0.104	0.130	0.275	0.174	0.209	0.251
				(0.006)	(0.007)	(0.007)	(0.006)	(0.037)	(0.044)	(0.040)	(0.036)	(0.067)	(0.087)	(0.081)	(0.070)
18	LEGAL & GENERAL GROUP PLC	277	0.112	0.028	0.022	0.027	0.022	0.246	0.194	0.242	0.194	0.505	0.384	0.484	0.375
				(0.006)	(0.008)	(0.006)	(0.006)	(0.054)	(0.067)	(0.054)	(0.056)	(0.096)	(0.133)	(0.108)	(0.108)
19	DIMENSIONAL FD ADVISORS, L.P.	269	0.356	0.039	0.043	-0.007	-0.005	0.109	0.121	-0.021	-0.014	0.032	-0.242	-0.017	0.055
				(0.017)	(0.020)	(0.013)	(0.011)	(0.047)	(0.056)	(0.037)	(0.030)	(0.114)	(0.112)	(0.113)	(0.097)
20	AXA FINANCIAL, INC.	267	0.371	0.015	0.003	-0.006	0.015	0.040	0.008	-0.017	0.040	0.129	-0.062	0.033	0.088
				(0.017)	(0.015)	(0.014)	(0.018)	(0.045)	(0.041)	(0.037)	(0.047)	(0.106)	(0.121)	(0.119)	(0.104)
21	MFS INVESTMENT MANAGEMENT	261	0.525	0.034	0.015	0.027	0.010	0.064	0.028	0.051	0.019	0.012	0.085	-0.116	0.064
				(0.020)	(0.020)	(0.021)	(0.019)	(0.039)	(0.038)	(0.040)	(0.036)	(0.101)	(0.110)	(0.109)	(0.100)
22	BANK OF AMERICA CORPORATION	245	0.218	0.014	0.011	0.006	0.017	0.063	0.051	0.029	0.079	0.074	0.154	0.090	0.160
				(0.034)	(0.035)	(0.009)	(0.009)	(0.154)	(0.159)	(0.040)	(0.041)	(0.097)	(0.324)	(0.104)	(0.089)
23	COLUMBIA THREADNEEDLE INVTS(US	244	0.314	0.044	0.030	0.038	0.043	0.141	0.094	0.121	0.138	0.377	0.191	0.245	0.268
				(0.018)	(0.020)	(0.019)	(0.019)	(0.056)	(0.064)	(0.061)	(0.060)	(0.114)	(0.134)	(0.131)	(0.118)
24	GOLDMAN SACHS & COMPANY	234	0.203	0.026	-0.005	0.024	0.015	0.128	-0.024	0.119	0.073	-0.060	0.038	-0.242	0.150
				(0.011)	(0.010)	(0.014)	(0.012)	(0.053)	(0.048)	(0.068)	(0.059)	(0.129)	(0.151)	(0.146)	(0.127)
25	UBS ASSET MGMT (AMERICAS) INC.	212	0.154	0.040	0.046	0.030	0.022	0.258	0.300	0.195	0.145	0.527	0.592	0.389	0.281
				(0.007)	(0.008)	(0.007)	(0.007)	(0.047)	(0.054)	(0.048)	(0.047)	(0.088)	(0.108)	(0.096)	(0.093)

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Table A.1 (Continued)

	Institution Name	AUM	AS	Tilt				Tilt / Active Share				GMB Tilt / Active Share			
				ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
26	FRANKLIN RESOURCES INC	204	0.404	0.031 (0.025)	0.015 (0.029)	-0.011 (0.020)	0.037 (0.028)	0.077 (0.062)	0.037 (0.072)	-0.027 (0.050)	0.092 (0.070)	0.089 (0.165)	-0.104 (0.194)	-0.029 (0.172)	0.204 (0.167)
27	MANAGED ACCT ADVR LLC	202	0.301	-0.001 (0.008)	0.008 (0.010)	0.000 (0.009)	-0.006 (0.007)	-0.002 (0.027)	0.026 (0.034)	-0.001 (0.029)	-0.019 (0.023)	0.083 (0.079)	0.076 (0.093)	0.034 (0.086)	0.013 (0.077)
28	JANUS HENDERSON INVESTORS	199	0.427	0.032 (0.022)	0.035 (0.028)	-0.001 (0.020)	0.014 (0.021)	0.075 (0.051)	0.082 (0.065)	-0.003 (0.047)	0.032 (0.049)	0.003 (0.125)	0.181 (0.154)	-0.050 (0.142)	0.098 (0.135)
29	PARAMETRIC PORTFOLIO ASSOC LLC	158	0.118	0.029 (0.005)	0.019 (0.006)	0.019 (0.005)	0.026 (0.005)	0.241 (0.042)	0.162 (0.047)	0.160 (0.045)	0.222 (0.043)	0.325 (0.087)	0.321 (0.093)	0.320 (0.089)	0.430 (0.083)
30	COLLEGE RETIRE EQUITIES	158	0.223	0.015 (0.006)	0.020 (0.007)	0.008 (0.006)	0.005 (0.005)	0.067 (0.025)	0.090 (0.033)	0.035 (0.027)	0.023 (0.021)	0.162 (0.052)	0.178 (0.066)	0.073 (0.059)	0.054 (0.051)
31	WACHOVIA CORPORATION	147	0.321	0.019 (0.008)	0.026 (0.012)	0.024 (0.010)	-0.002 (0.006)	0.060 (0.025)	0.080 (0.037)	0.074 (0.031)	-0.005 (0.019)	0.166 (0.056)	0.159 (0.073)	0.147 (0.062)	0.014 (0.058)
32	DEUTSCHE BK AKTIENGESELLSCHAFT	145	0.234	0.055 (0.010)	0.020 (0.010)	0.036 (0.011)	0.052 (0.010)	0.237 (0.042)	0.084 (0.042)	0.154 (0.046)	0.221 (0.041)	0.330 (0.081)	0.169 (0.089)	0.307 (0.093)	0.428 (0.080)
33	SWISS NATIONAL BANK	142	0.139	0.014 (0.002)	0.010 (0.003)	0.009 (0.002)	0.012 (0.002)	0.097 (0.017)	0.075 (0.019)	0.068 (0.016)	0.086 (0.017)	0.179 (0.030)	0.150 (0.042)	0.135 (0.032)	0.168 (0.033)
34	SUMITOMO MITSUI TR BK, LIMITED	136	0.141	0.048 (0.014)	0.055 (0.020)	0.061 (0.023)	0.007 (0.012)	0.343 (0.102)	0.391 (0.141)	0.433 (0.161)	0.049 (0.088)	0.590 (0.292)	0.772 (0.286)	0.871 (0.335)	-0.173 (0.265)
35	BAILLIE GIFFORD & CO.	130	0.785	0.029 (0.043)	0.002 (0.034)	0.041 (0.049)	0.034 (0.042)	0.037 (0.055)	0.002 (0.043)	0.052 (0.062)	0.043 (0.054)	-0.013 (0.155)	0.047 (0.120)	0.137 (0.163)	-0.125 (0.147)
36	MCDONALD & CO SECURITIES	129	0.234	0.006 (0.007)	-0.003 (0.007)	-0.006 (0.006)	0.011 (0.009)	0.028 (0.031)	-0.013 (0.029)	-0.027 (0.025)	0.049 (0.038)	-0.062 (0.080)	0.014 (0.091)	-0.015 (0.082)	0.099 (0.080)
37	CALIFORNIA PUBLIC EMP' RET SYS	127	0.218	0.020 (0.007)	0.016 (0.008)	0.016 (0.008)	0.019 (0.007)	0.093 (0.032)	0.076 (0.035)	0.072 (0.037)	0.087 (0.031)	0.173 (0.063)	0.150 (0.069)	0.145 (0.077)	0.169 (0.059)
38	AMERICAN CENT INVT MGMT, INC.	127	0.404	0.046 (0.026)	0.055 (0.036)	0.078 (0.038)	-0.015 (0.020)	0.114 (0.065)	0.136 (0.088)	0.193 (0.093)	-0.038 (0.050)	0.524 (0.180)	0.283 (0.197)	0.381 (0.188)	-0.029 (0.167)
39	JENNISON ASSOCIATES LLC	125	0.550	0.005 (0.022)	0.018 (0.026)	0.003 (0.026)	0.004 (0.019)	0.009 (0.039)	0.032 (0.047)	0.006 (0.047)	0.007 (0.034)	0.035 (0.125)	-0.103 (0.134)	-0.063 (0.139)	0.063 (0.106)
40	PRINCIPAL FINANCIAL GROUP INC	122	0.370	0.031 (0.019)	0.018 (0.021)	0.018 (0.018)	0.007 (0.016)	0.083 (0.051)	0.048 (0.056)	0.048 (0.049)	0.018 (0.042)	0.039 (0.107)	-0.111 (0.134)	0.120 (0.127)	-0.073 (0.122)
41	DODGE & COX	121	0.842	0.200 (0.085)	0.124 (0.088)	0.086 (0.085)	0.034 (0.050)	0.237 (0.100)	0.147 (0.105)	0.102 (0.100)	0.040 (0.060)	0.175 (0.216)	0.337 (0.270)	-0.259 (0.259)	0.169 (0.191)
42	PRIMECAP MANAGEMENT COMPANY	120	0.672	0.231 (0.065)	0.013 (0.061)	0.217 (0.080)	0.030 (0.056)	0.344 (0.097)	0.019 (0.091)	0.323 (0.120)	0.044 (0.084)	0.064 (0.269)	0.141 (0.265)	-0.654 (0.258)	-0.142 (0.226)
43	CLEARBRIDGE INVESTMENTS, LLC	119	0.501	0.067 (0.036)	0.015 (0.040)	0.071 (0.046)	0.054 (0.037)	0.135 (0.072)	0.030 (0.079)	0.141 (0.092)	0.108 (0.074)	-0.028 (0.190)	0.131 (0.216)	0.308 (0.220)	-0.237 (0.176)
44	FISHER INVESTMENTS	113	0.548	0.010 (0.024)	0.016 (0.027)	0.033 (0.028)	0.002 (0.019)	0.018 (0.044)	0.028 (0.049)	0.061 (0.051)	0.003 (0.035)	0.067 (0.115)	0.097 (0.134)	0.142 (0.128)	0.073 (0.119)
45	WELLS FARGO & (NORWEST CORP)	111	0.328	0.121 (0.032)	0.045 (0.030)	0.084 (0.031)	0.013 (0.024)	0.370 (0.098)	0.137 (0.091)	0.257 (0.095)	0.039 (0.073)	0.115 (0.198)	-0.296 (0.212)	0.510 (0.190)	0.129 (0.201)
46	NEUBERGER BERMAN, LLC	100	0.451	0.069 (0.039)	0.106 (0.050)	0.021 (0.036)	0.055 (0.039)	0.154 (0.086)	0.236 (0.110)	0.046 (0.079)	0.121 (0.086)	-0.324 (0.250)	-0.480 (0.244)	-0.195 (0.256)	-0.289 (0.221)
47	TEACHERS ADVR INC	100	0.128	0.056 (0.008)	0.058 (0.009)	0.030 (0.009)	0.042 (0.008)	0.434 (0.059)	0.454 (0.069)	0.230 (0.072)	0.328 (0.064)	0.813 (0.128)	0.897 (0.136)	0.459 (0.144)	0.636 (0.125)
48	KEYBANK NATIONAL ASSOCIATION	99	0.433	0.108 (0.044)	-0.006 (0.037)	0.096 (0.047)	0.051 (0.035)	0.249 (0.101)	-0.014 (0.085)	0.223 (0.108)	0.117 (0.080)	0.310 (0.170)	-0.049 (0.239)	0.447 (0.224)	0.230 (0.174)
49	DELAWARE MANAGEMENT CO	96	0.543	0.038 (0.046)	-0.030 (0.041)	0.038 (0.049)	0.057 (0.044)	0.069 (0.084)	-0.056 (0.075)	0.069 (0.091)	0.105 (0.080)	0.174 (0.227)	0.106 (0.247)	0.231 (0.267)	0.248 (0.208)
50	HARRIS FINANCIAL CORP	96	0.227	-0.007 (0.007)	0.000 (0.008)	-0.002 (0.007)	-0.004 (0.006)	-0.029 (0.030)	0.000 (0.037)	-0.010 (0.033)	-0.020 (0.026)	0.027 (0.090)	0.052 (0.112)	0.037 (0.107)	0.022 (0.091)

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Table A.1 (Continued)

	Institution Name	AUM	AS	Tilt				Tilt / Active Share				GMB Tilt / Active Share			
				ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
51	STATE FARM MUT AUTOMOBILE INS	94	0.728	0.238 (0.075)	0.157 (0.082)	0.166 (0.079)	0.119 (0.077)	0.328 (0.103)	0.215 (0.112)	0.228 (0.108)	0.164 (0.106)	0.198 (0.256)	-0.466 (0.285)	0.498 (0.273)	-0.327 (0.243)
52	CREDIT AGRICOLE	93	0.251	0.157 (0.018)	0.123 (0.021)	0.167 (0.019)	0.098 (0.019)	0.625 (0.070)	0.489 (0.083)	0.666 (0.076)	0.392 (0.075)	1.194 (0.170)	0.967 (0.164)	1.330 (0.151)	0.762 (0.145)
53	BARCLAYS BANK PLC	90	0.227	0.023 (0.012)	0.020 (0.014)	0.007 (0.011)	0.013 (0.012)	0.102 (0.052)	0.088 (0.061)	0.033 (0.047)	0.058 (0.052)	0.010 (0.119)	0.188 (0.137)	-0.086 (0.117)	0.128 (0.120)
54	NEW YORK STATE COMMON RET FD	88	0.118	0.029 (0.010)	0.038 (0.014)	0.033 (0.012)	-0.007 (0.008)	0.245 (0.082)	0.317 (0.115)	0.277 (0.102)	-0.061 (0.069)	0.422 (0.208)	0.629 (0.231)	0.554 (0.204)	0.002 (0.203)
55	FIRST TRUST ADVR L.P.	82	0.459	0.040 (0.028)	-0.026 (0.021)	0.048 (0.034)	-0.011 (0.021)	0.087 (0.061)	-0.056 (0.045)	0.105 (0.075)	-0.025 (0.045)	0.195 (0.144)	-0.026 (0.159)	0.212 (0.156)	0.016 (0.137)
56	CREDIT SUISSE ASSET MANAGEMENT	78	0.194	0.067 (0.020)	0.088 (0.025)	0.054 (0.020)	0.033 (0.018)	0.347 (0.101)	0.454 (0.128)	0.279 (0.103)	0.169 (0.090)	0.694 (0.197)	0.879 (0.249)	0.557 (0.211)	0.335 (0.191)
57	PICTET ASSET MANAGEMENT LTD.	77	0.536	0.218 (0.043)	0.117 (0.044)	0.217 (0.050)	0.149 (0.042)	0.407 (0.081)	0.219 (0.082)	0.404 (0.093)	0.278 (0.078)	0.955 (0.157)	0.432 (0.173)	0.804 (0.187)	0.539 (0.151)
58	CALIFORNIA STATE TEACH RET SYS	75	0.057	0.014 (0.002)	0.012 (0.002)	0.008 (0.002)	0.012 (0.002)	0.248 (0.034)	0.211 (0.039)	0.149 (0.037)	0.215 (0.032)	0.462 (0.058)	0.418 (0.077)	0.297 (0.074)	0.417 (0.062)
59	NORDEA INVT MGMT AB (DENMARK)	75	0.464	0.098 (0.033)	0.059 (0.035)	-0.012 (0.024)	0.079 (0.039)	0.211 (0.071)	0.127 (0.076)	-0.027 (0.052)	0.171 (0.084)	0.264 (0.167)	-0.234 (0.200)	0.062 (0.188)	0.338 (0.175)
60	RHUMBLINE ADVISERS LTD. PTNR	73	0.078	0.031 (0.005)	0.008 (0.005)	0.014 (0.005)	0.030 (0.005)	0.401 (0.061)	0.098 (0.063)	0.182 (0.061)	0.387 (0.060)	0.492 (0.111)	0.200 (0.135)	0.364 (0.123)	0.750 (0.116)
61	EATON VANCE MANAGEMENT	71	0.309	-0.012 (0.016)	-0.001 (0.018)	-0.007 (0.016)	0.001 (0.015)	-0.039 (0.052)	-0.003 (0.058)	-0.024 (0.051)	0.004 (0.049)	0.201 (0.144)	0.062 (0.173)	0.036 (0.160)	0.061 (0.143)
62	CITIGROUP INC	71	0.203	0.026 (0.009)	0.004 (0.009)	0.021 (0.013)	0.024 (0.011)	0.127 (0.044)	0.017 (0.047)	0.105 (0.063)	0.116 (0.057)	-0.111 (0.110)	-0.074 (0.132)	-0.214 (0.133)	0.230 (0.118)
63	LOOMIS, SAYLES & COMPANY, L.P.	70	0.702	0.116 (0.048)	-0.010 (0.034)	0.002 (0.044)	0.124 (0.051)	0.165 (0.068)	-0.015 (0.049)	0.003 (0.062)	0.177 (0.072)	-0.118 (0.174)	0.051 (0.153)	-0.078 (0.180)	-0.359 (0.152)
64	ALLIANZ DRESDNER ASSET MGMT AM	68	0.413	0.152 (0.040)	0.195 (0.054)	0.022 (0.038)	-0.027 (0.032)	0.369 (0.097)	0.471 (0.131)	0.054 (0.093)	-0.065 (0.077)	0.280 (0.250)	0.941 (0.259)	0.193 (0.269)	-0.052 (0.244)
65	BOSTON PTNR	67	0.775	0.091 (0.043)	0.128 (0.058)	0.036 (0.047)	0.070 (0.044)	0.118 (0.055)	0.165 (0.075)	0.047 (0.061)	0.090 (0.057)	0.234 (0.131)	0.333 (0.154)	0.124 (0.159)	0.182 (0.133)
66	TD ASSET MANAGEMENT INC.	66	0.315	0.017 (0.013)	0.004 (0.014)	0.015 (0.015)	-0.004 (0.011)	0.054 (0.041)	0.014 (0.044)	0.047 (0.047)	-0.012 (0.034)	-0.120 (0.113)	0.061 (0.121)	-0.121 (0.125)	0.025 (0.107)
67	HSBC HOLDINGS PLC	64	0.196	0.030 (0.010)	0.014 (0.011)	0.019 (0.012)	0.019 (0.010)	0.153 (0.049)	0.070 (0.054)	0.094 (0.060)	0.097 (0.052)	-0.025 (0.116)	0.157 (0.132)	-0.195 (0.130)	0.192 (0.110)
68	RAYMOND JAMES & ASSOC, INC.	64	0.241	0.029 (0.011)	-0.002 (0.009)	0.035 (0.013)	-0.006 (0.008)	0.120 (0.045)	-0.007 (0.035)	0.147 (0.055)	-0.026 (0.034)	0.146 (0.106)	0.041 (0.110)	0.294 (0.111)	0.015 (0.106)
69	BROWN ADVISORY LLC	61	0.629	0.150 (0.058)	0.170 (0.070)	0.177 (0.068)	-0.005 (0.040)	0.238 (0.092)	0.270 (0.111)	0.282 (0.108)	-0.008 (0.064)	0.488 (0.237)	0.539 (0.224)	0.578 (0.238)	-0.074 (0.194)
70	PRUDENTIAL INSUR CO OF AMERICA	61	0.189	0.010 (0.010)	0.005 (0.011)	0.000 (0.009)	0.015 (0.011)	0.050 (0.054)	0.027 (0.059)	0.002 (0.050)	0.080 (0.057)	0.172 (0.140)	0.112 (0.166)	0.070 (0.152)	0.174 (0.135)
71	LAZARD CAPITAL MARKETS LLC	60	0.576	0.131 (0.042)	0.000 (0.028)	0.134 (0.048)	0.085 (0.042)	0.228 (0.073)	0.000 (0.049)	0.233 (0.083)	0.148 (0.072)	0.399 (0.155)	0.082 (0.157)	0.466 (0.169)	0.291 (0.147)
72	PUTNAM INVESTMENT MGMT, L.L.C.	60	0.445	0.007 (0.017)	0.010 (0.019)	0.028 (0.023)	-0.010 (0.014)	0.015 (0.039)	0.023 (0.044)	0.063 (0.053)	-0.022 (0.033)	-0.098 (0.128)	-0.091 (0.134)	-0.149 (0.134)	-0.002 (0.117)
73	ARROWSTREET CAP, LIMITED PTNR	59	0.536	0.156 (0.028)	0.108 (0.033)	0.075 (0.030)	0.055 (0.028)	0.292 (0.052)	0.201 (0.062)	0.140 (0.057)	0.103 (0.051)	0.053 (0.124)	0.398 (0.124)	-0.284 (0.121)	0.200 (0.104)
74	MILLENNIUM MANAGEMENT LLC	59	0.448	0.068 (0.034)	0.050 (0.035)	0.052 (0.037)	0.083 (0.038)	0.152 (0.077)	0.112 (0.077)	0.117 (0.083)	0.186 (0.085)	0.201 (0.167)	0.244 (0.181)	0.243 (0.184)	0.356 (0.170)
75	CANADA PENS PLAN INVESTMENT BD	59	0.418	0.079 (0.052)	0.101 (0.059)	0.053 (0.050)	0.083 (0.056)	0.189 (0.124)	0.241 (0.142)	0.127 (0.121)	0.198 (0.133)	-0.258 (0.298)	0.548 (0.361)	0.358 (0.344)	0.442 (0.322)

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Table A.1 (Continued)

	Institution Name	AUM	AS	Tilt				Tilt / Active Share				GMB Tilt / Active Share			
				ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
76	PNC FINL SERVICES GROUP INC	59	0.456	0.038 (0.023)	0.008 (0.021)	0.008 (0.021)	0.046 (0.026)	0.082 (0.051)	0.018 (0.045)	0.017 (0.045)	0.100 (0.056)	-0.006 (0.139)	-0.106 (0.144)	-0.107 (0.135)	0.200 (0.119)
77	ALGEMEEN BURGERLIJK PENSIOENF.	57	0.454	0.040 (0.052)	0.026 (0.051)	0.016 (0.058)	-0.034 (0.039)	0.087 (0.114)	0.058 (0.113)	0.034 (0.127)	-0.076 (0.086)	-0.034 (0.302)	-0.248 (0.352)	0.192 (0.358)	-0.069 (0.262)
78	EDGEWOOD MANAGEMENT LLC	56	0.827	0.190 (0.088)	-0.001 (0.093)	-0.023 (0.075)	0.262 (0.084)	0.229 (0.107)	-0.001 (0.113)	-0.027 (0.091)	0.317 (0.102)	-0.208 (0.253)	0.089 (0.283)	0.125 (0.295)	-0.676 (0.255)
79	ARTISAN PTNR LIMITED PTNR	56	0.759	0.124 (0.057)	0.121 (0.066)	0.075 (0.070)	0.057 (0.061)	0.163 (0.076)	0.159 (0.086)	0.099 (0.092)	0.075 (0.080)	0.195 (0.226)	0.351 (0.204)	0.236 (0.242)	-0.208 (0.217)
80	T & D ASSET MGMT (US) INC.	55	0.424	0.076 (0.030)	0.027 (0.026)	0.035 (0.026)	0.048 (0.026)	0.179 (0.071)	0.064 (0.062)	0.082 (0.062)	0.113 (0.061)	-0.233 (0.144)	0.162 (0.163)	-0.192 (0.159)	-0.235 (0.142)
81	CITADEL ADVR LLC	55	0.498	0.004 (0.017)	-0.005 (0.021)	0.025 (0.022)	-0.018 (0.016)	0.009 (0.034)	-0.010 (0.043)	0.050 (0.043)	-0.037 (0.032)	-0.112 (0.094)	-0.036 (0.125)	-0.122 (0.112)	0.001 (0.103)
82	SCHRODER INV MGMT GROUP	53	0.435	0.118 (0.040)	-0.013 (0.027)	-0.005 (0.035)	0.138 (0.046)	0.272 (0.093)	-0.029 (0.062)	-0.012 (0.080)	0.318 (0.106)	0.246 (0.220)	-0.025 (0.214)	-0.039 (0.250)	0.615 (0.211)
83	RBC CAP MARKETS WEALTH MGMT	53	0.286	0.026 (0.009)	0.022 (0.011)	0.013 (0.008)	0.025 (0.009)	0.090 (0.031)	0.076 (0.039)	0.046 (0.028)	0.087 (0.030)	0.137 (0.065)	0.151 (0.081)	0.098 (0.067)	0.170 (0.061)
84	D. E. SHAW & CO., L.P.	52	0.471	0.068 (0.032)	0.097 (0.039)	0.025 (0.025)	0.037 (0.030)	0.145 (0.069)	0.206 (0.083)	0.053 (0.054)	0.079 (0.064)	0.082 (0.131)	0.413 (0.169)	0.141 (0.152)	0.171 (0.145)
85	POLEN CAPITAL MANAGEMENT, LLC	51	0.789	0.104 (0.049)	0.159 (0.057)	0.057 (0.046)	-0.018 (0.043)	0.131 (0.062)	0.202 (0.073)	0.073 (0.058)	-0.023 (0.054)	0.268 (0.185)	0.300 (0.109)	0.169 (0.157)	-0.058 (0.177)
86	HARRIS ASSOCIATES L.P.	51	0.841	0.222 (0.070)	0.152 (0.076)	-0.001 (0.061)	0.151 (0.055)	0.264 (0.084)	0.181 (0.090)	-0.001 (0.073)	0.179 (0.066)	0.095 (0.188)	0.382 (0.214)	-0.114 (0.232)	0.394 (0.176)
87	LSV ASSET MANAGEMENT	51	0.804	0.012 (0.043)	0.005 (0.047)	0.054 (0.050)	0.009 (0.045)	0.014 (0.053)	0.006 (0.058)	0.067 (0.062)	0.012 (0.056)	0.174 (0.146)	0.088 (0.177)	0.180 (0.178)	0.082 (0.161)
88	NATIONAL PENSION SERVICE	50	0.149	0.017 (0.007)	-0.004 (0.006)	0.008 (0.007)	0.018 (0.007)	0.112 (0.044)	-0.024 (0.038)	0.054 (0.049)	0.121 (0.049)	0.233 (0.114)	0.034 (0.126)	0.133 (0.131)	0.241 (0.101)
89	FLORIDA STATE BD ADMINISTRATIO	50	0.072	0.016 (0.003)	0.016 (0.004)	-0.002 (0.003)	0.003 (0.003)	0.215 (0.047)	0.227 (0.060)	-0.030 (0.038)	0.041 (0.043)	0.200 (0.107)	0.450 (0.119)	-0.012 (0.121)	0.103 (0.110)
90	RENAISSANCE TECHNOLOGIES LLC	50	0.599	0.009 (0.040)	0.032 (0.043)	0.024 (0.039)	0.012 (0.040)	0.015 (0.067)	0.053 (0.071)	0.040 (0.066)	0.020 (0.067)	-0.275 (0.182)	-0.158 (0.198)	-0.139 (0.186)	-0.112 (0.190)
91	AQR CAPITAL MANAGEMENT, LLC	48	0.358	-0.020 (0.013)	-0.012 (0.014)	-0.006 (0.013)	-0.009 (0.013)	-0.055 (0.037)	-0.034 (0.039)	-0.016 (0.036)	-0.026 (0.035)	0.067 (0.113)	0.019 (0.127)	0.024 (0.113)	0.016 (0.108)
92	ENVESTNET ASSET MGMT, INC.	47	0.256	0.020 (0.008)	0.027 (0.011)	0.021 (0.010)	-0.004 (0.006)	0.077 (0.030)	0.104 (0.042)	0.082 (0.040)	-0.015 (0.024)	0.140 (0.082)	0.208 (0.083)	0.165 (0.082)	-0.024 (0.074)
93	NEW YORK STATE TEACH' RET SYS	47	0.107	0.033 (0.008)	0.020 (0.008)	0.029 (0.009)	0.029 (0.008)	0.306 (0.072)	0.187 (0.078)	0.273 (0.080)	0.265 (0.075)	0.590 (0.140)	0.372 (0.158)	0.546 (0.159)	0.518 (0.146)
94	PROSHARE ADVR LLC	46	0.373	0.044 (0.016)	0.004 (0.016)	0.042 (0.020)	-0.010 (0.011)	0.117 (0.044)	0.012 (0.042)	0.111 (0.054)	-0.028 (0.030)	0.184 (0.109)	-0.067 (0.125)	0.229 (0.118)	-0.021 (0.104)
95	FIDELITY INTL LTD	46	0.532	0.091 (0.045)	0.115 (0.060)	0.133 (0.062)	-0.007 (0.036)	0.170 (0.085)	0.216 (0.114)	0.249 (0.116)	-0.012 (0.068)	0.593 (0.267)	0.452 (0.263)	0.512 (0.255)	-0.114 (0.229)
96	ENSIGN PEAK ADVISORS, INC.	45	0.286	0.062 (0.023)	0.076 (0.027)	0.055 (0.027)	0.037 (0.023)	0.217 (0.079)	0.267 (0.093)	0.193 (0.093)	0.130 (0.081)	0.464 (0.172)	0.528 (0.184)	0.387 (0.190)	0.257 (0.166)
97	RUSSELL INVESTMENTS	45	0.271	0.023 (0.022)	0.006 (0.022)	0.049 (0.030)	-0.017 (0.019)	0.083 (0.080)	0.024 (0.082)	0.180 (0.109)	-0.064 (0.069)	0.326 (0.212)	0.140 (0.247)	0.373 (0.239)	0.029 (0.230)
98	ADAGE CAPITAL MANAGEMENT, L.P.	44	0.234	0.162 (0.049)	0.035 (0.033)	0.187 (0.060)	0.034 (0.030)	0.692 (0.210)	0.148 (0.142)	0.801 (0.256)	0.145 (0.131)	-1.070 (0.488)	-0.344 (0.436)	-1.610 (0.522)	0.388 (0.366)
99	UNION INVESTMENT PRIVATFONDS G	44	0.496	0.008 (0.029)	0.013 (0.032)	0.033 (0.035)	0.005 (0.025)	0.016 (0.059)	0.026 (0.064)	0.067 (0.070)	0.010 (0.050)	0.047 (0.159)	0.093 (0.165)	0.153 (0.167)	-0.106 (0.153)
100	PARNASSUS INVESTMENTS	44	0.748	0.179 (0.064)	0.205 (0.074)	-0.033 (0.048)	-0.009 (0.042)	0.239 (0.085)	0.274 (0.098)	-0.044 (0.064)	-0.012 (0.056)	0.059 (0.211)	0.530 (0.195)	0.022 (0.197)	-0.109 (0.191)

Table A.2: Version of paper's Table 3 with time and institution fixed effects

This table shows results from panel regressions with dependent variable equal to GMB tilt and both time and institution fixed effects. Including these fixed effects requires dropping Trend and institution-type indicators from the regression. Remaining details are the same as in Table 3.

	ESG	Env.	Soc.	Gov.
log(AUM)	0.00394 (0.61)	-0.0163 (-2.14)	0.0131 (1.65)	-0.00328 (-0.49)
log(AUM) \times trend	0.0629 (4.77)	0.0317 (2.20)	0.0498 (3.32)	0.00253 (0.20)
Active share	-0.0543 (-1.14)	-0.137 (-2.47)	-0.0188 (-0.33)	-0.0724 (-1.48)
1(UNPRI)	0.0369 (2.33)	0.0408 (2.22)	0.0270 (1.66)	-0.00161 (-0.10)
R^2	0.444	0.463	0.501	0.434
R^2 (FEs only)	0.442	0.462	0.5	0.434

Table A.3: Version of paper's Table 4 with time fixed effects

This table is the same as Table 4 but includes time fixed effects, which requires dropping Trend from the regression.

	Green Tilts				Brown Tilts			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	0.00212 (1.47)	-0.00473 (-2.39)	0.00275 (1.54)	0.00323 (2.34)	-0.0131 (-7.30)	-0.00460 (-2.62)	-0.0178 (-8.09)	-0.0141 (-7.12)
log(AUM) × trend	0.0355 (5.28)	0.0261 (2.91)	0.0203 (2.66)	0.00393 (0.66)	-0.0403 (-5.68)	-0.0134 (-1.85)	-0.0327 (-3.94)	-0.00473 (-0.61)
Active share	0.0818 (8.20)	0.120 (8.58)	0.119 (9.70)	0.0754 (7.50)	0.105 (9.31)	0.164 (12.52)	0.122 (7.93)	0.162 (11.54)
1(UNPRI)	0.0253 (3.55)	0.0267 (3.33)	0.0178 (2.31)	0.0108 (1.89)	-0.0226 (-3.89)	-0.0261 (-4.41)	-0.0339 (-4.97)	-0.0230 (-3.57)
1(Inv. advisor)	-0.0109 (-1.02)	-0.00459 (-0.26)	0.00562 (0.52)	-0.0191 (-1.48)	0.0232 (2.95)	0.0104 (1.12)	0.0103 (0.50)	0.0119 (0.70)
1(Bank)	-0.0191 (-1.63)	-0.0156 (-0.83)	-0.0304 (-2.51)	-0.0309 (-2.20)	0.0548 (4.27)	0.0145 (1.24)	0.102 (3.87)	0.0292 (1.53)
1(Pension/endowment)	-0.0171 (-1.53)	-0.0175 (-0.89)	0.00884 (0.69)	-0.0182 (-1.26)	0.0115 (1.14)	0.0137 (1.05)	-0.00980 (-0.46)	-0.00345 (-0.19)
R^2	0.018	0.020	0.020	0.011	0.031	0.030	0.036	0.043
R^2 (FEs only)	0.004	0.003	0.002	0.003	0.008	0.002	0.004	0.005
p (Inst. types equal)	0.249	0.410	0.000	0.134	0.000	0.606	0.000	0.106

Table A.4: Version of paper's Table 4 with institution and time fixed effects

This table is the same as Table 4 but includes institution and time fixed effects, which requires dropping Trend and institution-type indicators from the regression.

	Green Tilts				Brown Tilts			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	-0.00156 (-0.41)	-0.0112 (-2.25)	0.00492 (1.07)	-0.00259 (-0.74)	-0.00586 (-1.45)	0.00483 (1.15)	-0.00880 (-1.76)	0.000413 (0.09)
log(AUM) × trend	0.0244 (3.21)	0.0239 (2.51)	0.0160 (1.92)	0.000437 (0.07)	-0.0391 (-4.81)	-0.00828 (-1.04)	-0.0342 (-3.58)	-0.00265 (-0.31)
Active share	0.0950 (3.50)	0.0570 (1.61)	0.119 (3.67)	0.0825 (3.14)	0.148 (4.75)	0.193 (5.98)	0.137 (3.71)	0.153 (4.71)
1(UNPRI)	0.0217 (2.14)	0.0175 (1.35)	0.00668 (0.69)	-0.00456 (-0.52)	-0.0155 (-1.76)	-0.0236 (-2.55)	-0.0203 (-2.08)	-0.00293 (-0.26)
R^2	0.394	0.441	0.443	0.360	0.444	0.455	0.503	0.449
R^2 (FEs only)	0.391	0.440	0.441	0.358	0.441	0.453	0.501	0.448

Table A.5
Additional details on aggregate tilts

Panel A: T

Year	Bias-Adj. Estimate	Standard Error	95% CI		Bias
			Low	High	
2012	0.070	0.002	0.065	0.074	0.012
2013	0.063	0.002	0.059	0.067	0.012
2014	0.061	0.002	0.057	0.064	0.012
2015	0.058	0.002	0.054	0.061	0.011
2016	0.051	0.002	0.048	0.054	0.012
2017	0.054	0.002	0.050	0.057	0.012
2018	0.055	0.002	0.052	0.059	0.011
2019	0.052	0.002	0.049	0.056	0.012
2020	0.061	0.002	0.057	0.064	0.008
2021	0.058	0.003	0.054	0.060	0.009

Panel B: T^{int}

Year	Bias-Adj. Estimate	Standard Error	95% CI		Bias
			Low	High	
2012	0.058	0.002	0.055	0.062	0.012
2013	0.052	0.002	0.049	0.056	0.013
2014	0.056	0.002	0.052	0.059	0.012
2015	0.051	0.002	0.047	0.054	0.011
2016	0.045	0.002	0.043	0.048	0.012
2017	0.047	0.002	0.044	0.051	0.012
2018	0.053	0.002	0.049	0.056	0.010
2019	0.049	0.002	0.046	0.052	0.012
2020	0.055	0.002	0.052	0.059	0.008
2021	0.054	0.002	0.050	0.057	0.008

Panel C: T^{ext}

Year	Bias-Adj. Estimate	Standard Error	95% CI		Bias
			Low	High	
2012	0.027	0.001	0.024	0.029	0.006
2013	0.026	0.001	0.024	0.027	0.005
2014	0.022	0.001	0.020	0.024	0.005
2015	0.021	0.001	0.019	0.023	0.005
2016	0.018	0.001	0.017	0.020	0.004
2017	0.018	0.001	0.016	0.020	0.004
2018	0.017	0.001	0.016	0.019	0.005
2019	0.018	0.001	0.016	0.020	0.004
2020	0.017	0.001	0.015	0.019	0.003
2021	0.016	0.002	0.014	0.018	0.003

Panel D: T^{Env}

Year	Bias-Adj. Estimate	Standard Error	95% CI		
			Low	High	Bias
2012	0.040	0.002	0.035	0.044	0.007
2013	0.039	0.002	0.035	0.044	0.008
2014	0.040	0.002	0.036	0.044	0.008
2015	0.037	0.002	0.033	0.041	0.008
2016	0.035	0.002	0.031	0.039	0.009
2017	0.040	0.002	0.035	0.045	0.008
2018	0.035	0.002	0.031	0.039	0.009
2019	0.036	0.002	0.031	0.041	0.009
2020	0.039	0.002	0.035	0.043	0.005
2021	0.034	0.002	0.030	0.038	0.005

Panel E: T^{Soc}

Year	Bias-Adj. Estimate	Standard Error	95% CI		
			Low	High	Bias
2012	0.037	0.002	0.033	0.043	0.007
2013	0.033	0.002	0.029	0.037	0.009
2014	0.035	0.002	0.031	0.040	0.008
2015	0.036	0.002	0.031	0.041	0.008
2016	0.032	0.002	0.029	0.036	0.009
2017	0.032	0.002	0.028	0.037	0.010
2018	0.039	0.002	0.035	0.044	0.007
2019	0.037	0.002	0.033	0.041	0.008
2020	0.038	0.002	0.034	0.042	0.005
2021	0.035	0.002	0.032	0.039	0.005

Panel F: T^{Gov}

Year	Bias-Adj. Estimate	Standard Error	95% CI		
			Low	High	Bias
2012	0.042	0.002	0.038	0.046	0.008
2013	0.036	0.002	0.032	0.040	0.008
2014	0.041	0.002	0.037	0.045	0.007
2015	0.037	0.002	0.033	0.040	0.007
2016	0.033	0.002	0.029	0.037	0.009
2017	0.031	0.002	0.026	0.035	0.009
2018	0.039	0.002	0.035	0.044	0.007
2019	0.043	0.002	0.038	0.047	0.008
2020	0.038	0.002	0.035	0.042	0.003
2021	0.033	0.002	0.030	0.037	0.005

Panel G: T^{GMB} / *Active Share*

Year	Bias-Adj. Estimate	Standard Error	95% CI		Bias
			Low	High	
2012	0.041	0.013	0.015	0.066	-0.0017
2013	0.018	0.012	-0.003	0.043	-0.0001
2014	0.088	0.014	0.062	0.115	-0.0003
2015	0.080	0.016	0.049	0.113	-0.0007
2016	0.094	0.015	0.064	0.124	0.0005
2017	0.113	0.018	0.077	0.151	0.0003
2018	0.154	0.019	0.113	0.188	0.0014
2019	0.226	0.019	0.188	0.261	0.0015
2020	0.298	0.019	0.260	0.334	-0.0006
2021	0.235	0.067	0.191	0.271	0.0021

Panel H: $T^{GMB,E}$ / *Active Share*

Year	Bias-Adj. Estimate	Standard Error	95% CI		Bias
			Low	High	
2012	0.061	0.015	0.031	0.091	0.0008
2013	0.050	0.015	0.023	0.084	-0.0029
2014	0.139	0.016	0.105	0.174	-0.0036
2015	0.119	0.019	0.077	0.152	-0.0038
2016	0.119	0.020	0.085	0.158	0.0001
2017	0.098	0.026	0.045	0.145	0.0021
2018	0.119	0.024	0.071	0.169	-0.0022
2019	0.249	0.029	0.190	0.304	0.0030
2020	0.190	0.024	0.142	0.239	-0.0043
2021	0.162	0.048	0.120	0.205	-0.0025

Panel I: $T^{GMB,S}$ / *Active Share*

Year	Bias-Adj. Estimate	Standard Error	95% CI		Bias
			Low	High	
2012	0.040	0.015	0.012	0.069	0.00110
2013	0.003	0.013	-0.022	0.029	-0.00128
2014	0.108	0.017	0.075	0.140	-0.00216
2015	0.063	0.020	0.021	0.098	0.00100
2016	0.070	0.022	0.032	0.115	0.00146
2017	0.123	0.025	0.072	0.178	0.00026
2018	0.168	0.023	0.122	0.205	0.00079
2019	0.261	0.026	0.211	0.314	0.00144
2020	0.221	0.022	0.179	0.270	-0.00003
2021	0.174	0.032	0.135	0.213	0.00038

Panel J: $T^{GMB,G}$ / *Active Share*

Year	Bias-Adj. Estimate	Standard Error	95% CI		Bias
			Low	High	
2012	0.130	0.014	0.101	0.155	0.0003
2013	0.085	0.012	0.061	0.112	0.0012
2014	0.141	0.016	0.111	0.170	-0.0020
2015	0.110	0.016	0.079	0.144	-0.0007
2016	0.109	0.019	0.075	0.151	-0.0002
2017	0.118	0.023	0.070	0.164	0.0007
2018	0.184	0.021	0.140	0.224	-0.0022
2019	0.332	0.028	0.278	0.390	0.0036
2020	0.241	0.017	0.209	0.277	-0.0010
2021	0.256	0.033	0.224	0.292	0.0017