

Green Tilts

Ľuboš Pástor

Robert F. Stambaugh

Lucian A. Taylor*

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Abstract

We estimate financial institutions' portfolio tilts that relate to stocks' environmental, social, and governance (ESG) characteristics. In 2021, ESG-related tilts total 6% of the investment industry's assets and average 22% of institutions' total portfolio tilts. ESG tilts are larger for less-volatile stocks and for institutions with smaller size and greater active share, consistent with our theoretical predictions. Significant ESG tilts arise from the choice of stocks held and, especially, the weights on stocks held. The largest institutions tilt increasingly toward green stocks, while other institutions and households tilt increasingly brown. UNPRI signatories and European institutions tilt greener, banks browner.

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*Pástor is at the University of Chicago Booth School of Business, NBER, and CEPR. Stambaugh is at the Wharton School of the University of Pennsylvania and the NBER. Taylor is at the Wharton School of the University of Pennsylvania. Pástor also serves as an independent director and trustee of Vanguard. The views expressed here are those of the authors and not necessarily those of Vanguard or the Vanguard Funds. We are grateful for comments from our discussants Sam Hartzmark, Kunal Sachdeva, Adam Winegar, and Shaojun Zhang; from Doug Diamond, Winston Dou, Joanna Harris, Christian Leuz, David Musto, Mike Sebastian, Yao Zeng, Olivier David Zerbib; conference participants at the 2023 BI Conference on Corporate Governance, 2023 Fall Chicago Quantitative Alliance meeting, 2023 FRA conference, 2023 Olin Finance Conference at Washington University, 2023 University of Houston/Dallas Fed Energy Finance and the Energy Transition Conference, 2023 University of Alberta Frontiers in Finance Conference; and seminar participants at the following universities: Alabama, Chicago, EDHEC, Emory, Florida State, Maryland, Peking, Penn State, Pennsylvania, and Tinbergen Institute. We dedicate this paper to the memory of Livia Amato, whose many contributions as a research professional have benefited this paper as well as our prior work. We also thank Vitor Furtado Farias and Vanessa Hu for excellent research assistance. This research was supported by the Fama-Miller Center for Research in Finance and the Robert King Steel Fellowship at the University of Chicago Booth School of Business.

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 toward green assets, and which ones make the offsetting brown tilts? These are the questions we pursue. They are important because tilting green likely comes at a financial cost, given both theoretical arguments and empirical evidence that green assets have lower expected returns.¹

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 it does not consider the degree to which such institutions actually modify their portfolios in ways related to assets’ ESG characteristics. 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. 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 portfolios of U.S. stocks, 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 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

¹See Pástor, Stambaugh, and Taylor (2021, 2022) and Bolton and Kacperczyk (2021, 2023), among others.

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 tilts at both margins, though the intensive-margin tilts are two to three times larger than the extensive-margin ones. 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. One institution might care about G but not S, while another 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 firms’ E, S, and G characteristics, along with their composite, from ratings provided by MSCI, a leading provider. If we restrict our estimation to the composite rather than its E, S, and G components, we find that over 40% of ESG-related tilts are missed.

We also consider an institution’s ESG tilt in the context of all its portfolio tilts. For an institution less inclined to deviate from the market portfolio for any reason, a given ESG tilt is more economically significant, as it 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 22% as large as total portfolio tilts at the end of our sample. So, while the industry’s ESG tilts are modest relative to AUM, they are more substantial relative to total tilts. Moreover, we find that while ESG tilts do not represent a growing fraction of AUM, they do represent a growing fraction of overall portfolio tilts.

To guide our empirical analysis, we build a theoretical model of optimal portfolio choice by an institution that cares about its alpha net of transaction costs, its tracking error, and the greenness of its portfolio. The model predicts that institution-level ESG tilts should be larger for institutions that are smaller and that have larger active shares. The model also predicts that stock-level ESG tilts—tilts aggregated across institutions to the stock level—should be larger for stocks with less volatile returns. We find strong empirical support for

these and other predictions from the model.

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. Offsetting that behavior, 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 tilt grows even faster for the “Big Three” institutions, especially BlackRock, but the other large institutions also have a positive and growing GMB tilt. In contrast, the GMB tilts of both the middle and bottom thirds of institutions are mostly negative and decreasing over time, meaning brown and increasingly so.

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. We find that UNPRI signatories are indeed significantly greener. Not only do we see this result strongly within the cross-section of institutions, but we also find that a given institution becomes greener after becoming a UNPRI signatory. In addition, we find that banks are browner than other institutions, especially insurance companies, and that European institutions are greener than U.S. ones.

ESG investing is distinct from index investing, i.e., holding the market portfolio. An ESG preference among investors can affect weights in the market portfolio, but we do not view a pure index investor as engaging in ESG investing. A pure index investor instead gets a zero ESG tilt, because we include market weights as a control when estimating tilts. We

later discuss the rationale for this aspect of our approach. As a separate but related point, we also show that over the past decade the market portfolio has increasingly placed greater weight on green stocks, especially those greener on the environmental (E) dimension.

Our 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 non-ESG stock characteristics that prior work relates to portfolio weights.

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. Starks (2023) shows that U.S. active mutual funds have increased their ownership of high-ESG firms between 2013 and 2021.

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;

²See, for example, Falkenstein (1996), Gompers and Metrick (2001), Edelen, Ince, and Kadlec (2016), DeVault, Sias, and Starks (2019), Koijen 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.

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 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.

In a complementary study, Cremers, Riley, and Zambrana (2023) develop a new measure of how actively a fund uses ESG information. Their measure, which they call active ESG share, is very different from ours—it compares the distribution of a portfolio’s stock-level ESG scores to that of its benchmark. Their focus is also different: they relate their measure to fund performance. They do not examine aggregate tilts or theoretical predictions, nor do they compare green vs. brown tilts or intensive vs. extensive margins.

Existing studies find mixed evidence on whether UNPRI signatories engage in ESG-related behavior, raising concerns about greenwashing (Gibson et al. (2022), Humphrey and Li (2021), Kim and Yoon (2023), and Liang, Sun, and Teo (2022)). We find that after institutions become UNPRI signatories, their ESG tilts do indeed 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 also relates to the literature exploring links between ownership by institutions, including responsible ones, and various aspects of corporate social responsibility.³ Our focus on institutions’ ESG tilts provides a different and complementary perspective on institutional responsibility. Finally, our study relates to those that estimate ESG-related asset demands in other ways, to address different issues, such as price impact.⁴

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, Oh, and Song (2023), and van der Beck

The remainder of the paper is organized as follows. Section 2 presents our definitions of ESG-related tilts. Section 3 lays out our theoretical framework. Section 4 explains our estimation procedure. Section 5 presents our evidence on the cross-sectional and time-series patterns of ESG tilts, including the tests of our theory. Section 6 separates green tilts from brown and analyzes their empirical patterns. Section 7 concludes.

2. ESG-related 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' 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

(2022).

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 $E[w_{in}|\cdot] = \text{Prob}\{w_{in} > 0|\cdot\} \times E\{w_{in}|w_{in} > 0, \cdot\}$, under the assumption that $w_{in} \geq 0$.⁵ Therefore, \mathcal{G} relates to w_{in} through two channels: the probability that investor i holds stock n and the amount invested in the stock if held. To quantify both channels, for any set of ESG characteristics $\tilde{\mathcal{G}}$, we denote

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

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

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?

⁵This assumption accommodates our dataset. Institutional holdings reported in 13F filings include only long stock positions. For all stocks that are not held long, we set $w_{in} = 0$ in our empirical implementation.

2.2. Institution-level tilts

As described at the outset, we aggregate ESG-related tilts to the institution level. Denoting an investor as an institution, we compute institution i 's ESG-related portfolio tilt by adding up the absolute values of the institution'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} is not simply a deviation of the stock's portfolio weight from its market weight. The division by two ensures that we avoid double-counting: for each stock the institution overweights because of \mathcal{G} , the institution 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 the institution's 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 $T_i \leq T_i^{int} + T_i^{ext}$.

It is also useful to split the extensive-margin tilt into components driven by investment and divestment. Recall that a positive (negative) value of Δ_{in}^{ext} indicates that the stock is overweighted (underweighted) due to its ESG characteristics on the extensive margin. We capture institution i 's "extensive investment" by $T_i^{ext,O}$, the sum of all positive values of Δ_{in}^{ext} , and "extensive divestment" by $T_i^{ext,U}$, minus the sum of all negative values, so that

$$T_i^{ext} = \frac{1}{2} \left(T_i^{ext,O} + T_i^{ext,U} \right). \quad (10)$$

2.3. Stock-level tilts

For any stock n , we define the stock's ESG-related tilt as

$$D_n = \frac{1}{2M_n} \sum_{i \in \mathcal{S}} A_i |\Delta_{in}|, \quad (11)$$

where M_n is the stock’s market capitalization, \mathcal{S} is a given set of investors, and A_i is the dollar value of investor i ’s assets. The value of D_n captures the fraction of the stock’s market capitalization that is over- or under-weighted in investors’ portfolios due to \mathcal{G} . Again, the division by two precludes double-counting: for each investor who overweights the stock because of \mathcal{G} , some other investor must underweight the stock. Put differently, $\sum_{i \in \mathcal{S}} A_i \Delta_{in} = 0$ for any n when \mathcal{S} includes all investors, as we prove in the Appendix (see equation (A.4)), so any positive values of $A_i \Delta_{in}$ are balanced by negative ones.

2.4. Aggregate tilts

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

$$T = \frac{1}{A} \sum_{i \in \mathcal{S}} A_i T_i, \quad (12)$$

where $A = \sum_{i \in \mathcal{S}} A_i$. T measures the fraction of total investor assets that is “tilted.”

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

$$T^{int} = \frac{1}{A} \sum_{i \in \mathcal{S}} A_i T_i^{int} \quad (13)$$

$$T^{ext} = \frac{1}{A} \sum_{i \in \mathcal{S}} A_i T_i^{ext}. \quad (14)$$

The above aggregates are computed by adding up investor-level tilts across investors. The same aggregates obtain by adding up stock-level tilts across stocks. Specifically, denote

$$D = \sum_{n=1}^N w_{mn} D_n, \quad (15)$$

where w_{mn} is stock n ’s weight in the market portfolio. We show in the Appendix that

$$D = \frac{A}{M} T, \quad (16)$$

where M is the total capitalization of all stocks. If \mathcal{S} includes all investors, then $A = M$ and thus $D = T$. The intensive- and extensive-margin tilts aggregate analogously.

2.5. 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):

$$\Delta_{in}^{OG} : \quad \text{when } \Delta_{in} > 0 \text{ and } g_n \geq g_0 : \text{ Overweight Green stocks (green tilt)} \quad (17)$$

$$\Delta_{in}^{UB} : \quad \text{when } \Delta_{in} < 0 \text{ and } g_n < g_0 : \text{ Underweight Brown stocks (green tilt)} \quad (18)$$

$$\Delta_{in}^{OB} : \quad \text{when } \Delta_{in} > 0 \text{ and } g_n < g_0 : \text{ Overweight Brown stocks (brown tilt)} \quad (19)$$

$$\Delta_{in}^{UG} : \quad \text{when } \Delta_{in} < 0 \text{ and } g_n \geq g_0 : \text{ Underweight Green stocks (brown tilt)}. \quad (20)$$

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

$$T_i^{OG} = \sum_{n=1}^N \Delta_{in}^{OG}, \quad T_i^{UB} = - \sum_{n=1}^N \Delta_{in}^{UB}, \quad T_i^{OB} = \sum_{n=1}^N \Delta_{in}^{OB}, \quad T_i^{UG} = - \sum_{n=1}^N \Delta_{in}^{UG}. \quad (21)$$

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):

$$T_i^G = T_i^{OG} + T_i^{UB} \geq 0 \quad (22)$$

$$T_i^B = T_i^{OB} + T_i^{UG} \geq 0. \quad (23)$$

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

$$T_i^{GMB} = T_i^G - T_i^B. \quad (24)$$

$T_i^{GMB} > 0$ 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

$$T_i = \frac{1}{2}(T_i^{OG} + T_i^{UB} + T_i^{OB} + T_i^{UG}) \quad (25)$$

$$= \frac{1}{2}(T_i^G + T_i^B). \quad (26)$$

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 (17) through (20) 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 (12) through (14), 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:

$$T^G = T^B, \quad (27)$$

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 subsets of investors, as we show later.

3. Theoretical predictions

What patterns in ESG-related tilts should we expect to see across institutions and across stocks? We address this question using a model that, although simple, predicts a number of patterns in ESG-related tilts. Propositions 1 through 5 below give these predictions, which we later test in Section 5. Proofs of the propositions are in the Appendix.

3.1. Portfolio optimization

For a given institution i , which we refer to as a fund, let $w_{i,B}$ denote the N -vector of weights on stocks in the benchmark, and let w_i denote the vector of the fund’s weights on those

stocks. The vector of the stocks' benchmark-adjusted returns is given by

$$r = \alpha + \eta, \quad (28)$$

where α is the vector of gross alphas, before trading costs, and η has zero mean and covariance matrix Σ . Let g denote the vector containing each stock's greenness measure. All funds perceive the same values of α , Σ , and g . The gross alphas are given by

$$\alpha = \epsilon - \theta g, \quad (29)$$

where the elements of ϵ are uncorrelated with those of g . The value of θ reflects any role of greenness in pricing (e.g., Pástor, Stambaugh, and Taylor, 2021). Define $\phi_i \equiv w_i - w_{i,B}$. The fund's greenness, $w'_i g$, is $g_B + \phi'_i g$, where $g_B = w'_B g$ is the greenness of the benchmark. The fund's tracking error, defined as the variance of its benchmark-adjusted return, is $\phi'_i \Sigma \phi_i$.

The fund's net alpha is its gross alpha, $\phi'_i \alpha$ ($= w'_i \alpha$), minus c_i , which is the fund's trading cost as a fraction of its AUM. We assume that this proportional trading cost is given by

$$c_i = \frac{\lambda_i}{2} \phi'_i \Sigma \phi_i. \quad (30)$$

This specification follows Garleanu and Pedersen (2013), who explain that it is implied by the model of Garleanu, Pedersen, and Poteshman (2009), in which risk-averse dealers are compensated for the inventory risks associated with taking the other side of the fund's trades. We assume that the fund can obtain benchmark exposure at essentially zero trading cost, so trading costs arise from benchmark deviations, ϕ_i . The value of λ_i is likely to be increasing in the fund's size, A_i , because the larger is the fund, the larger is the amount traded for a given deviation in weights. For simplicity, we specify

$$\lambda_i = \lambda_0 A_i, \quad (31)$$

with $\lambda_0 > 0$ constant across funds.

We assume the fund maximizes its net alpha, minus a penalty for tracking error, plus a reward for greenness. Specifically, the fund chooses ϕ_i to maximize utility as

$$\max_{\phi_i} \left\{ \phi'_i (\epsilon - \theta g) - \frac{\lambda_0 A_i}{2} \phi'_i \Sigma \phi_i - \frac{\gamma_i}{2} \phi'_i \Sigma \phi_i + d_i (g_B + \phi'_i g) \right\} \quad \text{subject to } \phi'_i \iota = 0, \quad (32)$$

where ι is the N -vector of ones, γ_i denotes the fund's aversion to tracking error, and d_i reflects utility derived from the greenness of the fund's portfolio.

We provide a closed-form solution for ϕ_i in the Appendix. Equation (A.13) implies that funds whose preference for greenness is sufficiently strong, so that $d_i > \theta$, generally tilt toward

green stocks and away from brown stocks, whereas funds with $d_i < \theta$ do the opposite.⁶ All portfolio tilts are muted for funds with larger values of A_i and γ_i .

Define the vector containing the fund’s ESG-related tilt on each stock as

$$\begin{aligned}\Delta_i &= w_i |g \text{ contains actual values} - w_i |g \text{ contains identical values} \\ &= \phi_i |g \text{ contains actual values} - \phi_i |g \text{ contains identical values},\end{aligned}\quad (33)$$

where each ϕ_i above is the solution to (32), given the specified g . The n -th element of Δ_i , which we denote as Δ_{in} , closely follows the empirical definition in equation (1). The fund’s total ESG-related tilt is $T_i = (1/2) \sum_{n=1}^N |\Delta_{in}|$, as defined earlier in equation (7). The formula for Δ_{in} is in equation (A.14) in the Appendix.

3.2. Institution-level predictions

Because the proportional trading cost increases in fund size, a larger fund size is accompanied by smaller deviations of the fund’s optimal portfolio from the benchmark (equation (A.13)). This effect includes ESG-related deviations:

Proposition 1. *The value of T_i is decreasing in the fund’s size.*

Larger fund size is not the only reason a fund’s portfolio tilts away less from the benchmark. Another reason is greater aversion to tracking error, that is, a higher value of γ_i in equation (32). Because ESG-related tilts are a part of total portfolio tilt, changes in fund size and γ_i move both tilts in the same direction. A simple measure of a fund’s total portfolio tilt is active share, defined by Cremers and Petajisto (2009) as

$$AS_i = \frac{1}{2} \sum_{n=1}^N |\phi_{i,n}|. \quad (34)$$

Our model thus implies that greater active share is accompanied by larger ESG-related tilts:

Proposition 2. *The value of T_i is increasing in the fund’s active share, holding constant the fund’s preference for greenness, and whether or not the fund’s size is held constant.*

In our empirical analysis, we denote an ESG tilt operating at the intensive margin as one that moves a stock’s (expected) weight from one positive value to another. The extensive-margin tilt instead moves a weight from positive to zero, or vice versa. The holdings reported

⁶The qualifier “generally” can be dropped when Σ is diagonal and the elements of ϵ are all equal.

in 13F filings exclude short positions. Therefore, our data and empirical setup give each institution either a zero weight or a positive weight on each stock. To consider extensive-margin tilts in the context of our theoretical model, in which optimal weights can be negative, we define a given Δ_{in} as operating at the extensive margin if it changes the sign of a weight.

Proposition 3. *The amount of a fund’s extensive tilt relative to its intensive tilt is non-increasing as fund size increases or active share decreases, holding constant the fund’s preference for greenness.*

The intuition is fairly straightforward. ESG tilts less often cause portfolio weights to change sign when the fund has smaller ESG tilts overall and thereby chooses weights closer to the (positive) benchmark weights. As the previous propositions establish, funds with larger size and lower active share tend to have smaller ESG tilts overall.

The next proposition considers extensive tilts operating in two directions. The first direction, “extensive divestment,” is when Δ_{in} moves the stock’s weight from being positive to non-positive. The second direction, “extensive investment,” is when Δ_{in} instead moves the weight from non-positive to positive. These quantities are the counterparts of $T_i^{ext,U}$ and $T_i^{ext,O}$ from equation (10) in the context of our model.

Proposition 4. *The amount of a fund’s extensive divestment relative to its extensive investment is non-increasing as fund size increases or active share decreases, holding constant the fund’s preference for greenness.*

Loosely speaking, as funds get larger or less active, they become less likely to drop than to add stocks for ESG reasons. The intuition here is somewhat more subtle. Suppose that at a given fund size and active share, ESG tilts drive some of the fund’s otherwise non-positive weights to become positive (extensive investment). As the fund’s size increases or its active share decreases, all of its portfolio weights deviate less from benchmark weights, which are positive. That means the weights made positive by ESG tilts stay positive, and thus extensive investment does not decrease. The latter also means extensive divestment does not increase, because the total extensive tilt (investment plus divestment) does not increase as fund size increases or active share decreases, in accord with Proposition 3.

3.3. Stock-level predictions

To obtain predictions about stock-level tilts, D_n (see equation (11)), we simplify our model to a setting in which the benchmark return captures the common variation in stock returns.

Specifically, we assume that Σ is diagonal, with n -th diagonal element equal to σ_n^2 . We show that this non-benchmark volatility then plays a key role in the stock’s ESG-related tilts.

Proposition 5. *The value of D_n is increasing in $(1/\sigma_n^2)|g_n - \tilde{g}|$, where $\tilde{g} = q'g$ and $q = (1/\iota'\Sigma^{-1}\iota)\Sigma^{-1}\iota$ is the vector of weights in the portfolio that minimizes tracking error.*

Proposition 5 implies two predictions for stock-level ESG-related tilts. First, D_n is greater when the stock is less volatile, for a given deviation of a stock’s greenness from its typical value.⁷ This prediction makes sense, because with lower volatility, a given deviation from the benchmark contributes less to both tracking error and trading cost. Second, D_n is also greater when the stock’s greenness deviates more from the typical value, for a given volatility. This prediction is less surprising, because ESG-related tilts are induced by deviations of ESG characteristics from their typical values (see equation (1)).

4. Estimation framework

To test the above predictions and compute the various portfolio tilts defined in Section 2, we need to estimate two quantities: π_{in} , the probability of institution i holding stock n , and w_{in}^+ , the expected weight conditional on holding the stock (see 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).⁸ We can then aggregate the Δ_{in} estimates into all other tilts defined in Section 2. We estimate π_{in} and w_{in}^+ separately for each quarter t , but we continue suppressing the t subscripts, as in Section 2.

Estimating π and w^+ requires a model for portfolio weights. In Section 4.1, we describe our econometric model for the extensive margin of portfolio weights, which yields an estimate of π . In Section 4.2, we present our model for the intensive margin, which yields an estimate of w^+ . Finally, in Section 4.3, 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

⁷Note that \tilde{g} can be thought of as a typical value of g_n because $q'\iota = 1$, so that \tilde{g} is a weighted average of g_n ’s across stocks. With Σ diagonal, the weight on g_n is simply proportional to $1/\sigma_n^2$.

⁸Note that Δ_{in} is defined for all stocks n , including stocks not actually held by investor i .

(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).

4.1. Extensive margin

Our model of the extensive margin gives the value of

$$\pi_{in} \equiv \text{Prob}\{w_{in} > 0 | X\}. \quad (35)$$

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

$$\pi_{in} = \frac{e^{X_n a_i}}{1 + e^{X_n a_i}}. \quad (36)$$

We estimate the model in equation (36) for each 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 $\hat{\pi}_{in}$, by construction, lie between 0 and 1 and average to the actual proportion of stocks held.

4.2. Intensive margin

Our model of the intensive margin gives the value of

$$w_{in}^+ \equiv \text{E}\{w_{in} | w_{in} > 0, X, \pi_i\}. \quad (37)$$

The expectation in equation (37) 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

$$\frac{w_{in}^+}{w_{mn}} = \sum_{j=1}^K c_{ij} x_{nj}, \quad n = 1, \dots, N, \quad (38)$$

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:

$$\sum_{n=1}^N \pi_{in} w_{in}^+ = 1, \quad (39)$$

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

$$\frac{w_{in}}{w_{mn}} = \sum_{j=1}^K b_{ij} \tilde{x}_{inj} + e_{in}, \quad n = 1, \dots, N, \quad (40)$$

where $\sum_{j=1}^K b_{ij} = 1$ and the j -th independent variable is

$$\tilde{x}_{inj} = \frac{x_{nj}}{\sum_{n=1}^N \pi_{in} w_{mn} x_{nj}}. \quad (41)$$

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

To derive the regression model in equation (40), we assume that for each stock n held by investor i , the actual portfolio weight w_{in} obeys

$$w_{in} = w_{in}^+ + \epsilon_{in}, \quad (42)$$

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 .

4.3 Bias adjustment and standard errors

The coefficients in equations (36) and (40) 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.

5. ESG tilts: Estimates and tests

In this section, we use the econometric framework described in Section 4 to estimate the various ESG-related tilts introduced in Section 2. We analyze various patterns in ESG tilts across time, institutions, and stocks.

5.1. 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.⁹ 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 follow Pástor, Stambaugh, and Taylor (2022), who use data from MSCI, the world’s largest provider of ESG ratings (Eccles and Stroehle, 2018). Berg, Heeb, and Koelbel (2023) find that among the ESG ratings from five major providers, MSCI’s rating is the most important in explaining ESG fund holdings. They also note that MSCI has the largest market share in the ESG data market. The MSCI data cover more companies than other ESG raters (Berg et al., 2022), have relatively low noise (Berg et al., 2023), and provide granular industry-unadjusted measures. 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

⁹We study stocks with CRSP share codes of 10, 11, 12, or 18.

Weight.”¹⁰ 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 online 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 model thus includes two different measures related to stock size.

5.2. The industry’s ESG-related tilts

The solid line in Panel A of Figure 1 displays quarterly estimates of T from equation (12) 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.

¹⁰Environmental 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.

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.

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.

Panel A of Figure 1 also displays estimates of the industry's tilts at the intensive and extensive margins, defined in equations (13) and (14). The extensive-margin tilt is typically around 2%, while the intensive-margin tilt is two to three times higher.

The greater role for the intensive-margin tilt could in principle be driven by institutions holding many stocks. After all, the extensive-margin tilt of an institution holding every stock (e.g., a total market index fund) is zero. Our aggregate tilts are AUM-weighted, and large institutions tend to hold more stocks. To investigate, we construct two counterparts of Panel A of Figure 1, where instead of aggregating tilts across all institutions, we aggregate them within two subsets. The first subset includes institutions that hold an above-median number of stocks in the given quarter, while the second subset includes institutions with a below-median number of holdings, typically fewer than 100.¹¹ (The plots are in the online

¹¹The median number of stocks held ranges from 103 to 118 across quarters, with the overall median of 114 across institution-quarters. The 90th percentile of the number of holdings across institution-quarters is 650, less than one third of all covered stocks in our sample. Most institutions hold relatively few stocks.

appendix.) We find that all tilts are substantially smaller for the first subset of institutions, which is as expected (Proposition 1), given those institutions tend to be larger. More importantly, for both subsets of institutions, the intensive-margin tilt always exceeds the extensive-margin tilt. Specifically, for the first subset, the intensive-to-extensive tilt ratio varies from 2.4 to 5 across quarters, while for the second subset it varies from 1.4 to 1.8. The higher ratios for the first subset are expected (Proposition 3), again because those institutions are larger. Nevertheless, even for institutions holding relatively few stocks, the intensive-margin tilt is substantially higher than the extensive-margin tilt. Therefore, our finding of a greater role for the intensive-margin tilt is not driven just by institutions that hold many stocks.

Table 1 reports fourth-quarter values, year by year, of the tilts plotted in Figure 1, along with bootstrapped standard errors.¹² 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. 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 online appendix reports the tilt estimates and standard errors for the 100 largest institutions 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. We also note that our measures of ESG investing exclude any greening of the market portfolio, as explained earlier, as well as any shareholder engagement.

¹²These standard errors lend themselves to the usual interpretation, because the 5th and 95th percentiles of the bootstrap distributions are close to the estimated tilts minus/plus twice the standard errors.

5.3. Institution-level tilts

In this section, we test our theoretical predictions from Section 3.2 about institution-level ESG tilts. To test Propositions 1 and 2, we regress T_i on active share and/or institution size (AUM). We run these panel regressions in logs, with and without fixed effects for time or institution. We compute each institution’s active share relative to the market benchmark, i.e., as $(1/2) \sum_{n=1}^N |w_{in} - w_{mn}|$. Panel A of Table 2 reports the results.

Consistent with Proposition 1, the AUM coefficient is significantly negative, 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, but a negative relation nevertheless survives the addition of institution fixed effects. Larger institutions have smaller ESG-related tilts, even controlling for active share.

Consistent with Proposition 2, active share enters very significantly, with t -statistics between 13 and 43. This strong relation between the institution’s ESG-related tilt and active share motivates the key role we assign to active share in subsequent analyses.

To test Propositions 3 and 4, we first construct panels of relevant ratios. For Proposition 3, we divide extensive tilt, T_{it}^{ext} , by intensive tilt, T_{it}^{int} , as defined in equations (8) and (9). For Proposition 4, we divide extensive divestment, $T_{it}^{ext,U}$, by extensive investment, $T_{it}^{ext,O}$, as defined in equation (10). We then regress these ratios on active share and/or AUM. As before, we run these regressions in logs, with and without fixed effects for time or institution. Panels B and C of Table 2 report the results for Propositions 3 and 4, respectively.

Consistent with Proposition 3, active share enters positively, with t -statistics between 8 and 20. Also consistent with Proposition 3, AUM always enters negatively, strongly so when included alone (t -statistics of about -9), and also when controlling for active share, quarter, and institution (t -statistic of -6).

Consistent with Proposition 4, active share enters positively, with t -statistics between 2 and 14. That relation is especially strong when isolating the cross-sectional relation with time fixed effects. The same is true of the negative relation with AUM, which also supports Proposition 4 (the t -statistics are -10 and -15).

Overall, our theoretical predictions about institution-level ESG tilts are strongly supported by the results in Table 2. We test our predictions about stock-level tilts in Section 5.5, after further exploring how active share helps us understand ESG tilts.

5.4. The role of 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 2021.¹³ Second, the typical actively managed fund has become more diversified over time, holding more stocks and weighting stocks more in line with 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 noted earlier, a simple measure of tilts made for any reason is active share. 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 2021.¹⁴ This fall in total tilts represents a headwind to institutions’ ESG tilts.

To take overall tilts into account, we divide each institution’s ESG tilt by the institution’s concurrent active share. Note that the coefficients on active share reported in Panel A of Table 2 are between 0.9 and 1.2. Given that we run the regressions in logs, a coefficient not far from unity suggests that simply dividing T_i by active share comes reasonably close to capturing active share’s role in explaining ESG-related tilt. We then aggregate those ratios to the industry level, again taking an AUM-weighted average, and plot them in Figure 3 in the same format as in Figure 1. In contrast to Figure 1, almost all of the series in Figure 3

¹³The 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%.

¹⁴A steady decline in active share has been reported by Cremers and Petajisto (2009), Stambaugh (2014), Kojien, Richmond, and Yogo (2022), and others. Kojien et al. argue that most of this decline is due to capital flows from active to passive investors rather than strategies becoming more passive.

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. By 2021, ESG-related tilts average 22% of total tilts.

Active share varies greatly across institutions. Panel B of Figure 2 plots time series of cross-sectional percentiles in active share. The 5th percentile hovers around 0.3, 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 also applies at the institution level. That is, gauging ESG tilts relative to institutions’ active shares can provide a perspective rather different from that of examining raw tilts.

To 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).

5.5. Stock-level tilts

In this section, we examine the cross section of stock-level ESG tilts. Our analysis is guided by the theoretical model from Section 3, specifically Proposition 5. That proposition addresses

stock n 's ESG tilt, D_n , defined in equation (11). According to this proposition, $\log(D_n)$ is decreasing in $\log(\sigma_n)$ and increasing in $\log(|g_n - \tilde{g}|)$, where σ_n is stock n 's idiosyncratic volatility, g_n is the stock's greenness, and \tilde{g} is a weighted average of the g_n 's across stocks, where the weights are proportional to $1/\sigma_n^2$. Given the well known negative correlation between σ_n^2 and stock n 's market capitalization, \tilde{g} is likely not far from the cap-weighted average of the g_n 's, which is zero, by construction. Therefore, we simply assume that $\tilde{g} = 0$ and test whether $\log(D_n)$ is increasing in $\log(|g_n|)$.

We run panel regressions of $\log(D_n)$ on $\log(\sigma_n)$ and $\log(|g_n|)$, with quarter fixed effects. We measure σ_n by stock n 's idiosyncratic volatility (IVOL), which we compute as the standard deviation of the residuals from the time-series regression of the stock's monthly excess returns on excess market returns. We run this regression using the 36 months of data ending in the previous month, requiring at least 24 months of data. We use four different specifications for \mathcal{G} in the estimation, either all three ESG characteristics jointly or just one of them at a time. When we include only one characteristic (E, S, or G) in \mathcal{G} , we measure g_n by that characteristic. When we use all three characteristics, we measure g_n by MSCI's Weighted-Average Key Issue score, which aggregates the E, S, and G scores. Either way, we subtract the market portfolio's greenness from the stock's greenness to arrive at g_n .

Table 3 shows that $\log(D_n)$ is negatively related to $\log(\sigma_n)$ and positively to $\log(|g_n|)$, as predicted by theory. Both relations are highly statistically significant, with t -statistics exceeding ten, and both obtain for all four specifications of \mathcal{G} . The positive relation between $\log(D_n)$ and $\log(|g_n|)$ is somewhat mechanical, because both D_n and $|g_n|$ are positive and they take some of their lowest values for stocks with $g_n = 0$. (ESG tilts of such stocks need not be zero, due to the interactions between ESG and non-ESG characteristics, but they are likely to be close to zero.) But there is nothing mechanical about the negative relation between $\log(D_n)$ and $\log(\sigma_n)$. Our finding that less-volatile stocks have larger ESG tilts seems novel and interesting, and it provides strong support for Proposition 5.

6. Green and brown portfolio tilts

In this section, we separate green tilts from brown and analyze their empirical patterns. Section 6.1 examines these patterns both across investors and over time, on both extensive and intensive margins. Section 6.2 analyzes how greenness varies across institutions with respect to institutional characteristics such as AUM, type, and location.

6.1. Components of GMB tilts

For any given univariate dimension of ESG, such as E or the composite ESG score, we can apply the classifications in (17) through (20) 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 (21) through (23), 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.¹⁵

If 13F-filing institutions tilt green, then other investors must tilt brown (see equation (27)). 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.

¹⁵These findings, especially the first and third, hold also when the raw tilts are not scaled by active share. For example, for the composite ESG score, the raw green tilt grows from 4% to 5% of assets over our sample period, whereas the raw brown tilt is approximately flat at 2% of assets. See the online appendix.

Some of the most vocal dialogue surrounding ESG investing calls for institutions to divest from brown stocks.¹⁶ 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). In other words, most brown-stock divestment is partial, reducing brown stocks’ weights, as opposed to total divestment that eliminates holdings. Unlike the extensive margin, the intensive one rises substantially over time, increasing threefold between 2012 and 2021.

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 averages of this value across institutions are plotted as dashed lines in Figure 9. These averages are typically smaller than those for the number of stocks dropped. Intuitively, institutions have added fewer brown stocks (a brown behavior) than they have dropped (a green behavior).

¹⁶For 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.

6.2. 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 mostly negative and decreasing (this is true for three of the four greenness measures; for the fourth measure, E, these tilts are positive and decreasing). In essence, the industry’s positive and increasing GMB tilt owes to just the largest institutions.

The GMB tilt grows particularly fast for the “Big Three” institutions: BlackRock, Vanguard, and State Street. These institutions account for about 30% of the total AUM in the large-institution category at the end of our sample. We find that the AUM-weighted average GMB tilt of the Big Three grows even faster than its large-institution counterpart, for all four measures of greenness. For example, when greenness is measured by the ESG composite, the large-institution GMB tilt grows to about 25% of active share (see Panel A of Figure 10), whereas the Big-Three GMB tilt grows to about 55% of active share. All of the Big Three exhibit growing GMB tilts, though BlackRock’s tilt rises the fastest. Nonetheless, even when we exclude the Big Three from the large-institution group, the remaining institutions in that group exhibit a positive and increasing GMB tilt, for all four measures of greenness. Therefore, the main patterns in Figure 10 are robust to the exclusion of the Big Three. The details of the Big Three results are in the online appendix.

The number of green-tilting institutions is 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.¹⁷ 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. Finally, we determine each institution’s geographical location based on the 13F filings and manual checks.

Table 4 reports the estimates from panel regressions of institutions’ GMB tilts on a number of explanatory variables that include UNPRI, institution-type, and location 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 online 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 institution-type dummies when including institution fixed effects).

A number of significant relations appear in Table 4. 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 2.2 percentage point (pp) increase in GMB tilt in 2021 and a 1.7 pp decrease in GMB tilt in 2012.¹⁸ 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

¹⁷We 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.

¹⁸The difference in $\log(\text{AUM})$ between the two percentiles is 1.43. Note that 0.022 equals 1.43×0.0155 , and -0.017 equals $1.43 \times [0.0155 - 0.36 \times 0.0764]$, where -0.36 is the value of Trend in 2012.

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 2.4–4.6 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 7.2–13.0 pp lower than those of insurance companies (the omitted type). Banks are also significantly browner than both investment advisors and pensions/endowments. When greenness is instead measured by E or G, banks again appear browner than the other institution types, but the differences are sometimes insignificant. According to most specifications, insurance companies are the greenest institution type.

In the online appendix, we show the time series of GMB tilts by institution type. For all four types, including banks, the GMB tilt is positive and growing over the sample period. The positive GMB tilt for banks may seem surprising, given the evidence discussed in the previous paragraph. The reason behind it is that the type-level GMB tilts are computed by AUM-weight-averaging the GMB tilts of institutions within the given type. While a typical bank is brown, the largest banks are green (recall the positive coefficients on AUM in Table 4), and their greenness disproportionately affects the AUM-weighted average.

As also shown by Table 4, European institutions are significantly greener than U.S. ones (the omitted category). Depending on the specification, European institutions' GMB tilts are 3.2–4.9 pp higher than those of U.S. institutions. The GMB tilts of institutions located in the rest of the world are between those of European and U.S. institutions.

For comparison, Koijen, Richmond, and Yogo (2022) find that non-U.S. investors have a higher demand for stocks with higher E scores but lower G scores. They also find differences in demand elasticities for E and G scores across institution types. However, they use a different methodology and different data; for example, their E scores come from Sustainalytics and their G scores reflect the number of entrenchment provisions. Atta-Darkua et al. (2022) find that European investors who are members of the CDP (formerly the Carbon Disclosure Project) have been decarbonizing their portfolios faster than other investors.

Table 5 explores whether the above 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 .¹⁹ 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 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 to active share, as the positive effects in the green and brown legs offset each other (Table 4). This result reinforces the importance of evaluating ESG-related tilts in relation to active share.

6.3. ESG investing versus index investing

As noted earlier, we distinguish ESG investing from index 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.

To say there is no ESG investing in that setting seems reasonable. For example, the standard CAPM is another setting in which investors all hold the market portfolio. In that setting, investors have a preference for low-beta stocks. That is, low-beta stocks have lower expected returns, so they have higher prices and thus greater market weights, other things equal. Presumably, though, one would characterize the CAPM setting as having only index investing, not “low-beta” investing.

The market portfolio’s weights depend on the average strength of ESG preferences, but without heterogeneity in those preferences, there would be no ESG investing. The latter arises from differences in ESG preferences across investors. Pástor, Stambaugh, and Taylor (2021), to simplify their theory, preclude reasons other than ESG for why investors deviate from the market portfolio. Here we allow additional stock characteristics to affect investors’ portfolio choices, given our empirical focus, but we maintain the same distinction between ESG and index investing by controlling for market weights when estimating tilts.

If the average ESG preference strengthens, then, all else equal, the market portfolio will allocate more to green stocks. To investigate this possibility, for each month t we compute

¹⁹Table 5 reports results from regressions without fixed effects. Results with fixed effects are in the online appendix. Results with time fixed effects are very similar to those reported in Table 5.

the quantity

$$\kappa_t = \sum_{n=1}^{N_{t-1}} (w_{mn,t} - w_{mn,t-1}) g_{n,t-1}, \quad (43)$$

where N_{t-1} is the number of stocks in our covered universe at the beginning of the month, and $w_{mn,s}$ is proportional to stock n 's market capitalization, summing to 1 across stocks for s equal to both $t-1$ and t . The value of κ_t is positive (negative) if market weights reallocate toward green (brown) stocks during month t . Recall that the greenness measure $g_{n,t-1}$ is expressed as a cross-sectional percentile, so κ_t is equivalent to the change in the fraction of stocks whose $g_{n,t-1}$ is less than the market-weighted $g_{n,t-1}$ across all stocks.

Figure 12 plots the cumulative sum of κ_t over the sample period for each of the four greenness measures. For the ESG composite, the cumulative reallocation is relatively flat until 2016 but then increases by 7 percentage points by late 2019, before dropping somewhat. The reallocation to E-friendly stocks increases steadily over the sample period by nearly 8 percentage points in total. Therefore, for greenness measured by the ESG composite or by E, the market portfolio's allocation to green stocks increases substantially overall between 2012 and 2020. In contrast, the reallocation to S-friendly stocks drops about 5 points between 2013 and 2015, subsequently recovering only about half that amount, while the market modestly reallocates away from G-friendly stocks throughout the period.

7. 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 12% to 22% over the last five years, indicating that ESG tilts are almost one quarter 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.

We document a rich set of patterns in our estimates of ESG tilts. For example, we find that ESG tilts are larger for smaller institutions, for institutions with larger active shares, and for stocks with less volatile returns. All of these patterns are consistent with our theoretical model of optimal institutional portfolio choice.

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. These results are consequential because green tilts likely impose a financial cost, as noted earlier.

We find that greenness varies strongly across institutions. Larger institutions are 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. UNPRI signatories are also greener, not only across institutions but also over time, indicating that a given institution becomes greener after becoming a signatory. European institutions are greener than American ones. The least green institution type is banks.

Our study opens many avenues for future research. For example, do institutions substitute voting green for tilting green, or are those actions complementary?²⁰ How do stocks’ ESG tilts relate to their expected returns? How large are the financial costs incurred by institutions with green tilts? One could also apply our methodology to measure portfolio tilts with respect to non-ESG characteristics as well as tilts in other asset classes, such as bonds, bank loans, and private equity.

²⁰A growing literature compares the effectiveness of exit and voice strategies at curtailing firms’ anti-social behavior. For a recent example of an empirical comparison, see Saint-Jean (2023).

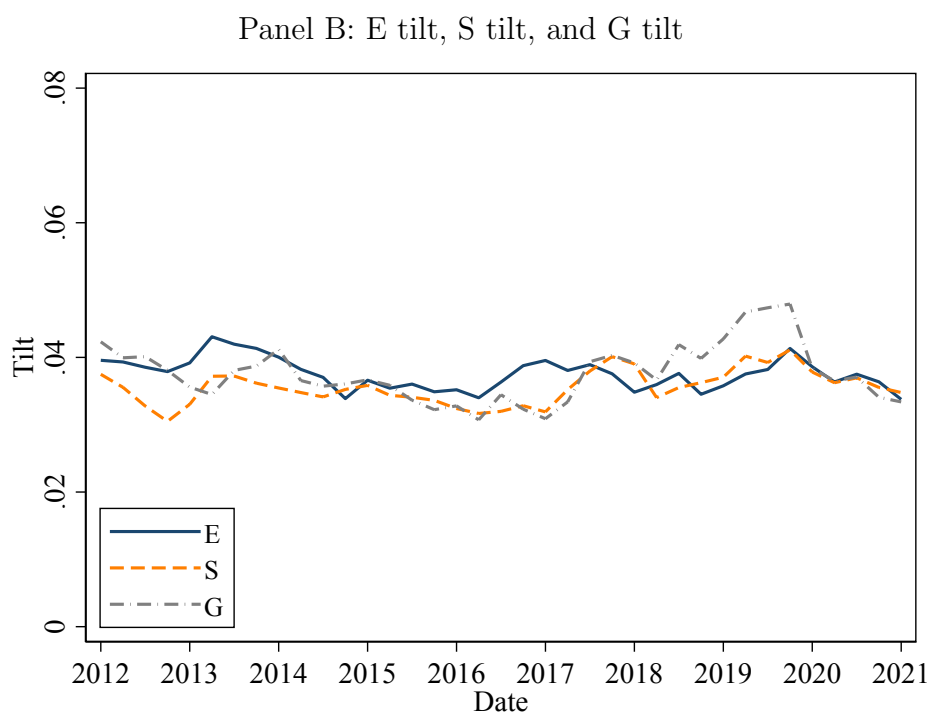
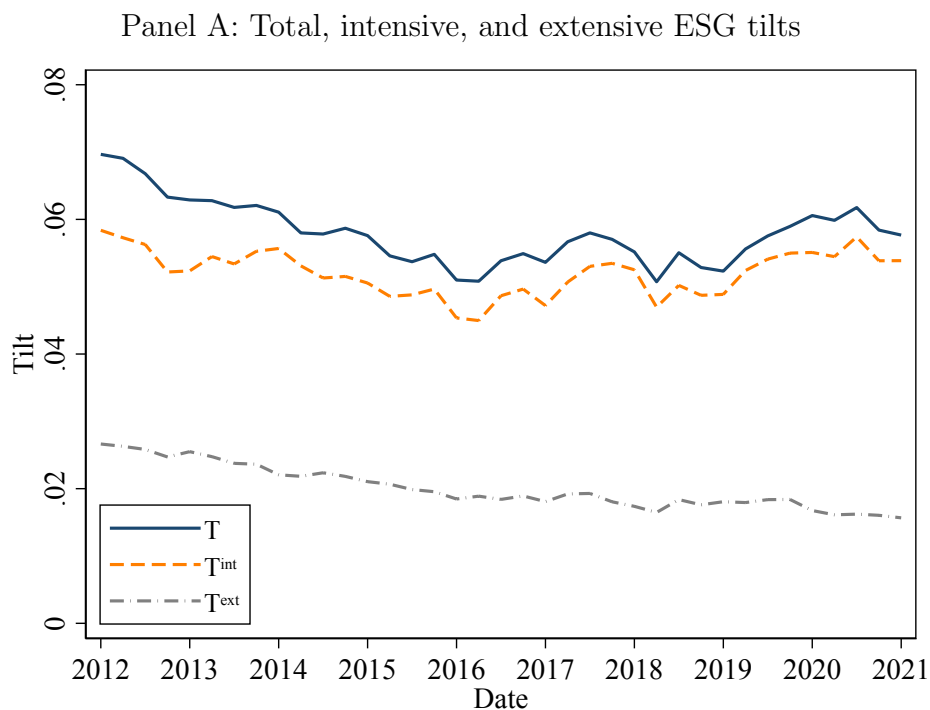
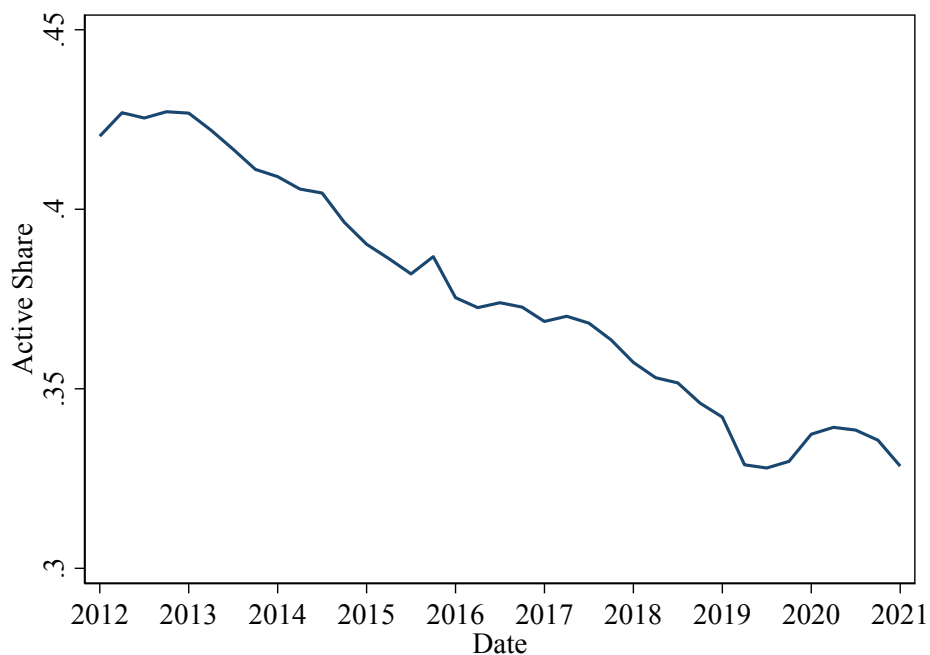


Figure 1. ESG-related tilts. Panel A plots the aggregate ESG-related tilt (T) and its decomposition into intensive and extensive tilts, T^{int} and T^{ext} , respectively. Panel B plots tilts for each ESG component: E, S, and G. Tilts are expressed as a fraction of institutions' aggregate AUM. Tick marks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

Panel A: AUM-weighted average



Panel B: Percentiles

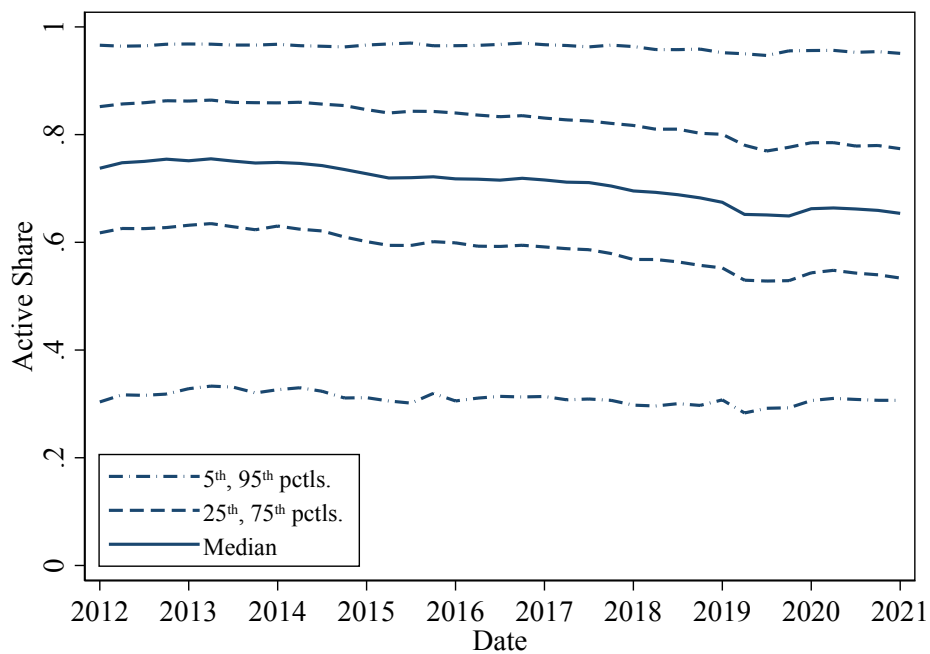
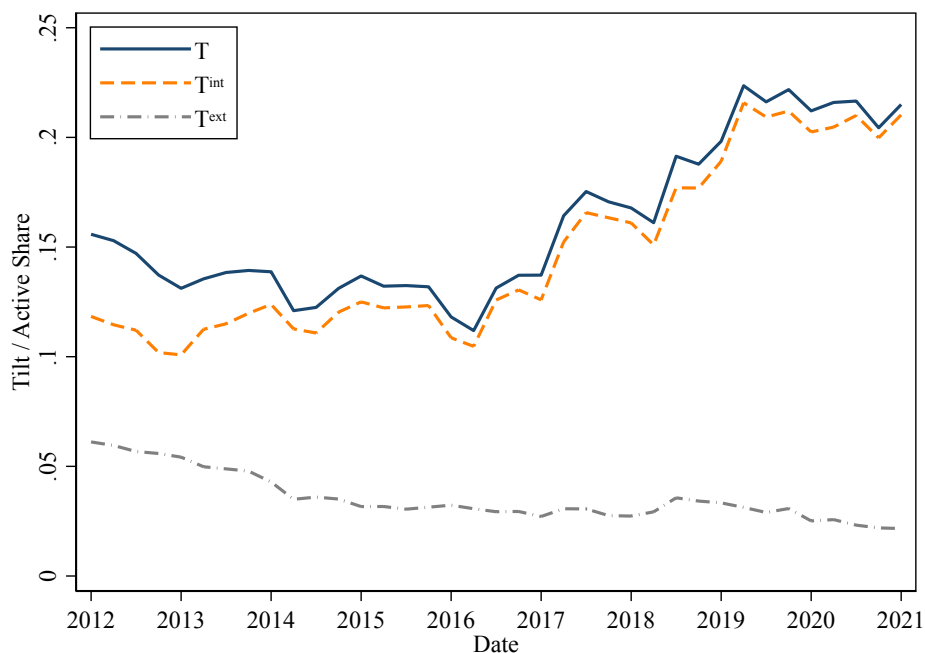


Figure 2. Active share. Panel A plots the AUM-weighted average of institutions' active share. Panel B plots the cross-sectional percentiles of active share.

Panel A: Total, intensive, and extensive ESG tilts



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

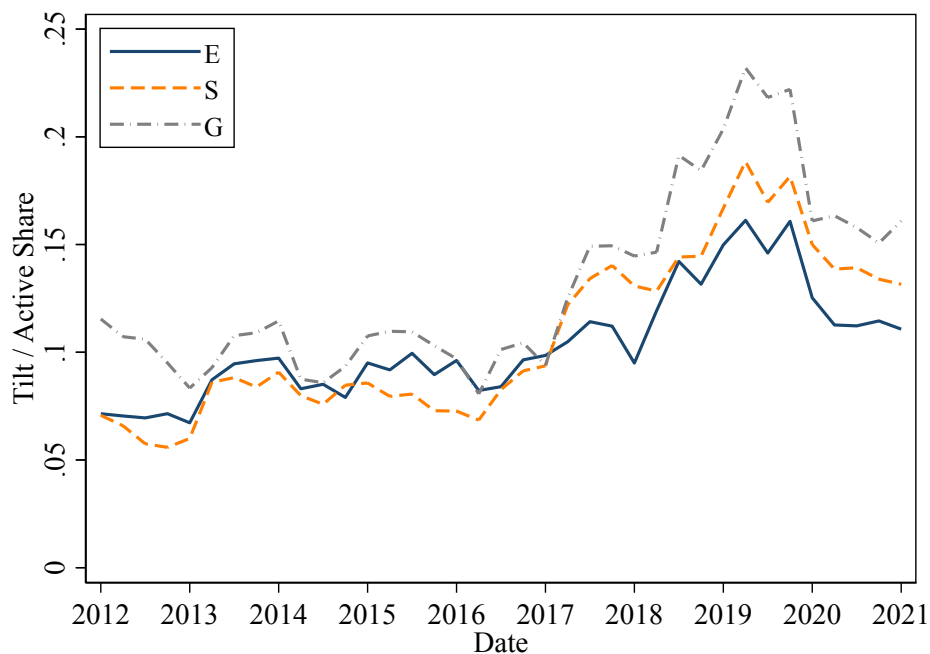
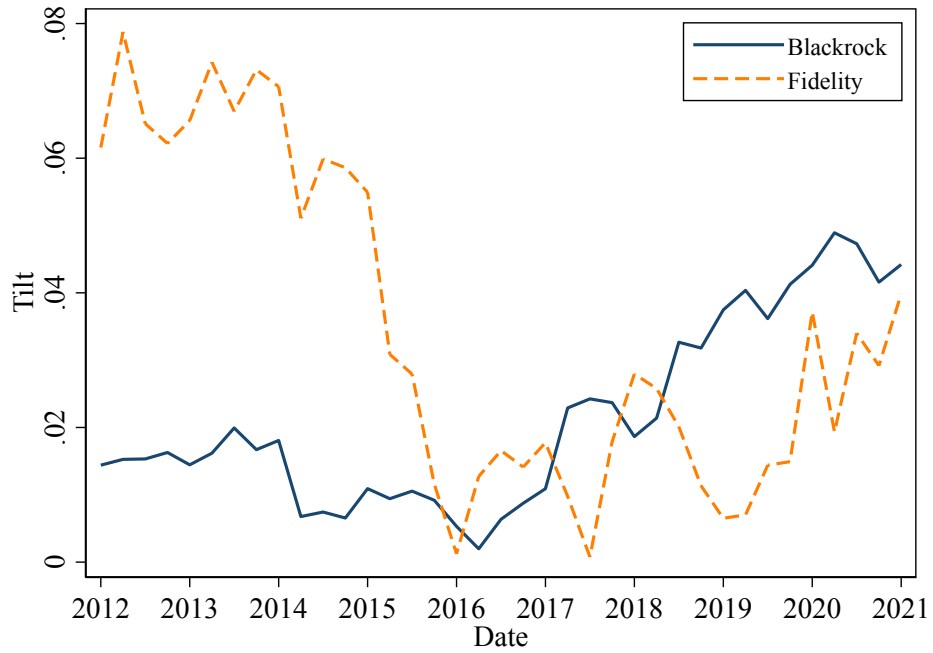


Figure 3. ESG-related tilts relative to active share. Tilts in both panels are the same as in Figure 1, but here we divide each institution's tilt by its active share and then plot the AUM-weighted average of the resulting quantities.

Panel A: Raw tilts



Panel B: Tilts divided by active share

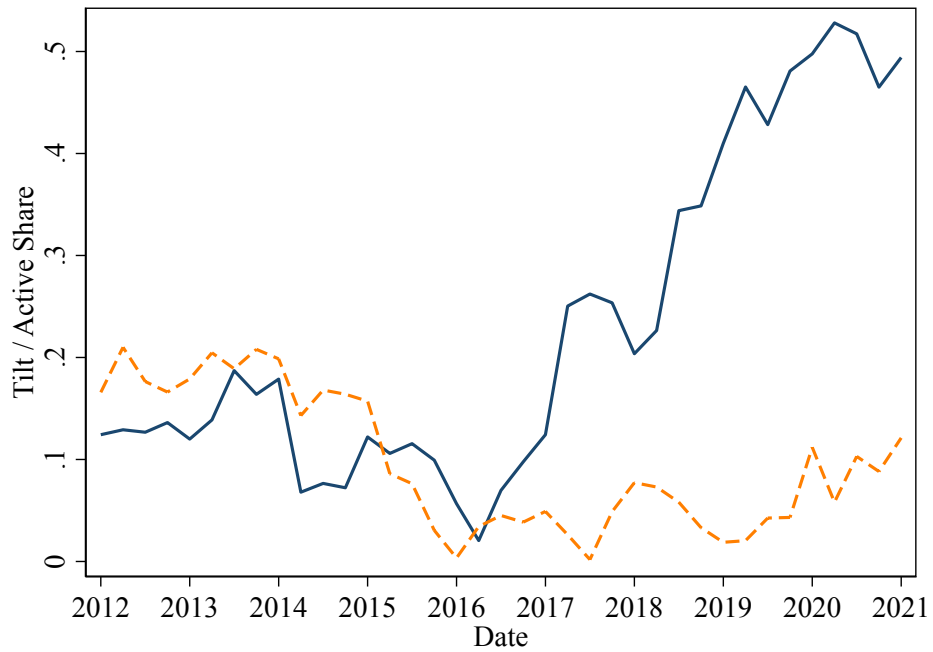


Figure 4. Tilts relative to active share. Panel A plots the time series of T_i , the ESG-related tilt, for BlackRock and Fidelity. Panel B plots each institution's ratio of T_i to active share.

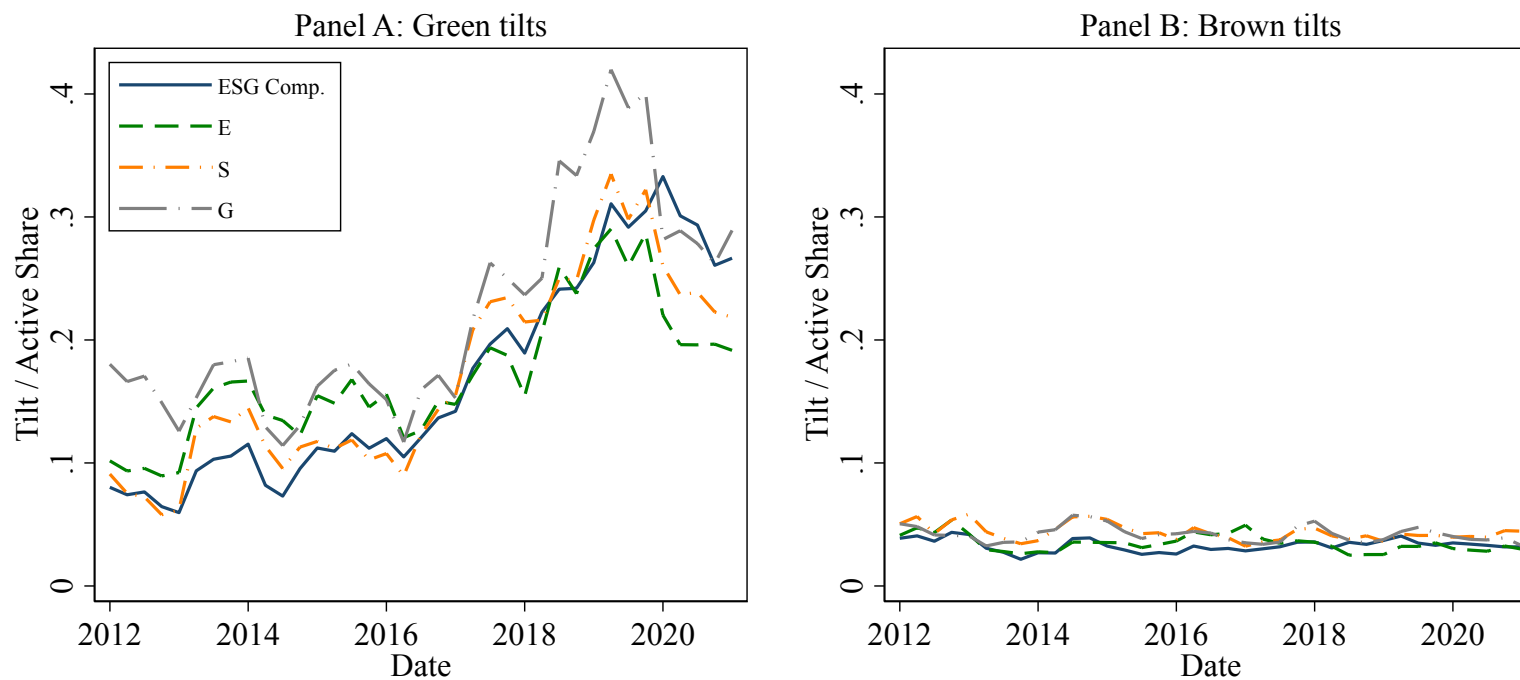


Figure 5. Green and brown tilts. The green and brown tilts for the ESG composite are from the model specification with a single ESG characteristic per stock. The other three pairs of tilts are from the specification with three ESG characteristics per stock, changing one of the three characteristics to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

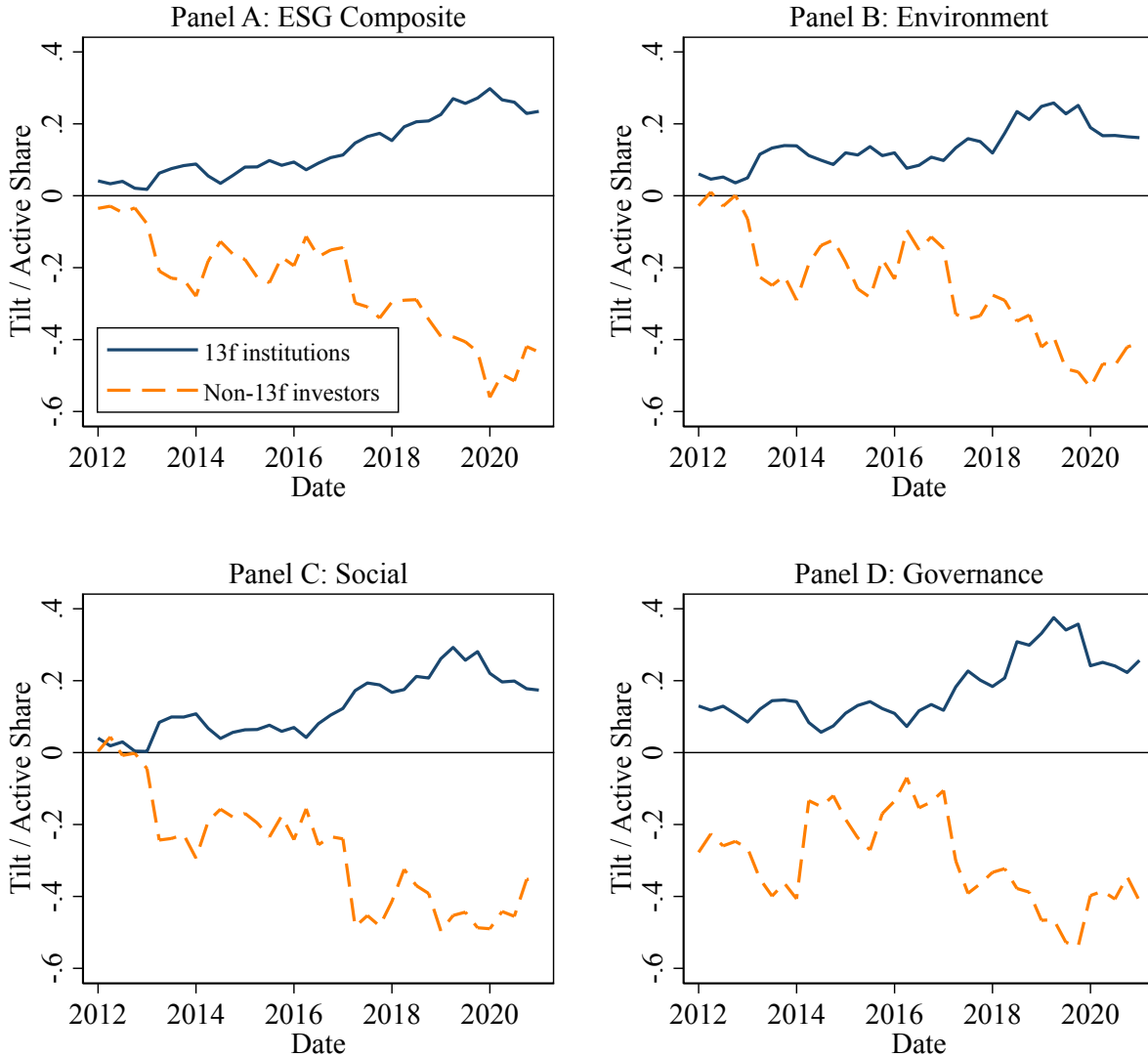


Figure 6. GMB tilts of 13F filers and non-filers. The solid line shows the AUM-weighted average of tilt divided by active share across sample 13F institutions. The dashed line shows the same quantity for non-13F investors, which we treat as a single quasi-institution whose dollar holding of each stock 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.

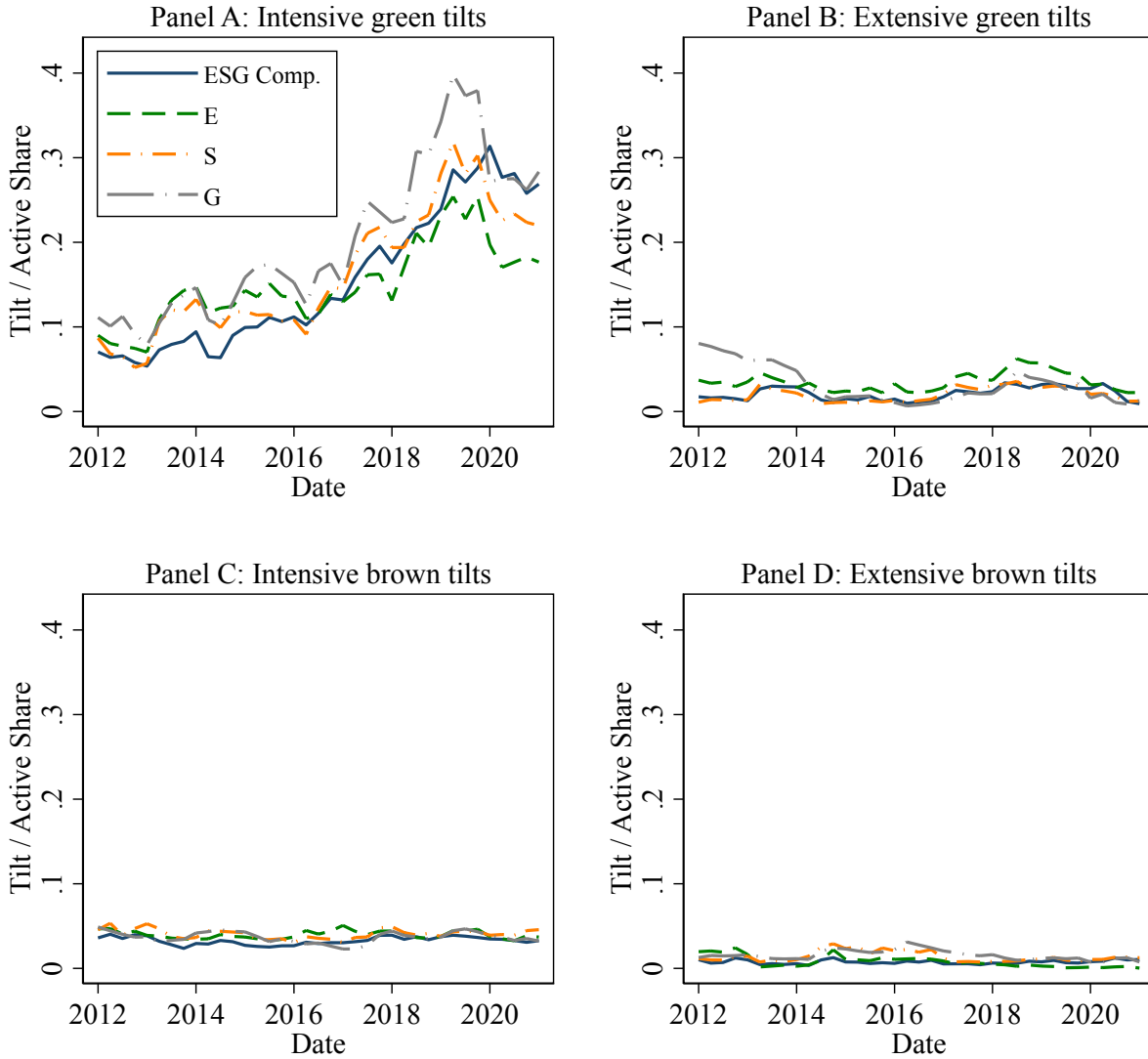


Figure 7. Components of green and brown tilts. Tilts using the ESG composite are from the model specification with a single ESG characteristic per stock, and other tilts are from the specification with three ESG characteristics per stock. We divide each institution's tilt by its active share and plot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

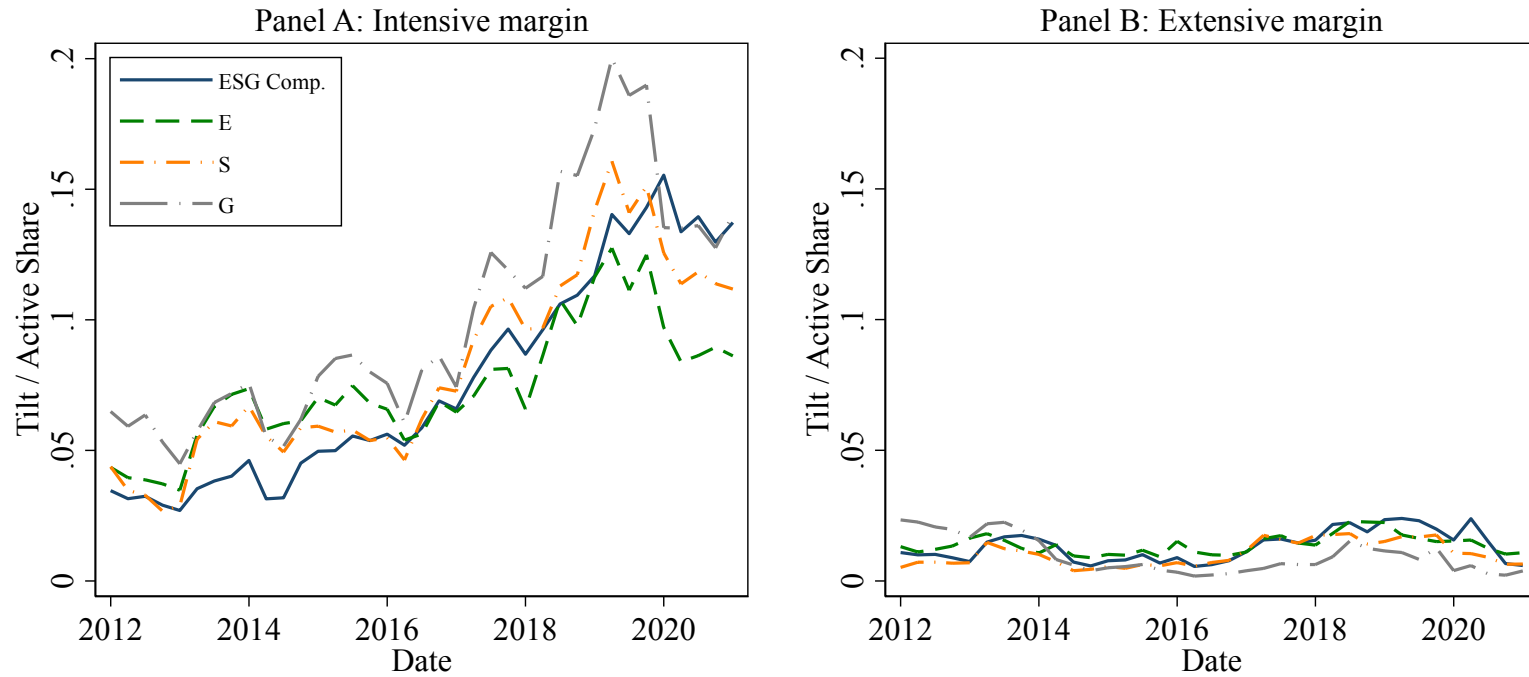


Figure 8. Divestment from brown stocks. Divestment from brown stocks, which is a component of green tilt, can be done on either the extensive margin (full divestment) or intensive margin (partial divestment). We show both. Panel A shows the component of intensive green tilts (from Panel A of Figure 7) 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.

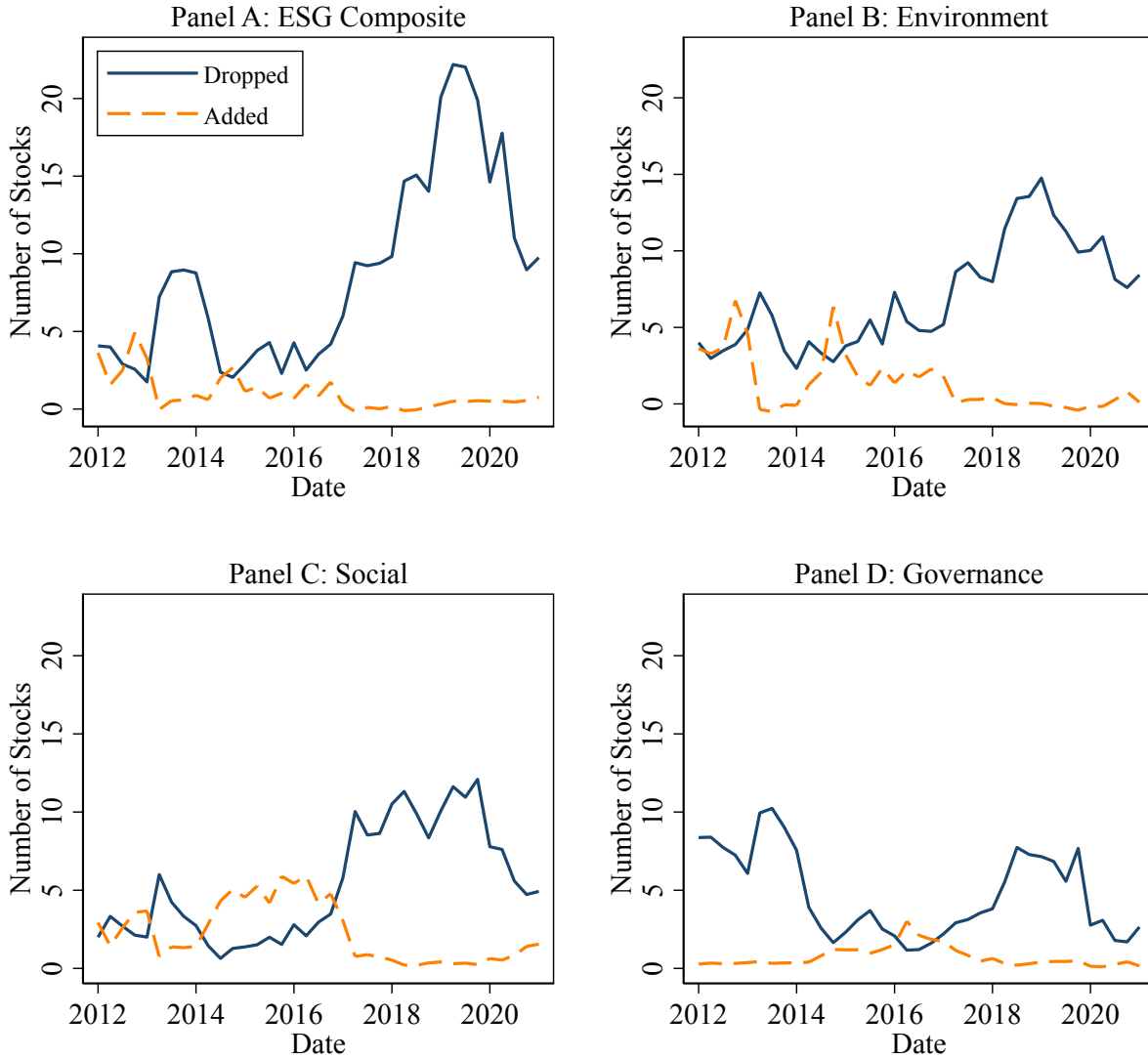


Figure 9. Number of brown stocks added and dropped. This figure shows the AUM-weighted average of institutions' expected number of brown stocks added and dropped. For example, on the Environment dimension, define $\Delta_{in}^{\pi} = \pi_{in}(\mathcal{G}) - \pi_{in}(\mathcal{G}_0^E)$, where \mathcal{G}_0^E 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.

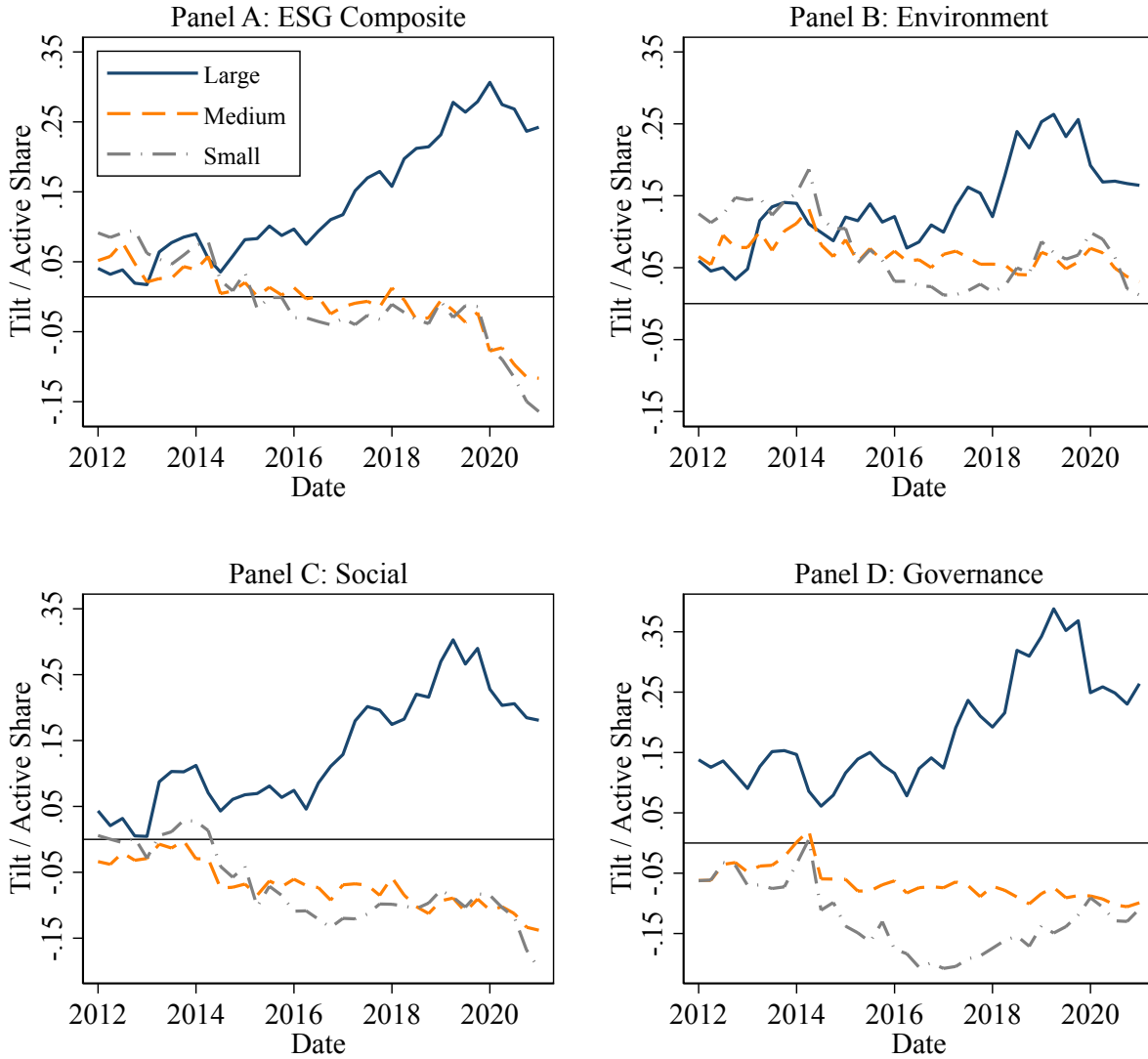


Figure 10. Institution size and greenness. This figure compares GMB tilts across subsamples formed on institution size. Each line shows the AUM-weighted average of GMB tilt divided by active share within a subsample of institutions. In Panel A, \mathcal{G} contains only the composite ESG score, and tilts 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.

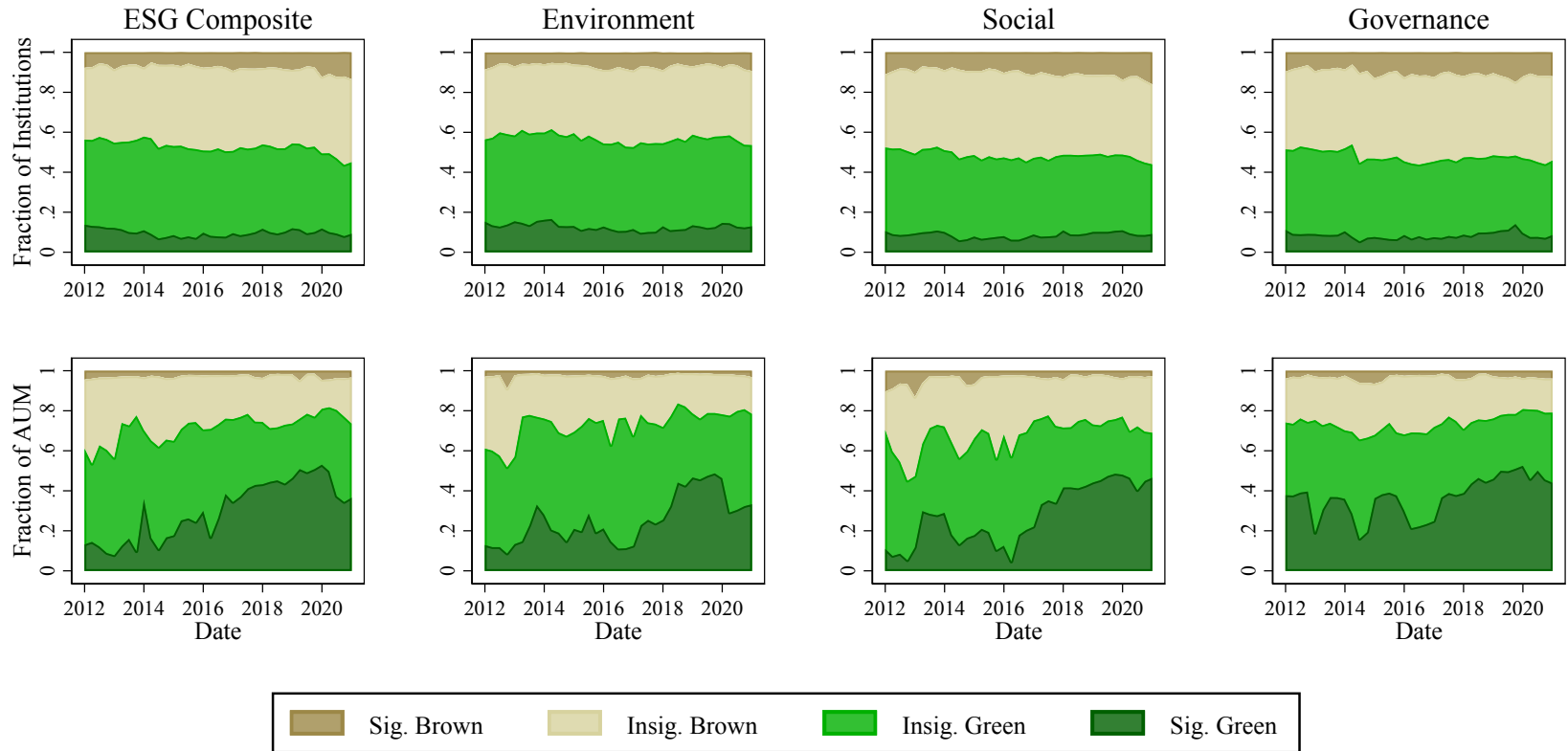


Figure 11. Fraction of institutions green vs. brown. The top row shows the fraction of institutions that are significantly brown at the 5% confidence level, insignificantly brown at the 5% confidence level, and similarly for green. The bottom row shows the fraction of sample covered AUM belonging to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

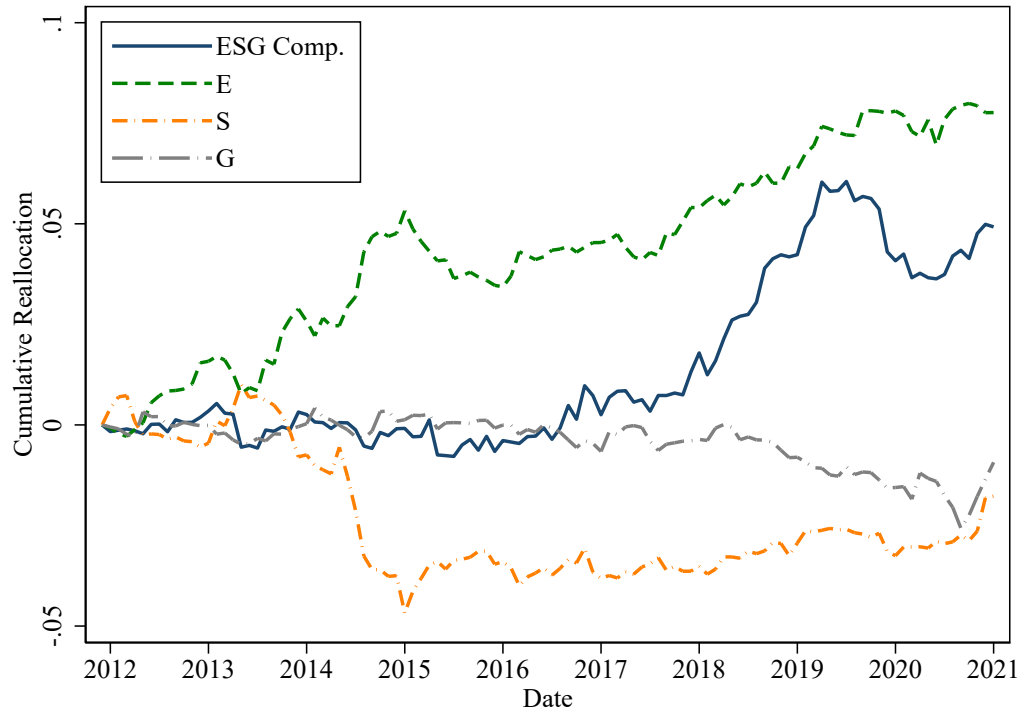


Figure 12. Market reallocation to green stocks. The figure plots the cumulative monthly change in the fraction of stocks whose greenness, g_n , is less than the value-weighted mean of g_n across all stocks. A positive (negative) change corresponds to the market placing greater (less) weight on green stocks relative to brown. The figure shows results with four versions of g_n : the composite ESG score as well as its separate E, S, and G components.

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
Institution-level ESG tilts

This table shows results from panel regressions at the institution-quarter level. The dependent variable in Panel A is the log of the institution's ESG-related tilt, T_{it} . The dependent variable in Panel B is the log of $T_{it}^{ext}/T_{it}^{int}$, the ratio of the institution's extensive to intensive tilt. The dependent variable in Panel C is the log of $T_{it}^{ext,U}/T_{it}^{ext,O}$, the ratio of the institution's ESG-related extensive divestment to extensive investment. AUM is divided by the total market capitalization of all covered stocks. All regressions in Panel A (B) [C] use 80,023 (72,777) [69,316] institution \times quarter observations from 2012q4–2021q4. Robust t -statistics clustered by institution are in parentheses. The bottom rows indicate the fixed effects (FEs) included. 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)
Panel A: Dependent variable $\log(T_{it})$									
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)	-0.084 (-5.00)	-0.093 (-15.13)	-0.090 (-14.09)	-0.032 (-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
Panel B: Dependent variable $\log(T_{it}^{ext}/T_{it}^{int})$									
log(Active share)	1.110 (20.03)	1.092 (19.71)	1.045 (9.83)				1.103 (19.54)	1.066 (18.60)	0.906 (8.41)
log(AUM)				-0.095 (-8.46)	-0.110 (-9.52)	-0.194 (-8.48)	-0.004 (-0.39)	-0.015 (-1.48)	-0.140 (-6.10)
R^2	0.095	0.100	0.439	0.014	0.027	0.437	0.095	0.100	0.440
R^2 (FEs only)	N/A	0.009	0.435	N/A	0.009	0.435	N/A	0.009	0.435
Panel C: Dependent variable $\log(T_{it}^{ext,U}/T_{it}^{ext,O})$									
log(Active share)	0.427 (13.67)	0.433 (13.71)	0.192 (2.16)				0.274 (7.44)	0.283 (7.55)	0.203 (2.19)
log(AUM)				-0.112 (-15.50)	-0.109 (-14.97)	-0.001 (-0.04)	-0.089 (-10.84)	-0.083 (-9.96)	0.011 (0.47)
R^2	0.015	0.046	0.428	0.021	0.051	0.428	0.027	0.056	0.428
R^2 (FEs only)	N/A	0.031	0.428	N/A	0.031	0.428	N/A	0.031	0.428
Time FEs	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Institution FEs	No	No	Yes	No	No	Yes	No	No	Yes

Table 3
Stock-level ESG tilts

This table shows results from panel regressions at the stock-quarter level. The dependent variable is the log of the stock’s ESG-related tilt, D_{nt} . Stock-level tilts are aggregated across all 13F institutions. Column headers denote the ESG variable(s) used to compute tilts, with “ESG” referring to the 3×1 vector g_{nt} . IVOL is the stock’s idiosyncratic volatility, computed as the standard deviation of residuals from a monthly time-series regression of the stock’s excess returns on excess market returns using the 36 months of data ending in the previous month, requiring at least 24 months of data. $\log(|g|)$ is the log absolute value of the stock’s greenness, computed as the stock’s raw greenness minus the market’s greenness, not converted to a percentile. Greenness in column one is computed using MSCI’s Weighted-Average Key Issue Score. All regressions include quarter fixed effects. Robust t -statistics clustered by stock are in parentheses. We tabulate the regression R^2 as well as the R^2 from a regression on quarter FEs only.

	(1)	(2)	(3)	(4)
	ESG	Env.	Soc.	Gov.
log(IVOL)	-0.175 (-18.05)	-0.180 (-14.97)	-0.177 (-23.10)	-0.114 (-11.71)
log(g)	0.108 (27.66)	0.562 (88.03)	0.661 (113.17)	0.577 (90.64)
Observations	77,225	77,208	77,193	77,177
R^2	0.161	0.610	0.791	0.525
R^2 (FEs only)	0.040	0.027	0.032	0.039

Table 4: Which institutions are greener?

This table shows results from panel regressions with the dependent variable equal to the institution's GMB tilt, T_{it}^{GMB} . The greenness measure is noted in the column headers. All regressions use 78,693 institution \times quarter non-missing 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. Institution types are from Bushee et al. (2014), with 1(Insurance) the excluded category. Institution locations are from the 13F filings, with 1(United States) the excluded category. 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 p -values testing whether the coefficients are equal across the four institution-type indicators (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)	0.0155 (5.72)	-0.0020 (-0.66)	0.0199 (5.97)	0.0150 (5.34)	0.0148 (5.42)	-0.0005 (-0.15)	0.0202 (6.01)	0.0169 (5.93)	0.0027 (0.41)	-0.0184 (-2.40)	0.0117 (1.46)	-0.0055 (-0.82)
log(AUM) \times trend	0.0764 (6.60)	0.0310 (2.30)	0.0504 (3.75)	-0.0014 (-0.13)	0.0731 (6.24)	0.0385 (2.83)	0.0519 (3.82)	0.0082 (0.71)	0.0652 (4.99)	0.0259 (1.82)	0.0495 (3.33)	-0.0056 (-0.45)
Trend	0.5814 (4.99)	0.1906 (1.40)	0.3830 (2.84)	-0.0655 (-0.56)					0.4504 (3.60)	0.0802 (0.57)	0.3690 (2.57)	-0.1123 (-0.90)
Active share	-0.0224 (-1.24)	-0.0428 (-1.88)	-0.0022 (-0.09)	-0.0885 (-4.25)	-0.0212 (-1.18)	-0.0414 (-1.82)	-0.0012 (-0.05)	-0.0871 (-4.18)	-0.0698 (-1.48)	-0.1547 (-2.81)	-0.0292 (-0.51)	-0.0890 (-1.83)
1(UNPRI)	0.0402 (3.79)	0.0421 (3.49)	0.0421 (3.50)	0.0263 (2.55)	0.0406 (3.83)	0.0402 (3.33)	0.0415 (3.45)	0.0242 (2.35)	0.0363 (2.30)	0.0462 (2.51)	0.0285 (1.75)	0.0047 (0.28)
1(Inv. advisor)	-0.0324 (-2.02)	-0.0111 (-0.51)	-0.0022 (-0.08)	-0.0285 (-1.12)	-0.0327 (-2.04)	-0.0109 (-0.50)	-0.0021 (-0.08)	-0.0283 (-1.11)				
1(Bank)	-0.0724 (-3.46)	-0.0266 (-1.07)	-0.1304 (-3.82)	-0.0586 (-2.05)	-0.0725 (-3.47)	-0.0263 (-1.06)	-0.1304 (-3.81)	-0.0584 (-2.04)				
1(Pension/endowment)	-0.0272 (-1.47)	-0.0274 (-1.02)	0.0202 (0.68)	-0.0127 (-0.46)	-0.0270 (-1.46)	-0.0271 (-1.01)	0.0204 (0.69)	-0.0124 (-0.45)				
1(Europe)	0.0324 (2.36)	0.0491 (3.17)	0.0466 (2.81)	0.0440 (3.01)	0.0319 (2.32)	0.0494 (3.18)	0.0465 (2.80)	0.0444 (3.03)				
1(Rest of world)	0.0111 (0.71)	0.0297 (1.70)	0.0176 (0.89)	0.0150 (0.79)	0.0109 (0.69)	0.0309 (1.77)	0.0180 (0.92)	0.0163 (0.86)				
R^2	0.013	0.004	0.019	0.016	0.015	0.007	0.020	0.019	0.441	0.460	0.499	0.430
R^2 (FEs only)	N/A	N/A	N/A	N/A	0.007	0.003	0.003	0.003	0.437	0.457	0.497	0.430
p (Inst. types equal)	0.006	0.552	0.000	0.077	0.006	0.558	0.000	0.077	N/A	N/A	N/A	N/A

Table 5: Green and brown tilts

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

	Green Tilts				Brown Tilts			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	0.0015 (1.06)	-0.0058 (-2.97)	0.0022 (1.23)	0.0034 (2.48)	-0.0140 (-7.80)	-0.0038 (-2.17)	-0.0176 (-8.09)	-0.0116 (-5.98)
log(AUM) \times trend	0.0310 (4.71)	0.0209 (2.35)	0.0175 (2.31)	0.0049 (0.83)	-0.0454 (-6.36)	-0.0101 (-1.41)	-0.0328 (-3.95)	0.0063 (0.82)
Trend	0.2584 (3.87)	0.1472 (1.64)	0.1781 (2.30)	0.0531 (0.87)	-0.3230 (-4.50)	-0.0437 (-0.59)	-0.2042 (-2.48)	0.1183 (1.52)
Active share	0.0831 (8.28)	0.1220 (8.66)	0.1204 (9.70)	0.0754 (7.45)	0.1056 (9.27)	0.1642 (12.41)	0.1225 (7.87)	0.1637 (11.56)
1(UNPRI)	0.0194 (2.84)	0.0185 (2.28)	0.0117 (1.58)	0.0030 (0.53)	-0.0207 (-3.60)	-0.0235 (-3.83)	-0.0304 (-4.40)	-0.0233 (-3.55)
1(Inv. advisor)	-0.0090 (-0.88)	-0.0018 (-0.10)	0.0077 (0.73)	-0.0161 (-1.29)	0.0234 (2.93)	0.0094 (1.02)	0.0098 (0.47)	0.0123 (0.72)
1(Bank)	-0.0175 (-1.54)	-0.0132 (-0.72)	-0.0285 (-2.43)	-0.0288 (-2.10)	0.0549 (4.26)	0.0133 (1.15)	0.1019 (3.85)	0.0298 (1.54)
1(Pension/endowment)	-0.0156 (-1.43)	-0.0152 (-0.79)	0.0102 (0.81)	-0.0164 (-1.18)	0.0116 (1.15)	0.0122 (0.95)	-0.0100 (-0.47)	-0.0037 (-0.20)
1(Europe)	0.0236 (2.53)	0.0360 (3.43)	0.0266 (2.44)	0.0298 (3.44)	-0.0088 (-1.16)	-0.0131 (-1.61)	-0.0200 (-2.14)	-0.0143 (-1.66)
1(Rest of world)	0.0139 (1.41)	0.0198 (1.66)	0.0163 (1.34)	0.0180 (1.85)	0.0028 (0.32)	-0.0101 (-1.09)	-0.0012 (-0.11)	0.0031 (0.25)
R^2	0.016	0.020	0.020	0.009	0.030	0.029	0.036	0.039
p (Inst. types equal)	0.266	0.392	0.000	0.147	0.000	0.674	0.000	0.091

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Appendix

A.1. Aggregating tilts across stocks vs. across investors

In this section, we prove the statement in equation (16): that summing up stock-level tilts across stocks produces the same aggregate as summing up investor-level tilts across investors.

$$\begin{aligned}
 D &= \sum_n w_{mn} D_n = \sum_n \frac{M_n}{M} \frac{1}{2M_n} \sum_{i \in \mathcal{S}} A_i |\Delta_{in}| = \frac{1}{2M} \sum_n \sum_{i \in \mathcal{S}} A_i |\Delta_{in}| = \\
 &= \frac{A}{M} \sum_{i \in \mathcal{S}} \frac{A_i}{A} \left(\frac{1}{2} \sum_n |\Delta_{in}| \right) = \frac{A}{M} \sum_{i \in \mathcal{S}} \frac{A_i}{A} T_i = \frac{A}{M} T.
 \end{aligned} \tag{A.1}$$

When the set \mathcal{S} includes all investors, then $A = M$ and thus $D = T$. \square

A.2. Green and brown tilts net to zero across all investors

In this section, we prove the statement in equation (27), 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 ,

$$\sum_i \phi_i w_{in} = \sum_i \frac{A_i}{A} \frac{M_{in}}{A_i} = \sum_i \frac{M_{in}}{A} = \sum_i \frac{M_{in}}{M} = \frac{M_n}{M} = w_{mn}, \tag{A.2}$$

with the sums taken across all investors. Taking conditional expectations of both sides of equation (A.2), we obtain

$$\sum_i \phi_i \mathbb{E}\{w_{in} | \mathcal{G}, \mathcal{C}\} = \sum_i \phi_i \mathbb{E}\{w_{in} | \mathcal{G}_0, \mathcal{C}\} = w_{mn}, \tag{A.3}$$

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.3) immediately implies that

$$\sum_i \phi_i \Delta_{in} = 0 \tag{A.4}$$

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 (17) through (20) that

$\Delta_{in} = \Delta_{in}^{OG} + \Delta_{in}^{UG}$. Summing both sides of equation (A.4) across all green stocks, using the definitions in (21), 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

$$T^{OG} = T^{UG}, \quad (\text{A.5})$$

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.4) across all brown stocks, we obtain

$$T^{OB} = T^{UB}, \quad (\text{A.6})$$

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 (27):

$$T^G = T^B, \quad (\text{A.7})$$

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 (22) and (23). \square

A.3. Proofs of Propositions 1 through 5

Proof of Proposition 1: The Lagrangian for the constrained maximization is

$$\mathcal{L} = \phi'_i [\epsilon + (d_i - \theta)g] - \left(\frac{\lambda_0 A_i + \gamma_i}{2} \right) \phi'_i \Sigma \phi_i + d_i g_B - \xi_i \phi'_i \iota, \quad (\text{A.8})$$

where ξ_i is the multiplier associated with the constraint that $\phi'_i \iota = 0$. Differentiating \mathcal{L} with respect to ϕ_i and setting the result to zero gives

$$[\epsilon + (d_i - \theta)g] - (\lambda_0 A_i + \gamma_i) \Sigma \phi_i - \xi_i \iota = 0. \quad (\text{A.9})$$

Solving the above for ϕ_i gives

$$\phi_i = (\lambda_0 A_i + \gamma_i)^{-1} \Sigma^{-1} [\epsilon + (d_i - \theta)g - \xi_i \iota]. \quad (\text{A.10})$$

Multiplying both sides by ι' and imposing $\iota' \phi_i = 0$ gives

$$0 = (\lambda_0 A_i + \gamma_i)^{-1} [\iota' \Sigma^{-1} \epsilon + (d_i - \theta) \iota' \Sigma^{-1} g - \xi_i \iota' \Sigma^{-1} \iota]. \quad (\text{A.11})$$

Because $\lambda_0 A_i + \gamma_i > 0$, the bracketed quantity must be zero, implying

$$\begin{aligned} \xi_i &= \frac{1}{\iota' \Sigma^{-1} \iota} [\iota' \Sigma^{-1} \epsilon + (d_i - \theta) \iota' \Sigma^{-1} g] \\ &= q' \epsilon + h_i q' g, \end{aligned} \quad (\text{A.12})$$

where $h_i \equiv d_i - \theta$ and q contains the weights in the minimum-tracking-error portfolio, i.e., $q = (1/\iota'\Sigma^{-1}\iota)\Sigma^{-1}\iota$. Substituting for ξ_i in equation (A.10) gives the fund's optimal deviations from the benchmark as

$$\phi_i = (\lambda_0 A_i + \gamma_i)^{-1} [\Sigma^{-1}(\epsilon - \tilde{\epsilon}\iota) + h_i \Sigma^{-1}(g - \tilde{g}\iota)], \quad (\text{A.13})$$

where $\tilde{\epsilon} = q'\epsilon$ and $\tilde{g} = q'g$. Combining equations (33) and (A.13) gives

$$\Delta_i = (\lambda_0 A_i + \gamma_i)^{-1} h_i \Sigma^{-1}(g - \tilde{g}\iota), \quad (\text{A.14})$$

with the n th element of Δ_i thus given by

$$\Delta_{in} = \psi_i \delta_{i,n}, \quad (\text{A.15})$$

where $\psi_i = (\lambda_0 A_i + \gamma_i)^{-1}$ and $\delta_{i,n}$ is the n -th element of $h_i \Sigma^{-1}(g - \tilde{g}\iota)$. Equation (A.15) then implies that for each stock n , $|\Delta_{in}|$ is decreasing in A_i , noting ψ_i is positive and decreasing in A_i and that the latter does not enter $\delta_{i,n}$. Therefore, T_i is decreasing in A_i . \square

Proof of Proposition 2: Let $\phi_{i,n}$ denote the n -th element of ϕ_i . From equation (A.13), and for ψ_i and $\delta_{i,n}$ defined above,

$$\phi_{i,n} = \psi_i(\mu_n + \delta_{i,n}), \quad (\text{A.16})$$

where μ_n is the n -th element of $\Sigma^{-1}(\epsilon - \tilde{\epsilon}\iota)$. The value of μ_n is a stock-specific constant, and under the proposition's assumption $\delta_{i,n}$ is held constant, so each $|\phi_{i,n}|$, and thus AS_i , varies only with ψ_i , which in equation (A.15) multiplies $\delta_{i,n}$ to obtain Δ_{in} . Therefore, each $|\Delta_{in}|$, and thus T_i , is a positive constant times AS_i , with both T_i and AS_i increasing in the value of ψ_i . That value can increase whether or not A_i is constant, as it depends also on γ_i . \square

Proof of Proposition 3: Recall that in our theoretical model in Section 3, we define a given Δ_{in} as operating at the extensive (intensive) margin if it changes (does not change) the sign of a portfolio weight. Therefore, for a given stock n , $|\Delta_{in}|$ contributes to either fund i 's intensive tilt or its extensive tilt, but not both. Let \mathcal{N}_i^{ext} denote the set of stocks for which $|\Delta_{in}|$ contributes to the fund's extensive tilt and \mathcal{N}_i^{int} denote the set of stocks for which $|\Delta_{in}|$ contributes to the fund's intensive tilt, so that each stock belongs to either \mathcal{N}_i^{ext} or \mathcal{N}_i^{int} but not both. Then for all $n \in \mathcal{N}_i^{ext}$, $|\Delta_{in}^{ext}| = |\Delta_{in}|$ and $|\Delta_{in}^{int}| = 0$, and for all $n \in \mathcal{N}_i^{int}$, $|\Delta_{in}^{int}| = |\Delta_{in}|$ and $|\Delta_{in}^{ext}| = 0$. From equations (8), (9), and (A.15), we then have

$$T_i^{ext} = \frac{1}{2} \sum_{n=1}^N |\Delta_{in}^{ext}| = \frac{1}{2} \sum_{n \in \mathcal{N}_i^{ext}} |\Delta_{in}| = \frac{\psi_i}{2} \sum_{n \in \mathcal{N}_i^{ext}} |\delta_{i,n}| \quad (\text{A.17})$$

$$T_i^{int} = \frac{1}{2} \sum_{n=1}^N |\Delta_{in}^{int}| = \frac{1}{2} \sum_{n \in \mathcal{N}_i^{int}} |\Delta_{in}| = \frac{\psi_i}{2} \sum_{n \in \mathcal{N}_i^{int}} |\delta_{i,n}|, \quad (\text{A.18})$$

so that

$$\frac{T_i^{ext}}{T_i^{int}} = \frac{\sum_{n \in \mathcal{N}_i^{ext}} |\delta_{i,n}|}{\sum_{n \in \mathcal{N}_i^{int}} |\delta_{i,n}|}. \quad (\text{A.19})$$

Under the proposition's assumptions, the values of $\delta_{i,n}$ are held constant. Therefore, the ratio in equation (A.19) does not increase if the set \mathcal{N}_i^{int} does not decrease (or, equivalently, if \mathcal{N}_i^{ext} does not increase). The value of ψ_i in equation (A.15) is decreasing in fund size, A_i , and increasing in active share, AS_i , recalling the latter from the proof of Proposition 2. Therefore what remains to show is that the set \mathcal{N}_i^{int} does not decrease as ψ_i decreases.

Let $w_{i,n}$ and $w_{i,B,n}$ denote the n -th elements of w_i and $w_{i,B}$. With the ESG-related tilt included,

$$w_{i,n} = w_{i,B,n} + \psi_i(\mu_n + \delta_{i,n}), \quad (\text{A.20})$$

using equation (A.16) and recalling the definition $\phi_{i,n} = w_{i,n} - w_{i,B,n}$. With the ESG-related tilt excluded, (i.e., $\delta_{i,n} = 0$), the weight in stock n instead becomes

$$w_{i,n}^- = w_{i,B,n} + \psi_i \mu_n. \quad (\text{A.21})$$

If $w_{i,n}$ and $w_{i,n}^-$ are both positive, then $n \in \mathcal{N}_i^{int}$. The conditions that $w_{i,n}$ and $w_{i,n}^-$ are both positive are equivalent to the conditions that $\psi_i(\mu_n + \delta_{i,n})$ and $\psi_i \mu_n$ both exceed $-w_{i,B,n}$. If those conditions hold to begin with, then they continue to hold as ψ_i decreases, because $-w_{i,B,n}$ is negative and both $\psi_i(\mu_n + \delta_{i,n})$ and $\psi_i \mu_n$ move closer to zero as ψ_i decreases. Therefore $w_{i,n}$ and $w_{i,n}^-$ both remain positive as ψ_i decreases, and thus \mathcal{N}_i^{int} does not decrease. \square

Proof of Proposition 4: Recall that each $|\Delta_{in}|$ contributes to fund i 's extensive tilt via either extensive investment (when Δ_{in} moves stock n 's weight from non-positive to positive) or extensive divestment (when Δ_{in} moves the stock's weight from positive to non-positive), but not both. Let $\mathcal{N}_i^{ext,O}$ denote the set of stocks for which $|\Delta_{in}|$ contributes to the fund's extensive tilt via extensive investment and $\mathcal{N}_i^{ext,U}$ denote the set of stocks for which $|\Delta_{in}|$ contributes to the fund's extensive tilt via extensive divestment, so that each stock in the set \mathcal{N}_i^{ext} belongs to either $\mathcal{N}_i^{ext,O}$ or $\mathcal{N}_i^{ext,U}$ but not both. Then, using the same arguments as in the proof of Proposition 3, we obtain

$$\frac{T_i^{ext,U}}{T_i^{ext,O}} = \frac{\sum_{n \in \mathcal{N}_i^{ext,U}} |\delta_{i,n}|}{\sum_{n \in \mathcal{N}_i^{ext,O}} |\delta_{i,n}|}. \quad (\text{A.22})$$

Under the proposition's assumptions, the values of $\delta_{i,n}$ are held constant. Therefore, the ratio in equation (A.22) does not increase if the set $\mathcal{N}_i^{ext,O}$ does not decrease and $\mathcal{N}_i^{ext,U}$ does not increase. The value of ψ_i in equation (A.15) is decreasing in fund size, A_i , and increasing in active share, AS_i , recalling the latter from the proof of Proposition 2. Also recall from the proof of Proposition 3 that as ψ_i decreases, \mathcal{N}_i^{ext} does not increase, because as shown there \mathcal{N}_i^{int} does not decrease (and because $\mathcal{N}_i^{ext} \cup \mathcal{N}_i^{int}$ is fixed and those sets are disjoint). This implies that if $\mathcal{N}_i^{ext,O}$ does not decrease as ψ_i decreases, then $\mathcal{N}_i^{ext,U}$ does not increase, because $\mathcal{N}_i^{ext} = \mathcal{N}_i^{ext,O} \cup \mathcal{N}_i^{ext,U}$ and the latter sets are disjoint. Therefore what remains to show is that the set $\mathcal{N}_i^{ext,O}$ does not decrease as ψ_i decreases.

For any stock n with a non-positive $w_{i,n}^-$, equation (A.20) implies that getting a positive

$w_{i,n}$ (extensive investment) requires

$$\delta_{i,n} > - \left(\frac{w_{i,B,n}}{\psi_i} + \mu_n \right). \quad (\text{A.23})$$

If the inequality in (A.23) is satisfied at a given value of ψ_i , then it is satisfied at any smaller value of ψ_i . Therefore, the set $\mathcal{N}_i^{ext,O}$ cannot decrease as ψ_i decreases. \square

Proof of Proposition 5: Under the proposition's assumption, equation (A.14) implies that

$$|\Delta_{in}| = (\lambda_0 A_i + \gamma_i)^{-1} |h_i| (1/\sigma_n^2) |g_n - \tilde{g}|, \quad (\text{A.24})$$

which is increasing in $(1/\sigma_n^2)|g_i - \tilde{g}|$. This is true for each fund i , so it is true for D_n , a positive-weight sum of $|\Delta_{in}|$ across i . \square

A.4. Estimating the intensive-margin model

This section extends the discussion from Section 4.2 by providing a detailed justification for the regression model in equation (40). 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:

$$\frac{w_{in}^+}{w_{mn}} = \sum_{j=1}^K c_{ij} x_{nj}, \quad n = 1, \dots, N. \quad (\text{A.25})$$

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:

$$\sum_{n=1}^N \bar{w}_{in} = \sum_{n=1}^N \pi_{in} w_{in}^+ = 1. \quad (\text{A.26})$$

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,

$$c_{ij} = b_{ij} / \sum_{n=1}^N \pi_{in} w_{mn} x_{nj}, \quad j = 1, \dots, K, \quad (\text{A.27})$$

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

$$\sum_{j=1}^K b_{ij} = 1. \quad (\text{A.28})$$

Substituting the right-hand side of equation (A.27) into equation (A.25) gives

$$\frac{w_{in}^+}{w_{mn}} = \sum_{j=1}^K b_{ij} \left(\frac{x_{nj}}{\sum_{n=1}^N \pi_{in} w_{mn} x_{nj}} \right). \quad (\text{A.29})$$

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

$$w_{in} = w_{in}^+ + \epsilon_{in}, \quad (\text{A.30})$$

where ϵ_{in} has zero mean conditional on X . Combining equations (A.29) and (A.30) gives the following regression model for the stocks held:

$$\frac{w_{in}}{w_{mn}} = \sum_{j=1}^K b_{ij} \tilde{x}_{n,j} + e_{in}, \quad (\text{A.31})$$

where the j -th independent variable is

$$\tilde{x}_{nj} = \frac{x_{nj}}{\sum_{n=1}^N \pi_{in} w_{mn} x_{nj}}. \quad (\text{A.32})$$

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 $\tilde{x}_{n,j}$ s, because the n -th row of X includes w_{mn} (as noted earlier). The regression coefficients in (A.31) must obey the restriction in equation (A.28). 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

$$y_{in} = \sum_{j=1}^{K-1} \gamma_{ij} z_{nj} + e_{in}, \quad (\text{A.33})$$

where

$$y_{in} = w_{in}/w_{mn} - \tilde{x}_{n1}, \quad (\text{A.34})$$

$$z_{nj} = \tilde{x}_{n,j+1} - \tilde{x}_{n1}, \quad (\text{A.35})$$

$$\gamma_{ij} = b_{i,j+1}, \quad \text{and} \quad (\text{A.36})$$

$$1 - \sum_{j=1}^{K-1} \gamma_{ij} = b_{i1}. \quad (\text{A.37})$$

We estimate the regression in (A.33) 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.32). 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.36) and (A.37). Finally, we plug those estimates into equation (A.29) 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.5. 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 4.3. 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.31)). 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

$\log(M_n)$.²¹ 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} .
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.29) while using the estimates of \hat{b}_i and $\hat{\pi}_{in}$ from step 1. Following equations (A.29) and (A.31), 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.29) to (A.37), 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.29) 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 $TBias_i = \bar{\tilde{T}}_i - T_i^{raw}$, where $\bar{\tilde{T}}_i$ 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 :

$$\hat{T}_i = T_i^{raw} - TBias_i. \quad (\text{A.38})$$

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 $V_T/NSim$.

²¹In 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.

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 $\text{Gap}_{2.5} = \bar{\tilde{T}}_i - \tilde{T}_i^{2.5}$ 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 $\text{Gap}_{97.5} = \tilde{T}_i^{97.5} - \bar{\tilde{T}}_i$ is the gap between the 97.5th percentile and the mean of \tilde{T}_i across simulated trials.

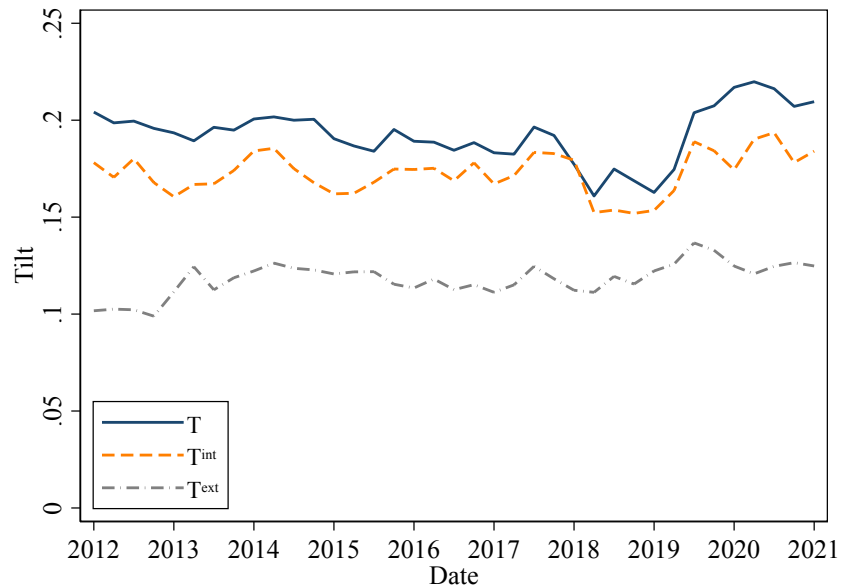
Online appendix

B.1. 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.

B.2. Additional results

Panel A: Institutions holding a below-median number of stocks



Panel B: Institutions holding an above-median number of stocks

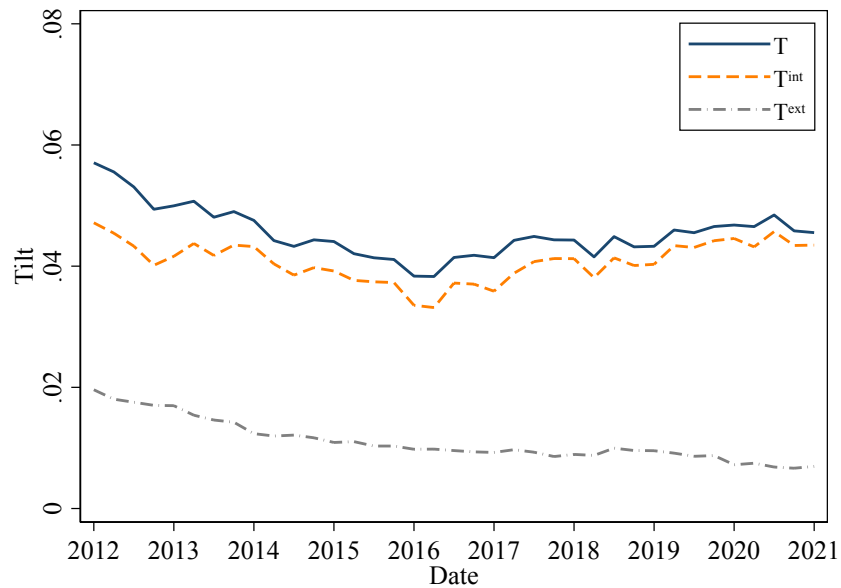


Figure B.1. ESG-related tilts in subsamples based on number of stocks held. Tilts in this figure are the same as in the paper’s Figure 1 Panel A, except we show tilts aggregated within two subsamples. In each quarter, we calculate the median number of stocks held across institutions, and we split the institutions in two groups based on whether their number of stocks held is below the median (Panel A) or at or above the median (Panel B). The median number of holdings ranges from 103 to 118 across quarters.



Figure B.2. Aggregate green, brown, and GMB tilts. This figure plots each quarter's AUM-weighted averages of T_i^G (Panel A), T_i^B (Panel B), and T_i^{GMB} (Panel C). Panels A and B are the same as the corresponding panels in the paper's Figure 5, except here we do not divide tilts by active share.

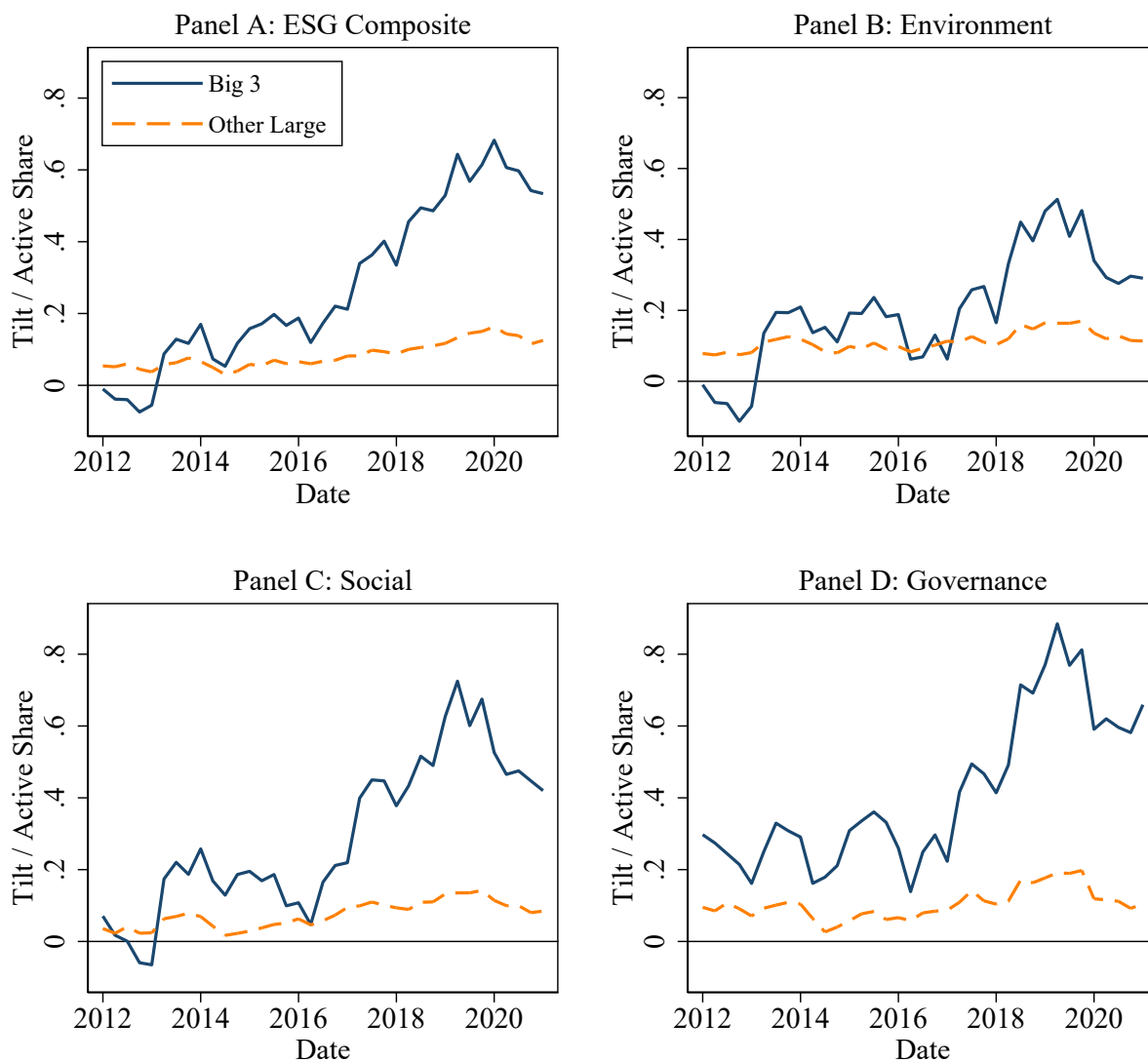


Figure B.3. GMB tilts of the Big Three and other large institutions. This figure compares GMB tilts between the subsample of Big Three institutions and other large institutions. Each line shows the AUM-weighted average of GMB tilt divided by active share within a subsample of institutions. The lines denoted “Large” in the paper’s Figure 10 are AUM-weighted averages of the two lines in each panel of this figure.

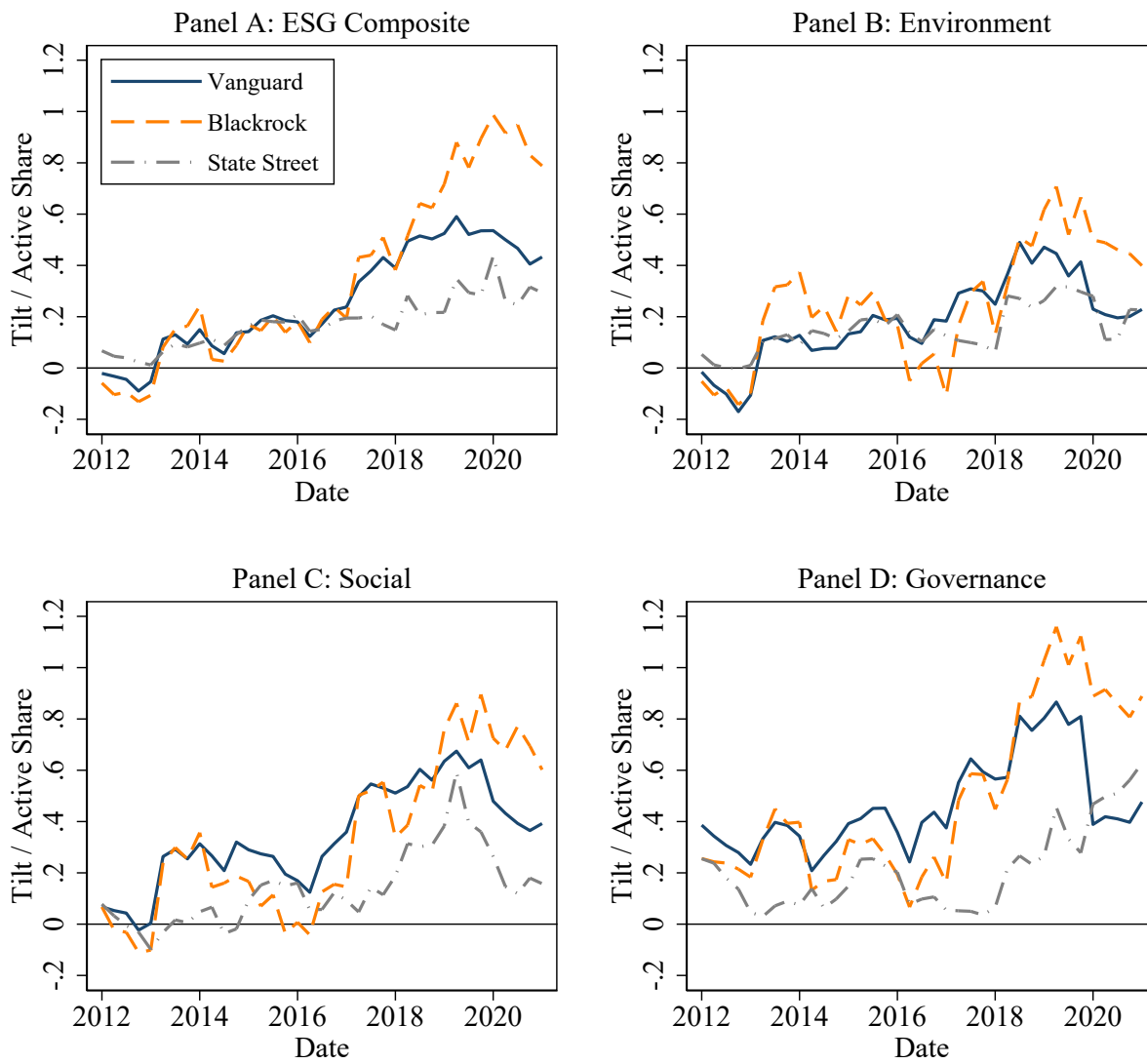


Figure B.4. GMB tilts of the Big Three. This figure plots the ratio of GMB tilt to active share for each of the Big Three institutions.

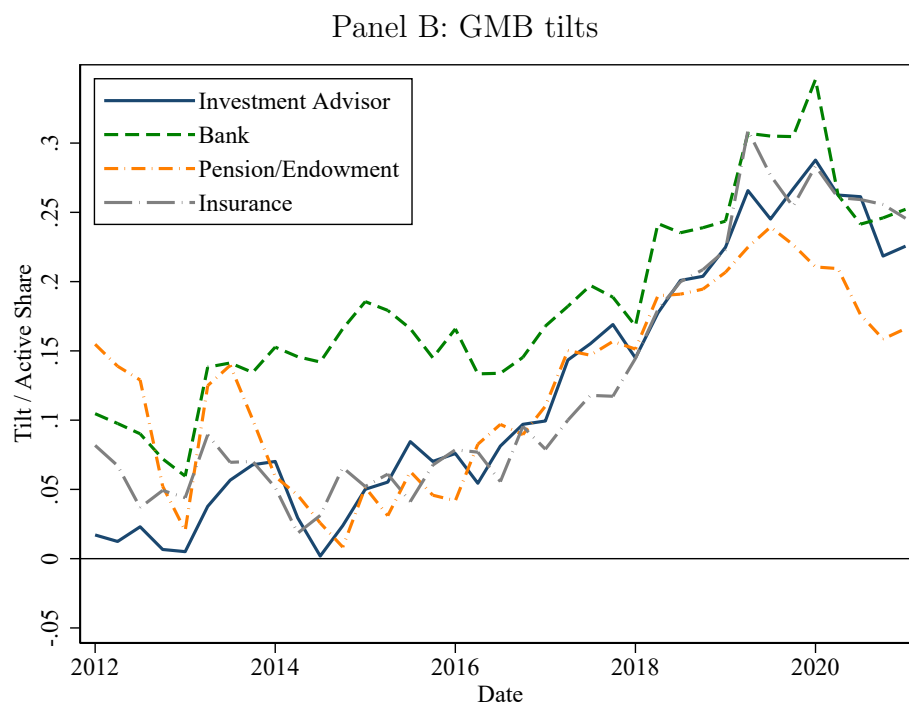
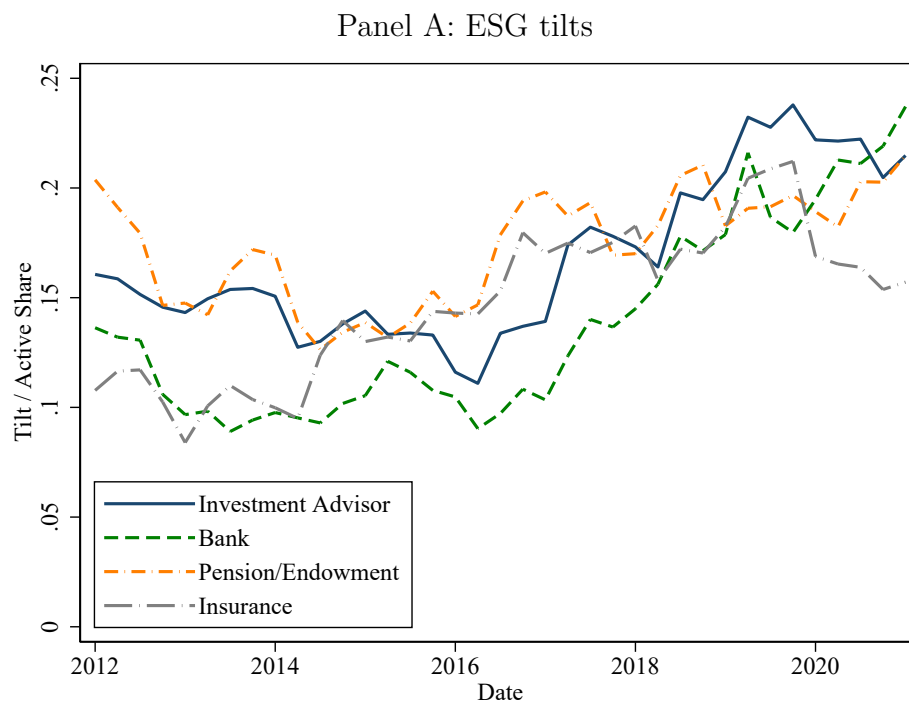


Figure B.5. Comparing tilts across institution types. Panel A (B) plots the AUM-weighted average of the ratio of T_i (T_i^{GMB}) to active share. GMB tilts are computed using the ESG composite score to measure greenness.

Table B.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)

(continued next page)

Table B.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 B.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 B.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 B.2: Version of paper's Table 4 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, institution-type indicators, and indicators for geographical location from the regression. Remaining details are the same as in Table 4.

	ESG	Env.	Soc.	Gov.
log(AUM)	0.0032 (0.49)	-0.0168 (-2.19)	0.0126 (1.57)	-0.0035 (-0.52)
log(AUM) \times trend	0.0630 (4.77)	0.0312 (2.17)	0.0499 (3.32)	0.0021 (0.17)
Active share	-0.0585 (-1.22)	-0.1425 (-2.56)	-0.0213 (-0.37)	-0.0746 (-1.52)
1(UNPRI)	0.0368 (2.33)	0.0409 (2.23)	0.0269 (1.66)	-0.0016 (-0.09)
R^2	0.443	0.462	0.500	0.433
R^2 (FEs only)	0.441	0.461	0.499	0.432

Table B.3: Version of paper's Table 5 with time fixed effects

This table is the same as Table 5 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)	0.0019 (1.32)	-0.0050 (-2.51)	0.0025 (1.41)	0.0031 (2.24)	-0.0130 (-7.19)	-0.0045 (-2.57)	-0.0177 (-8.01)	-0.0138 (-7.01)
log(AUM) x trend	0.0332 (4.93)	0.0247 (2.74)	0.0190 (2.48)	0.0034 (0.57)	-0.0400 (-5.60)	-0.0138 (-1.89)	-0.0327 (-3.92)	-0.0048 (-0.62)
Active share	0.0843 (8.41)	0.1229 (8.72)	0.1214 (9.78)	0.0767 (7.59)	0.1056 (9.26)	0.1636 (12.37)	0.1225 (7.86)	0.1636 (11.54)
1(UNPRI)	0.0190 (2.77)	0.0175 (2.16)	0.0113 (1.52)	0.0031 (0.56)	-0.0217 (-3.76)	-0.0227 (-3.69)	-0.0302 (-4.37)	-0.0210 (-3.21)
1(Inv. advisor)	-0.0091 (-0.89)	-0.0017 (-0.10)	0.0076 (0.72)	-0.0164 (-1.31)	0.0236 (2.96)	0.0092 (1.00)	0.0097 (0.47)	0.0118 (0.69)
1(Bank)	-0.0175 (-1.54)	-0.0132 (-0.72)	-0.0285 (-2.43)	-0.0289 (-2.10)	0.0550 (4.27)	0.0131 (1.13)	0.1018 (3.85)	0.0295 (1.53)
1(Pension/endowment)	-0.0154 (-1.41)	-0.0150 (-0.78)	0.0104 (0.82)	-0.0162 (-1.16)	0.0116 (1.15)	0.0120 (0.93)	-0.0100 (-0.47)	-0.0038 (-0.20)
1(Europe)	0.0235 (2.52)	0.0362 (3.44)	0.0265 (2.44)	0.0295 (3.40)	-0.0085 (-1.12)	-0.0133 (-1.62)	-0.0200 (-2.13)	-0.0150 (-1.74)
1(Rest of world)	0.0142 (1.45)	0.0205 (1.71)	0.0167 (1.37)	0.0180 (1.84)	0.0033 (0.39)	-0.0106 (-1.15)	-0.0013 (-0.12)	0.0017 (0.14)
R^2	0.018	0.022	0.022	0.013	0.031	0.031	0.037	0.043
R^2 (FEs only)	0.004	0.003	0.002	0.003	0.008	0.002	0.004	0.004
p (inst. types equal)	0.282	0.396	0.000	0.148	0.000	0.685	0.000	0.095

Table B.4: Version of paper's Table 5 with institution and time fixed effects

This table is the same as Table 5 but includes institution and time fixed effects, which requires dropping Trend, institution-type indicators, and indicators for geographical location from the regression.

	Green Tilts				Brown Tilts			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	-0.0016 (-0.41)	-0.0112 (-2.25)	0.0049 (1.07)	-0.0026 (-0.74)	-0.0059 (-1.45)	0.0048 (1.15)	-0.0088 (-1.76)	0.0004 (0.09)
log(AUM) \times trend	0.0244 (3.21)	0.0239 (2.51)	0.0160 (1.92)	0.0004 (0.07)	-0.0391 (-4.81)	-0.0083 (-1.04)	-0.0342 (-3.58)	-0.0026 (-0.31)
Active share	0.0950 (3.50)	0.0570 (1.61)	0.1190 (3.67)	0.0825 (3.14)	0.1482 (4.75)	0.1932 (5.98)	0.1369 (3.71)	0.1526 (4.71)
1(UNPRI)	0.0217 (2.14)	0.0175 (1.35)	0.0067 (0.69)	-0.0046 (-0.52)	-0.0155 (-1.76)	-0.0236 (-2.55)	-0.0203 (-2.08)	-0.0029 (-0.26)
R^2	0.394	0.441	0.443	0.360	0.444	0.455	0.503	0.449
R^2 (FEs only)	0.388	0.438	0.439	0.357	0.440	0.452	0.501	0.447

Table B.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