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Green tilts[☆]

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ABSTRACT

We estimate financial institutions' portfolio tilts related to U.S. stocks' environmental, social, and governance (ESG) characteristics. From 2012 to 2023, ESG-related tilts consistently total about 6% of the investment industry's assets and rise from 17% to 27% of institutions' total portfolio tilts. 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. Divestment from brown stocks is typically partial rather than full, even for individual mutual funds. UNPRI signatories and European institutions tilt greener; banks tilt browner.

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 with numbers like this introduce countless papers on ESG investing. Those numbers show that ESG matters to many financial institutions, but not *how much* it matters. How much do institutions' portfolio weights differ from what they would be without ESG considerations? We estimate these ESG-related portfolio tilts and explore various additional questions. For example, how have ESG-related tilts evolved over time? Which investors tilt toward "green" assets with favorable ESG characteristics, and which ones make the offsetting "brown" tilts? These questions are important because tilting green could have financial implications, given both theoretical arguments and empirical evidence that green assets have lower expected returns.[1]

We assess the amount of ESG investing by estimating the size of institutions' ESG-related portfolio tilts. Our approach has three main virtues. First, when estimating how stocks' ESG characteristics relate to portfolio weights, we control for non-ESG stock characteristics. We thus separate ESG tilts from investment styles such as large-cap growth. This is useful because non-ESG attributes such as size and book-to-market are correlated with ESG characteristics. Second, our approach measures ESG-related tilts at both the extensive margin (i.e., which stocks are held) and the intensive margin (i.e., weights on stocks held).

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[1] See Pástor et al. (2021, 2022) and Bolton and Kacperczyk (2021, 2023), among others.

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This allows us, for example, to assess the relative importance of partial versus full divestment of brown stocks. Third, our approach allows a stock's E, S, and G characteristics to relate separately to portfolio weights. This helps when, say, some investors care primarily about G, and one stock has good G and bad S, while another has the opposite. A composite ESG score could rate both stocks equally, but these investors will overweight the first stock and underweight the second, creating tilts explained by G but not by composite ESG.

We do not confine ESG investing to motives related to social responsibility. ESG characteristics could also enter for financial or other reasons.[2] For example, an institution could overweight brown stocks because it sees them as underpriced, or it could overweight green stocks because it sees them as a hedge against climate risk. We do confine ESG investing to portfolio choice, excluding shareholder engagement.

Our empirical implementation focuses on U.S. stocks and institutional holdings from 13F filings. After computing institution-level ESG-related portfolio tilts, we aggregate them across institutions to estimate the total ESG tilt in the investment industry. We find that this tilt consistently accounts for about 6% of the industry's U.S. equity AUM between years 2012 and 2023, reaching 6.5% by the end of the sample. Our approach's three virtues are confirmed by our results: First, controlling for non-ESG characteristics avoids overstating the total ESG tilt by nearly twice. Second, separating the extensive- and intensive-margin tilts reveals that both are significant, with the intensive being two to four times larger. Finally, allowing E, S, and G to enter separately avoids understating the total tilt by over 40%, which occurs if just a composite ESG score is used.

We also assess ESG tilts in the context of institutions' overall 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 total portfolio tilts — deviations of portfolio weights from market weights for any reason — we use the active share measure of Cremers and Petajisto (2009). On average, ESG tilts are about 20% as large as active share during our sample period. So, while ESG tilts are modest relative to AUM, they are more substantial relative to total tilts. Moreover, although ESG tilts have not grown as a share of AUM, they have grown as a share of total tilts: the average ratio of ESG tilt to active share has grown from 17% in 2012 to 27% in 2023.

We then examine whether ESG tilts are green or brown. Given the multiple dimensions of ESG, any of them can be used to measure greenness. For each dimension, we compute each institution's net tilt toward green stocks, or "GMB" tilt (green minus brown). From 2012 until a modest downturn in 2023, institutions become increasingly green, exhibiting a positive and rising aggregate GMB tilt. Offsetting that behavior, the aggregate portfolio of non-13F investors becomes browner, with a negative and decreasing GMB tilt. The rise in GMB tilts of 13F institutions occurs primarily via the intensive margin, that is, by increasingly overweighting green stocks and underweighting brown stocks. For example, divestment from brown stocks, a long-standing theme, occurs largely at the intensive margin, by reducing positions rather than eliminating them. All of these findings are robust across our four measures of greenness: E, S, G, and the composite score.

Our green tilt measure clearly differs from several potential alternatives. For example, at the end of our sample, the aggregate institutional GMB tilt is 4.2%. Without controlling for non-ESG characteristics, this tilt would be almost three times larger, 11.2%. An even simpler alternative measure, a difference between the portfolio's total weights in green and brown stocks, produces an even larger aggregate value, 27.6%. Both larger values reflect at least in part the institutions' well known preference for large-cap stocks and growth stocks, which tend to score higher on ESG than small-cap or value stocks. All of these values pale in comparison with 76.1%, the share of our sample's U.S. equity AUM managed by institutions that have signed the United Nations' Principles for Responsible Investment (UNPRI). Numbers like that show ESG is widely endorsed, but clearly overstate its investment role.

Even though much of their investing is unrelated to ESG, UNPRI signatories do have significantly larger GMB tilts. We find this greener tilt not only across institutions but, for environmental greenness, also over time: institutions tend to become greener after signing the UNPRI. We also find that banks are browner than other institutions, especially insurance companies, and that European institutions are greener (i.e., European institutions' holdings of U.S. equities are greener than U.S. institutions' holdings of those equities).

ESG investing varies greatly across 13F-filing institutions. For example, the rise in the investment industry's aggregate greenness is driven by the largest institutions. 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. In contrast, the GMB tilts of the middle and bottom thirds of institutions are mostly negative and decreasing over time—meaning brown and becoming browner. For the biggest institution, BlackRock, the GMB tilt becomes especially large through 2020 but declines thereafter.

We construct firms' ESG characteristics using ESG ratings from MSCI, a leading data provider. For robustness, we re-estimate institutional tilts using ratings from Sustainalytics. The results are very similar; for example, the aggregate ESG-related tilt ranges from 5.9% to 6.7% of AUM, and our main conclusions remain unchanged.

Results are also similar when using industry-adjusted ESG scores, computed by subtracting industry averages from firms' scores. The resulting ESG tilts are smaller, averaging 4% to 5%, but otherwise behave similarly to the unadjusted tilts. The same holds for industry-adjusted green and brown tilts. Again, our conclusions remain unchanged.

ESG tilts reflect decisions having diverse origins, such as different managerial layers within an institution. In a mutual fund family, for example, an active fund's tilt is chosen by the fund's portfolio manager, while a passive fund inherits the tilt of the index it tracks, chosen by fund-family management. In other cases, ESG tilts reflect decisions made outside the institution. For example, client mandates could dictate ESG tilts (or the absence thereof) in the portfolios of bank-administered trusts or advisor-managed separate accounts. We adopt an inclusive approach, not confining our analysis to tilts traceable to particular decision origins. Moreover, we focus on AUM-weighted tilts, which ultimately reflect the decisions of asset owners, who decide where the AUM resides.

Computing an institution's ESG tilt from 13F holdings may obscure offsetting tilts across separate investing entities within the institution. For example, a mutual fund family with half its AUM in green-tilting funds and half in brown-tilting funds may show little ESG tilt in its 13F holdings. In that sense, our estimates likely understate the tilts we would see if we could disaggregate the entities within each institution. Even for institutions that available data allow us to disaggregate, namely mutual fund families, the data limit the disaggregation. For example, mutual funds often employ multiple managers or sub-advisors managing separate "sleeves" that aggregate to the observed fund portfolio. It seems hard, even in theory, to identify a uniquely meaningful level of disaggregation. Quite simply, institutions' 13F holdings offer a consistent and feasible level of aggregation for analyzing ESG tilts across the investment industry.

To complement this institution-level analysis, we estimate ESG tilts for U.S. equity mutual funds, using fund-level holdings from the S12 dataset. Disaggregating the holdings of mutual fund families allows us to uncover ESG tilts that offset within families. We find these offsets to be modest: in 2023, they account for 1.8% of fund families' AUM, or just under 0.5% of aggregate AUM—one fourteenth of the total ESG tilt.

[2] In their global survey of equity portfolio managers, Edmans et al. (2025) find that managers' primary motivation for using environmental and social criteria is to improve financial performance.

Mutual funds' total ESG tilt ranges from 6% to 10% of AUM, and from 10% to 13% for actively managed funds. Extensive-margin tilts are about twice as large as those for institutions but remain below intensive-margin tilts. Similarly, extensive-margin divestment from brown stocks exceeds that of institutions but still falls short of intensive-margin divestment, indicating that for mutual funds, just like for 13F institutions, brown divestment is more partial than full. Mutual funds collectively tilt green, though not as much as institutions in aggregate. ESG-labeled funds exhibit larger green tilts and smaller brown tilts than non-ESG funds. Funds with higher Morningstar globe ratings also tilt greener.

ESG investing is distinct from index investing, i.e., holding the market portfolio. While investors' ESG preferences can affect market weights, we do not view pure index investors as engaging in ESG investing. Our framework assigns zero ESG tilts to index investors, as we control for market weights when estimating tilts. We also show that over the past decade, the market portfolio itself has increasingly tilted toward environmentally green stocks.

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.[3] 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. (2023) find that institutions that join climate-related investor initiatives increase their holdings of firms with low carbon emissions. Starks et al. (2023) find that institutions with longer investment horizons tilt their portfolios more towards firms with high ESG scores. Brandon et al. (2021) relate institutions' portfolio-level environmental and social scores to performance. Nofsinger et al. (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 et al. (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 some of these studies, we find that institutions' portfolios tilt green, and increasingly so. However, our approach to measuring ESG-related portfolio tilts is fundamentally different. Most importantly, the above studies do not quantify the total amount of institutions' ESG-related investing. Moreover, we do not analyze portfolio-level ESG characteristics because they reflect also stocks' non-ESG characteristics such as size and book-to-market, for which we control. Our approach has two additional advantages. First, measuring the extensive- and intensive-margin components of ESG tilts delivers new insights, such as that divestment from brown stocks occurs largely at the intensive margin. Second, instead of analyzing one ESG characteristic at a time, we find it important to allow all three characteristics to enter simultaneously.

In a complementary study, Cremers et al. (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 in that they relate their measure to fund performance. They do not examine aggregate tilts, 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 (Brandon et al. (2022), Humphrey and Li (2021), Kim and Yoon (2023), and Liang et al. (2022)). We find that UNPRI signatories' portfolios tend to exhibit greener tilts.

Prior evidence on ESG-related trading by retail investors is also mixed. On the one hand, Choi et al. (2020b) find that retail investors, but not institutions, respond to abnormally warm temperatures by selling stocks of carbon-intensive firms. Li et al. (2023) find that retail investors' trades respond to a broader set of ESG news events. On the other hand, Moss et al. (2020) 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.[4] 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.[5]

The remainder of the paper is organized as follows. Section 2 defines ESG-related tilts. Section 3 outlines our estimation procedure. Section 4 presents evidence on ESG tilts for a large sample of institutional investors. Section 5 examines mutual funds' tilts. Section 6 compares our green tilt measures to several alternatives. Section 7 analyzes the greening of the market portfolio. Section 8 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

$$\Delta_{in} = \mathrm{E}[w_{in}|\mathcal{G}, \mathcal{C}] - \mathrm{E}[w_{in}|\mathcal{G}_0, \mathcal{C}], \tag{1}$$

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 et al. (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.

[3] See, for example, Falkenstein (1996), Gompers and Metrick (2001), Edelen et al. (2016), DeVault et al. (2019), Koijen and Yogo (2019), and Lettau et al. (2021). Lewellen (2011) shows that institutions' aggregate holdings closely resemble those of the market portfolio.

[4] See, for example, Chen et al. (2020), Choi et al. (2023), Dyck et al. (2019), Gantchev et al. (2022), Heath et al. (2021), Hwang et al. (2022), Ilhan et al. (2020), and Li and Raghunandan (2021).

[5] See Koijen et al. (2024), Noh et al. (2023), and van der Beck (2022).

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

2.1. Extensive- and intensive-margin tilts

The conditional expectations entering the value of Δ_{in} in Eq. (1) can be written as $\mathrm{E}[w_{in}|\cdot] = \mathrm{Prob}\{w_{in} > 0|\cdot\} \times \mathrm{E}[w_{in}|w_{in} > 0, \cdot]$, under the assumption that $w_{in} \geq 0$.[6] 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

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

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

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 Eq. (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,

$$\Delta_{in} = \Delta_{in}^{ext} + \Delta_{in}^{int}\,, \tag{4}$$

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

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

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

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 answers the question: how much of investor i's 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 answers the question: how much of investor i's weight in stock n relates to the stock's ESG characteristics, conditional on holding the stock?

2.2. Investor-level tilts

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

$$T_i = \frac{1}{2}\sum_{n=1}^{N} |\Delta_{in}|\,. \tag{7}$$

This definition parallels that of the ESG tilt in Pástor et al. (2021), except that here Δ_{in} is not simply a deviation of the stock's portfolio weight from its market weight. The division by 2 ensures that we avoid double-counting: for each stock the investor overweights because of $\mathcal{G}$, the investor must underweight one or more other stocks. Put differently, $\sum_{n=1}^{N} \Delta_{in} = 0$ for all i, which follows from Eq. (1), so any positive Δ_{in}'s must be balanced by negative ones.

We similarly compute the investor's intensive- and extensive-margin tilts:

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

$$T_i^{ext} = \frac{1}{2}\sum_{n=1}^{N} |\Delta_{in}^{ext}|\,. \tag{9}$$

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 Eq. (4)), decomposing $|\Delta_{in}|$ is less straightforward. In particular, $|\Delta_{in}| = |\Delta_{in}^{int} + \Delta_{in}^{ext}| \leq |\Delta_{in}^{int}| + |\Delta_{in}^{ext}|$, and the inequality is strict if and only if Δ_{in}^{int} and Δ_{in}^{ext} have opposite signs. It follows immediately that $T_i \leq T_i^{int} + T_i^{ext}$.

2.3. Aggregate tilts

Let A_i denote the dollar value of investor i's assets. For any given set of investors, $\mathcal{S}$, we can compute the aggregate tilt as an asset-weighted average tilt across investors:

$$T = \frac{1}{A}\sum_{i\in\mathcal{S}} A_i T_i\,, \tag{10}$$

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:

$$T^{int} = \frac{1}{A}\sum_{i\in\mathcal{S}} A_i T_i^{int} \tag{11}$$

$$T^{ext} = \frac{1}{A}\sum_{i\in\mathcal{S}} A_i T_i^{ext}\,. \tag{12}$$

2.4. Green and brown tilts

The tilt measures presented so far capture all ESG-related portfolio tilts, regardless of their direction. Two investors with identical T_i values 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 must designate stocks as green or brown. That is not straightforward with multiple ESG characteristics, as stocks with high values of one 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 the characteristic's neutral value — the capitalization-weighted average of g_n across stocks. We classify the stock as green if $g_n \geq g_0$ and brown if $g_n < g_0$. In other words, a stock is 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 Eq. (1) takes one of the following four values (the other three are zero):

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

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

$$\Delta_{in}^{OB}: \text{ when } \Delta_{in} > 0 \text{ and } g_n < g_0$$

[6] This assumption accommodates our data. Reported holdings of institutions and funds include only long stock positions. For stocks that are not held long, we set $w_{in} = 0$ in our empirical implementation.

$$\rightarrow \text{ Overweight Brown stocks (brown tilt)} \tag{15}$$

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

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

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

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

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

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

$$T_i^G = T_i^{OG} + T_i^{UB} \geq 0 \tag{18}$$
$$T_i^B = T_i^{OB} + T_i^{UG} \geq 0. \tag{19}$$

We also compute the investor's green-minus-brown tilt as[7]

$$T_i^{GMB} = T_i^G - T_i^B. \tag{20}$$

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

$$T_i = \frac{1}{2}(T_i^{OG} + T_i^{UB} + T_i^{OB} + T_i^{UG}) \tag{21}$$
$$= \frac{1}{2}(T_i^G + T_i^B). \tag{22}$$

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

We also compute asset-weighted averages across investors, analogous to Eqs. (10) through (12), yielding the aggregate tilt measures T^G, T^B, and T^{GMB}. If the aggregates are computed across all investors, the green and brown tilts are always equal:

$$T^G = T^B, \tag{23}$$

as we prove in Appendix A. 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.

Finally, we separate the green and brown tilts into their extensive- and intensive-margin components. We first split the Δ_{in}'s in Eqs. (13) through (16) into two parts, as in Eq. (4). We then aggregate those parts to the investor level, as in Eqs. (8) and (9), and then to the aggregate level, as in Eqs. (10) through (12).

3. Estimation framework

To estimate the portfolio tilts from Section 2, we first estimate two quantities: π_{in}, the probability of investor i holding stock n, and w_{in}^+, the expected weight conditional on holding the stock (see Eqs. (2) and (3)). With those estimates in hand, we compute the components of Δ_{in} in Eqs. (5) and (6), which yield Δ_{in} in Eq. (4).[8] We then aggregate the Δ_{in} estimates into the 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 3.1, we describe our econometric model for the extensive margin of portfolio weights, which yields an estimate of π. In Section 3.2, we present our model for the intensive margin, which yields an estimate of w^+, after incorporating a selection correction described in Section 3.3. In Section 3.4, we discuss how we adjust our estimates for potential bias and compute their standard errors.

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

We estimate tilts related to ESG characteristics, but our methodology can be used to estimate tilts related to other characteristics of interest. That is, let $\mathcal{G}$ contain those characteristics and $\mathcal{C}$ contain other characteristics included as controls. The tilts defined in Section 2 are then reinterpreted as tilts related to the characteristics in $\mathcal{G}$. A key aspect of our methodology in general is that it estimates tilts at the extensive margin in addition to the intensive margin. An alternative approach for analyzing primarily the latter is Koijen and Yogo (2019), who take as exogenous the subset of stocks an institution can weight positively.

3.1. Extensive margin

Our model of the extensive margin gives the value of

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

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

$$\pi_{in} = \Phi(X_n a_i), \tag{25}$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution.

We estimate the model in Eq. (25) for each investor i 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 fitted value by $\hat{\pi}_{in}$. The estimated probabilities $\hat{\pi}_{in}$ lie between 0 and 1, by construction. Additional details, including on goodness of fit, are in the Internet Appendix.

Suppose X were to include all of the information used by investor i, such that $1_{w_{in}>0}$ depends deterministically on X. The latter dependence could involve all rows of X, not just X_n, but that dependence would likely be complicated, having no analytic solution, especially with realistic constraints on asset weights faced by many institutions.[9] Given that any X we specify empirically is only a subset of the investor's information, the dependence of $1_{w_{in}>0}$ on X is probabilistic, not deterministic. We condition the probability in Eq. (25) on just X_n for parsimony and tractability. The modeled randomness in $1_{w_{in}>0}$ therefore reflects the omission of information as well as uncertainty

[7] An alternative way to compute this quantity is $T_i^{GMB} = \sum_{n\in\mathcal{S}_G} \Delta_{in} - \sum_{n\in\mathcal{S}_B} \Delta_{in}$, where $\mathcal{S}_G$ and $\mathcal{S}_B$ denote the sets of all green and brown stocks, respectively.

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

[9] For example, even a standard mean–variance optimization with short-sale constraints generally does not admit an analytic solution.

about how information determines the institution's asset choices. We construct X_n as the cross-sectional percentiles of asset n's characteristics, as explained later, so to that extent X_n incorporates cross-asset information. All stocks' X_n values affect the probit estimate of a_i, which is another way cross-asset information enters.

3.2. Intensive margin

Our model of the intensive margin gives the value of

$$w_{in}^{+} \equiv \mathrm{E}[w_{in} | w_{in} > 0, X, \pi_i] . \tag{26}$$

The expectation in Eq. (26) conditions on the full set of probabilities $\pi_i \equiv [\pi_{i1} \cdots \pi_{iN}]'$ and the full matrix X, because an investor's expected weight on a given stock can depend on what other stocks, and characteristics thereof, the investor could hold as well. For example, the portfolio weight on each stock held by the investor can depend on the greenness of all stocks, including stocks not held.

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

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

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

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

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

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

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

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

This regression's error term, e_{in}, could in principle be heteroskedastic, but this concern should be alleviated by our use of scaled portfolio weights, w_{in}/w_{mn}, on the left-hand side. In fact, the main reason why we scale w_{in} by the market weight in Eq. (27) is to reduce the heteroskedasticity in e_{in}. If we worked with raw weights w_{in} instead, e_{in}'s would likely be more volatile for larger firms (whose portfolio weights tend to be larger).

To derive the regression model in Eq. (29), we assume that for each stock n,

$$w_{in} = w_{in}^{+} + \epsilon_{in} , \tag{31}$$

with $\mathrm{E}[\epsilon_{in} | X] = 0$. The assumption that $\mathrm{E}[\epsilon_{in} | X] = 0$ merits discussion in light of alternative treatments such as Koijen 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 $\mathrm{E}[\epsilon_{in} | X] = 0$ 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. Suppose the investor is an actively managed fund. (For a passive fund, 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 fund's λ_i the opposite sign of $\bar{\lambda}$. That opposite sign occurs even if the fund 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 fund'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 $\mathrm{E}[\epsilon_{in} | X] = 0$ as a reasonable simplification. Also motivating this simplification is that we do not focus on the relation between w_{in} and the price-related variables in X.

3.3. Selection correction

The regression in Eq. (29) assumes that for each stock n in the N-stock universe, if investor i were to hold the stock, the weight they would place on it, w_{in}, would obey that equation, with $\mathrm{E}[e_{in} | X] = 0$. The values of w_{in} we use in estimating the regression in Eq. (29) can be only those for the subset of stocks actually held by the investor. If the probability of holding stock n is correlated with e_{in}, then e_{in} need not have zero expectation conditional on stock n being in that selected subset. Estimates of b_{ij} can be inconsistent if this selection effect is not corrected.

To correct for selection, we follow the two-step procedure of Heckman (1979), as described in Appendix A. We find empirically that the selection correction matters more for institutions holding fewer stocks, for which selection is more likely to matter. Given that institutions holding fewer stocks tend to be smaller, the correction makes relatively little difference in the aggregate asset-weighted tilt estimates (see the Internet Appendix).

3.4. Bias adjustment and standard errors

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

For example, to de-bias the raw estimates of T_i, which we denote by T_i^{raw}, we simulate many samples of portfolio weights, which we denote by $\tilde{w}_{in}$, by resampling the residuals from the extensive- and intensive-margin regressions estimated on the sample of observed weights, w_{in}. For each simulated sample $\tilde{w}_{in}$, we estimate the extensive- and intensive-margin regressions on that sample, obtaining an estimate of the investor-level tilt, which we denote by $\tilde{T}_i$. We estimate the bias in T_i^{raw} as $TBias_i = \bar{\tilde{T}}_i - T_i^{raw}$, where $\bar{\tilde{T}}_i$ is the average value of $\tilde{T}_i$ across simulations. Our bias-adjusted estimate of T_i is $T_i^{raw} - TBias_i$. An important by-product of the bootstrap analysis is the standard error of T_i, which we obtain from the standard deviation of the $\tilde{T}_i$'s across simulations. The details of the bootstrap procedure are in Appendix A.

4. Estimates of ESG tilts: Financial institutions

This section presents our main empirical findings. Using the econometric framework from Section 3, we estimate the ESG-related portfolio tilts introduced in Section 2 for a comprehensive sample of institutional investors. After describing our data in Section 4.1, we analyze total ESG tilts in Section 4.2, followed by green and brown tilts in Section 4.3. In Section 4.4, we examine how the tilts vary across institutions. In Section 4.5, we study tilts based on industry-adjusted ESG scores. Finally, in Section 4.6, we assess the robustness of our results using ESG metrics from an alternative data provider.

4.1. Data

We estimate the model using quarterly panel data on institutional investment managers that file Form 13F with the Securities and Exchange Commission. An institution is required to file this form if its holdings of U.S. stocks exceed $100 million. Here, "institution" refers to an investment company such as Fidelity, 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 2023, covered stocks account for 86% of the combined market capitalization of all CRSP stocks.[10] 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 3.8% of covered stocks' total market capitalization in 2023.

The number of institutions in our sample ranges from 1,727 in 2012 to 3,260 in 2023. Institutions' combined AUM increases from $9.7 trillion to $31.5 trillion during that period. The institutions hold between 63% and 70% of covered stocks' combined market capitalization during our sample period.

Our measures of ESG characteristics follow Pástor et al. (2022), who use data from MSCI, the world's largest provider of ESG ratings (e.g., Eccles and Stroehle (2018), and Berg et al. (2023b)). Berg et al. (2023a) 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) and provide granular industry-unadjusted measures. Our sample begins in 2012q4, when MSCI greatly expanded its coverage.

We compute environmental greenness as in Pástor et al. (2022), interacting the MSCI variables "Environmental Pillar Score" and "Environmental Pillar Weight".[11] We compute social and governance greenness the same way, replacing MSCI's E variables with their S and G counterparts. In most of our analysis, each stock's ESG characteristics are represented by a 3×1 vector representing E, S, and G greenness. In some of our analysis, there is only one ESG characteristic per stock: the stock's composite ESG score, which is 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.

In 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 over the past 12 months, excluding the most recent month. All seven variables are motivated by evidence from prior work cited earlier. For example, Koijen and Yogo (2019) use essentially the same variables, except for the last one, which is motivated by Gompers and Metrick (2001). In the intensive-margin model, non-ESG characteristics also include 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. All variables are computed from CRSP and Compustat data. Their precise definitions are in the Internet Appendix.

Some of the non-ESG stock characteristics, such as market capitalization, exhibit significant skewness. Therefore, instead of using their raw values, we employ their cross-sectional percentiles. For consistency, we also use cross-sectional percentiles of stocks' E, S, and G greenness values, as well as of the stock's ESG composite score. In short, both sets $\mathcal{G}$ and $\mathcal{C}$ contain the cross-sectional percentiles of stocks' characteristics rather than raw values. Finally, 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 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.

4.2. Total ESG tilts

The solid line in Panel A of Fig. 1 displays quarterly estimates of T from Eq. (10) computed across all sample 13F institutions, i.e., the aggregate ESG-related tilt. The series begins at 6.9% in 2012, drops as low as 5.2% in 2016, and ends at 6.5% in 2023. In other words, the dollar amount of ESG-related effects in each institution's stock holdings, summed across institutions, has consistently been about 6% of the institutions' total AUM.

The estimates of T are bias-adjusted using the bootstrap procedure explained earlier, which also provides standard errors. The bootstrap results validate well our estimation approach under the model assumptions, as the estimates of T require minimal bias adjustment and have low standard errors. The bias adjustment in T averages just 0.1% across quarters, and the standard errors in T are at most 0.2%. Table 1 reports fourth-quarter values, year by year, of the tilts plotted in Fig. 1, along with the bootstrap standard errors.[12] A key reason behind the low standard errors of T is that estimation error in each institution's T_i diversifies across institutions when computing the weighted sum in Eq. (10); a standard error of T_i is typically much larger than that of T. In the last quarter of 2023, for example, the estimate of Fidelity's T_i has a standard error of 1.2%, as compared to the 0.1% standard error of T in Table 1. Fidelity's estimated T_i in that quarter is 5.5%, after a bias adjustment of 0.2%. Recall that Fidelity's bias adjustment and standard error reflect a bootstrap simulation conducted separately for each institution and quarter.

A key feature of our estimation approach is that it 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 2023, for example, that alternative estimate is 11.5%, more than three-fourths higher than our estimate of 6.5% when controls are included. Across institutions, the correlation between T_i values estimated with and without controls is just 0.42. Again in the case of Fidelity, the 5.5% value of T_i noted above instead becomes 7.8% without controls, more than a 40% increase. Such results underscore the importance of controlling for non-ESG characteristics when computing ESG-related tilts.

As noted earlier, $\mathcal{G}$ includes three ESG characteristics per stock—cross-sectional percentiles of the E, S, and G greenness measures. To complement this baseline analysis, we re-estimate the model with $\mathcal{G}$ containing only one ESG characteristic: the composite ESG score, also expressed as a cross-sectional percentile. The resulting estimates of T are substantially smaller. In 2023, for example, our estimate of T that

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

[11] Environmental 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 et al. (2022) explain, interacting pillar scores and weights in this way is important for producing a meaningful measure of greenness.

[12] These 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.

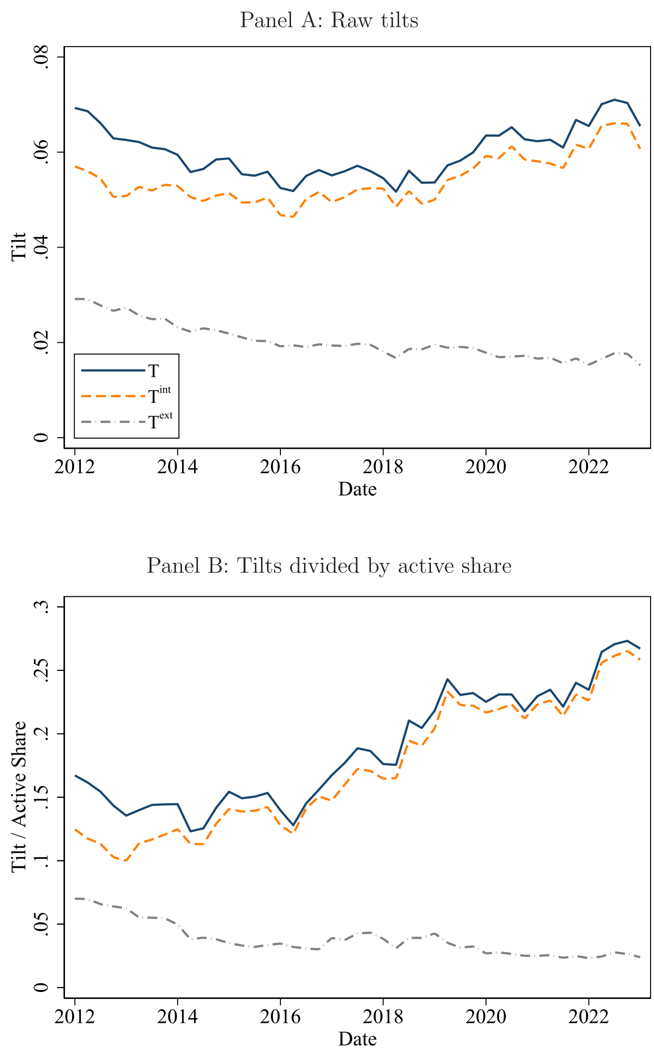

Fig. 1. Total, intensive, and extensive ESG tilts. Panel A plots the aggregate ESG-related tilt (T) and its decomposition into intensive and extensive tilts, T^{int} and T^{ext}, respectively. In Panel B, we divide each institution's tilt by its active share and then plot the AUM-weighted average of the resulting quantities. Tilt estimates are from the specification in which $\mathcal{G}$ contains three ESG characteristics (E, S, and G) per stock. Tick marks are at the fourth quarter of each year.

allows the three ESG dimensions to matter individually is 1.7 times the estimate based on the composite. A single ESG score thus fails to capture the full extent of ESG-related tilts. The three dimensions of ESG are distinct, and institutions differ in how much importance they assign to each dimension.

Panel A of Fig. 1 also displays estimates of the aggregate tilts at the intensive and extensive margins, defined in Eqs. (11) and (12). The extensive-margin tilt is typically around 2%, while the intensive-margin tilt is two to four 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 Fig. 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

Table 1
Aggregate tilts.
This table shows estimated aggregate tilts from each year's fourth quarter. Tilts are estimated from the specification in which $\mathcal{G}$ contains three ESG characteristics (E, S, and G) per stock. Columns 2 to 4 report the estimated tilts, and columns 5 to 7 show the bootstrapped standard errors. Tilts are expressed as a fraction of institutions' aggregate covered AUM.

	Estimated tilt			Standard error		
Year	Total	Intensive	Extensive	Total	Intensive	Extensive
2012	0.069	0.057	0.029	0.002	0.002	0.001
2013	0.063	0.051	0.027	0.002	0.002	0.001
2014	0.059	0.053	0.023	0.002	0.002	0.001
2015	0.059	0.051	0.022	0.002	0.002	0.001
2016	0.052	0.047	0.019	0.002	0.002	0.001
2017	0.055	0.050	0.019	0.002	0.002	0.001
2018	0.055	0.052	0.018	0.002	0.002	0.001
2019	0.054	0.050	0.020	0.002	0.001	0.001
2020	0.063	0.059	0.018	0.002	0.002	0.001
2021	0.062	0.058	0.017	0.001	0.001	0.001
2022	0.065	0.061	0.015	0.002	0.002	0.001
2023	0.065	0.061	0.015	0.001	0.001	0.000

with a below-median number of holdings, typically fewer than 100.[13] (The plots are in the Internet Appendix.) We find that all tilts are substantially smaller for the first subset of institutions, which is not surprising, as larger institutions tend to tilt less. 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 2.1 to 6.4 across quarters, while for the second subset it varies from 1.2 to 2.1. So, 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.

Our 6% headline number of the aggregate ESG tilt rests on a variety of modeling choices. As noted earlier, this number would rise if we were to leave out controls for non-ESG characteristics, and it would fall if we were to replace the E, S, and G scores with the ESG composite. It would also rise if we were to disaggregate the holdings of mutual fund families (see Section 5), but it might fall if we were to include more non-ESG characteristics beyond the seven already included. The number is also conditional on the functional forms of our extensive- and intensive-margin models as well as ESG ratings from a specific provider (see Section 4.6 for an alternative). 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 potential greening of the market portfolio (see Section 7) as well as shareholder engagement.

4.2.1. ESG tilts in the context of total portfolio tilts

Many discussions of ESG investing note its growing popularity over the past decade. It may therefore seem puzzling that Panel A of Fig. 1 shows no clear upward trend in the aggregate ESG-related tilt. Instead, the pattern is relatively flat, with the largest estimates of T appearing both early and late in the sample period.

To understand this seeming puzzle, it is useful to note that ESG investing is not the only trend in the U.S. investment industry. Two other trends also matter in this context. First, indexing has steadily gained

[13] The median number of stocks held ranges from 104 to 121 across quarters, with the overall median of 115 across institution-quarters. The 90th percentile of the number of holdings across institution-quarters is 653, less than one third of all covered stocks in our sample. Most institutions hold relatively few stocks.

market share relative to active management.[14] Second, actively managed funds have become more diversified, increasingly holding more stocks and aligning more closely with benchmark weights (e.g., Pástor et al., 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 broader decline in portfolio tilts, it is less surprising that ESG-related tilts have not increased. We suggest gauging ESG tilts within the context of this overall reduction in active tilts. A simple measure of institution i's total portfolio tilt is active share, defined by Cremers and Petajisto (2009) as

$$AS_i = \frac{1}{2}\sum_{n=1}^{N} |w_{in} - w_{mn}| \,. \tag{32}$$

Active share varies both over time and across institutions. Panel A of Fig. 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 0.42 to 0.30 between 2012 and 2023.[15] This fall in total tilts represents a headwind to institutions' ESG tilts. Panel B of Fig. 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. This large dispersion in active share reflects heterogeneity in institutions' investment approaches. For example, institutions with a large presence in indexing tend to have low active shares. Given their weaker propensity to tilt overall, such institutions typically have relatively low ESG tilts, too.[16]

To account for overall tilts, we divide each institution's ESG tilt by its concurrent active share. We then compute an AUM-weighted average of these ratios and plot the resulting aggregate, essentially a scaled version of T, in Panel B of Fig. 1. In contrast to Panel A, the scaled T trends clearly upward, especially after 2016. Adjusting for active share thus presents a different picture of ESG investing's importance over time: even though ESG tilts are not a growing share of AUM, they are a growing share of total portfolio tilts. The latter share doubles between 2016 and 2023, reaching 27% by the end of our sample.

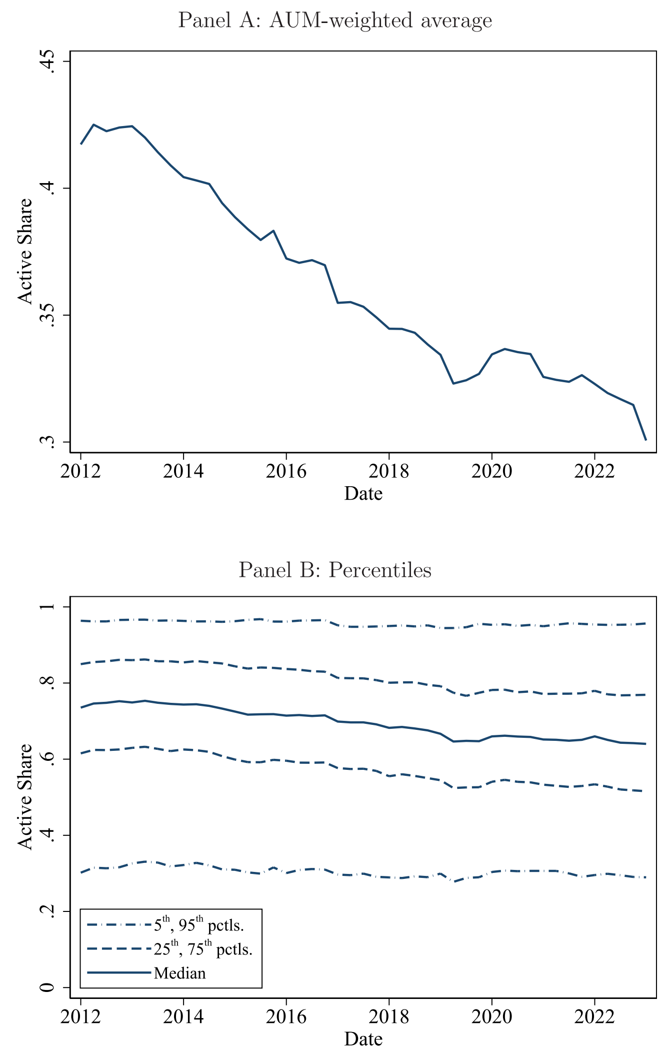

Fig. 2. Active share. Panel A plots the AUM-weighted average of institutions' active share. Panel B plots the cross-sectional percentiles of active share.

4.3. Green and brown portfolio tilts

Next, we separate green tilts from brown. For any given dimension of ESG, such as E or the composite ESG score, we compute the various tilts defined in Section 2.4. For example, by taking AUM-weighted averages of T_i^G and T_i^B defined via Eqs. (17) through (19), we compute the aggregate green and brown tilts, T^G and T^B, respectively. In this section, we examine the empirical patterns in green and brown tilts both across investors and over time, considering both extensive and intensive margins.

Fig. 3 plots the time series of T^G (Panel A) and T^B (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, T^G always exceeds T^B, indicating that financial institutions as a whole tilt green throughout the sample period. Second, T^G trends upward whereas T^B is fairly constant, implying that institutions are becoming increasingly green. Third, all of these patterns are similar across the four greenness measures.

If 13F-filing institutions tilt green, other investors must tilt brown (see Eq. (23)). We illustrate this point in Fig. 4. 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 shows 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-filers.

Some of the most vocal dialogue surrounding ESG investing calls for institutions to divest from brown stocks.[17] Such divestment is the component of green tilt that we denote as underweighting brown stocks (Eq. (14)). In this context, divestment includes both avoidance of brown

[14] For example, among equity mutual funds and ETFs, index funds' ownership of the U.S. stock market increased from 9% to 18%, while active funds' ownership share dropped from 19% to 13% between 2013 and 2023 (see the Investment Company Institute's *2024 Investment Company Fact Book*, page 29).

[15] A steady decline in active share has been reported by Cremers and Petajisto (2009), Stambaugh (2014), Koijen et al. (2024), and others. Koijen et al. argue that most of this decline is due to capital flows from active to passive investors rather than strategies becoming more passive.

[16] In an earlier version of this paper, we present regression evidence showing a significant positive relation between institutions' ESG tilts and their active shares, across both time and institutions.

[17] For 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.

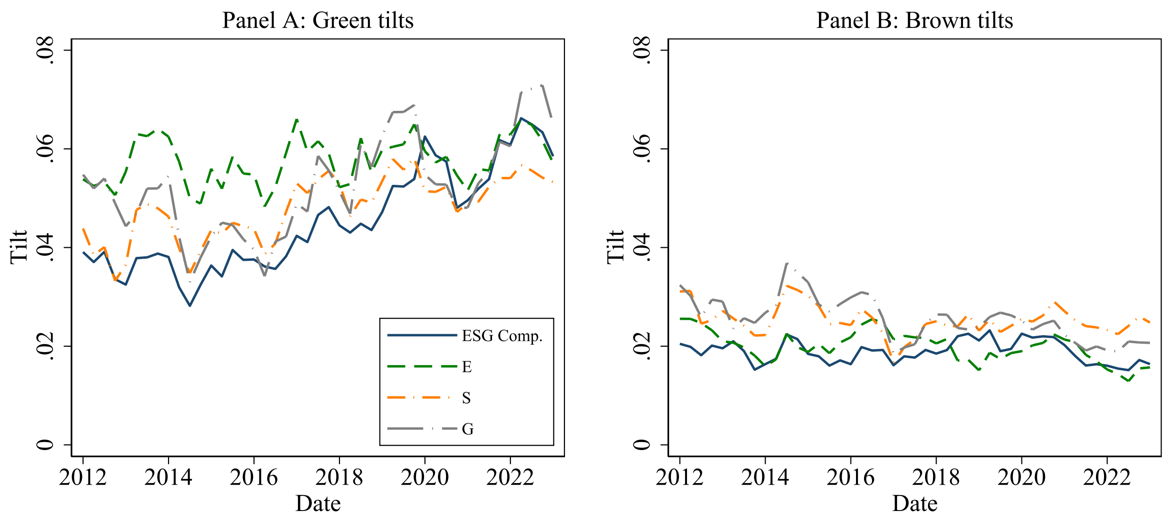

Fig. 3. Green and brown tilts. The green and brown tilts for the ESG composite are from the model specification with a single ESG characteristic per stock. The other three pairs of tilts are from the specification with three ESG characteristics per stock, changing one of the three characteristics to its neutral value while holding the other two characteristics at their sample values. We plot the AUM-weighted average of the tilts.

stocks and reduction of existing positions. Fig. 5 shows that divestment at the intensive margin (Panel A) is consistently larger than divestment at the extensive margin (Panel B). In other words, most divestment is partial, reducing brown stocks' weights, as opposed to total divestment that eliminates holdings. This finding is consistent with the theory of Edmans et al. (2024), in which full divestment can be suboptimal from the perspective of a responsible investor, because it does not incentivize firms to mitigate their externalities. We find that, unlike the extensive margin, the intensive one rises substantially over time, especially from 2017 to 2022.

4.4. Which institutions are greener?

In this section, we analyze how greenness varies across institutions with respect to institutional characteristics such as size, type, and location. We begin with institution size.

In Fig. 6 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 mostly increasing GMB tilts. In other words, large institutions are green, and increasingly so. In contrast, the GMB tilts of medium and small institutions are often negative and mostly decreasing. In essence, the 13F filers' positive and growing GMB tilt, observed earlier in Fig. 4, owes to just the largest institutions.

The world's largest institution, BlackRock, increasingly emphasized sustainability in the late 2010s. This emphasis culminated in January 2020, when BlackRock declared that sustainability should be its new standard for investing (BlackRock, 2020). After 2020, BlackRock's emphasis on sustainability waned. In line with these public stances, BlackRock's GMB tilt grew rapidly in the 2010s for all four measures of greenness, peaked in 2020, and declined afterwards. For example, based on the ESG composite, BlackRock's tilt rose from nil in 2013 to 9% of AUM in 2020, before dropping to 5.5% of AUM by 2023. BlackRock's GMB tilt outpaced its large-institution counterpart, which reached 4.2% of AUM in 2020 (see Panel A of Fig. 6). Nonetheless, even when we exclude BlackRock from the large-institution group, the remaining institutions in that group still display a positive and rising GMB tilt for all four greenness measures. Similarly, when we exclude the "Big Three" institutions — BlackRock, State Street, and Vanguard — from the large-institution group, the remaining large institutions have a positive and increasing GMB tilt. The main patterns in Fig. 6 are thus robust to the exclusions of BlackRock and the Big Three. See the Internet Appendix for details.

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 et al. (2014). Following those studies, we classify institutions as (i) investment advisors, (ii) banks, (iii) insurance companies, or (iv) pensions/endowments.[18] 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 2 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 Internet 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 2. 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 2023, 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 3.2 percentage point (pp) increase in GMB tilt in 2023 and a 1.6 pp

[18] We 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.

Fig. 4. GMB tilts of 13F filers and non-filers. The solid line shows the AUM-weighted average of GMB tilt 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 holdings 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.

decrease in GMB tilt in 2012.[19] These relations, including their reversal over time, are consistent with the patterns in Fig. 6.

UNPRI signatories have significantly greener tilts. This relation holds strongly across institutions (i.e., in specifications with time fixed effects), for all four greenness measures. The relation has the same estimated sign also within institutions (i.e., in specifications with institution fixed effects), but it is significant only for the E measure of greenness, indicating that an institution becomes environmentally greener after signing UNPRI. Across institutions, UNPRI signatories' GMB tilts are higher by a sizable 1.8–4.7 pp. The regressions' low R^2 values, however, suggest that UNPRI status is far from a perfect indicator of an institution's greenness. Moreover, these simple regressions do not establish any causal relation. Nonetheless, it seems useful to document that institutions that sign a commitment to invest responsibly tilt their portfolios toward greener stocks.

GMB tilts also differ significantly across the four institution types. F-tests strongly reject equality of tilts across institution types, except for the E measure of greenness. Depending on the specification, banks' GMB tilts are 2.9–14.0 pp lower than those of insurance companies (the omitted type), and the difference is significant for each greenness measure except E. Banks are also browner than both investment advisors and pensions/endowments. In most specifications, insurance companies are the greenest institution type.

In the Internet Appendix, we show the time series of GMB tilts by institution type. For all four types, including banks, the GMB tilt is mostly 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 2), and their greenness disproportionately affects the AUM-weighted average.

As also shown by Table 2, European institutions are significantly greener than U.S. ones (the omitted category). More precisely, European institutions' holdings of U.S. stocks are greener than U.S. institutions' holdings of U.S. stocks, as measured by GMB tilts. Depending

[19] The difference in log(AUM) between the two percentiles is 1.40. Note that 0.032 equals 1.40 × 0.0229, and −0.016 equals $1.40 \times [0.0229 - 0.44 \times 0.0779]$, where −0.44 is the value of Trend in 2012.

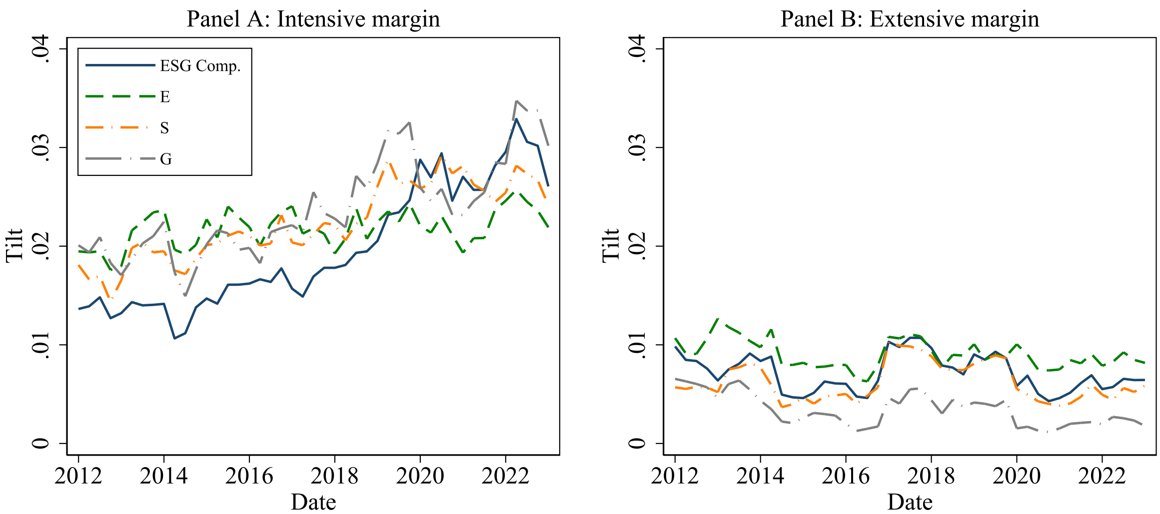

Fig. 5. Divestment from brown stocks. Divestment from brown stocks, which is a component of green tilt, can be done on either the extensive margin (full divestment) or intensive margin (partial divestment). We show both. Panel A shows the component of intensive green tilts coming from under-weighting brown stocks. Panel B shows the component of the extensive green tilts 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 plot the AUM-weighted average of the tilts.

Table 2
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 100,357 institution×quarter non-missing observations from 2012q4–2023q4. AUM is divided by the total market capitalization of all covered stocks. Trend equals the observation's quarter minus 2023q4, 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)	0.0229	0.0043	0.0245	0.0179	0.0231	0.0056	0.0251	0.0194	0.0085	−0.0157	0.0111	−0.0020
	(8.50)	(1.42)	(7.48)	(6.91)	(8.56)	(1.85)	(7.64)	(7.53)	(1.46)	(−2.24)	(1.55)	(−0.34)
log(AUM) × trend	0.0779	0.0428	0.0513	0.0031	0.0803	0.0486	0.0551	0.0100	0.0652	0.0347	0.0471	0.0020
	(8.19)	(3.87)	(4.66)	(0.33)	(8.41)	(4.37)	(4.98)	(1.06)	(5.98)	(2.93)	(3.86)	(0.18)
Trend	0.6341	0.3585	0.4315	0.0276					0.5056	0.2303	0.3996	0.0150
	(6.53)	(3.18)	(3.85)	(0.28)					(4.79)	(1.97)	(3.36)	(0.14)
Active share	−0.0012	−0.0119	0.0138	−0.0459	−0.0016	−0.0120	0.0128	−0.0461	−0.0094	−0.0511	0.0410	−0.0383
	(−0.07)	(−0.58)	(0.63)	(−2.52)	(−0.10)	(−0.58)	(0.58)	(−2.53)	(−0.22)	(−1.00)	(0.80)	(−0.90)
1(UNPRI)	0.0452	0.0453	0.0473	0.0196	0.0452	0.0438	0.0469	0.0180	0.0261	0.0500	0.0190	0.0008
	(4.64)	(4.09)	(4.28)	(2.22)	(4.63)	(3.96)	(4.25)	(2.04)	(1.75)	(2.86)	(1.21)	(0.06)
1(Inv. advisor)	−0.0244	0.0019	−0.0058	−0.0214	−0.0246	0.0020	−0.0058	−0.0213				
	(−1.68)	(0.10)	(−0.24)	(−0.99)	(−1.69)	(0.11)	(−0.24)	(−0.98)				
1(Bank)	−0.0855	−0.0292	−0.1398	−0.0623	−0.0858	−0.0291	−0.1399	−0.0624				
	(−4.28)	(−1.36)	(−4.39)	(−2.47)	(−4.29)	(−1.35)	(−4.39)	(−2.47)				
1(Pension/endowment)	−0.0128	−0.0135	0.0211	0.0059	−0.0128	−0.0134	0.0210	0.0059				
	(−0.75)	(−0.58)	(0.78)	(0.24)	(−0.75)	(−0.58)	(0.78)	(0.24)				
1(Europe)	0.0345	0.0502	0.0514	0.0377	0.0349	0.0510	0.0521	0.0386				
	(2.49)	(3.27)	(3.25)	(2.89)	(2.51)	(3.30)	(3.30)	(2.96)				
1(Rest of world)	0.0113	0.0381	0.0224	0.0112	0.0118	0.0395	0.0233	0.0128				
	(0.75)	(2.23)	(1.22)	(0.66)	(0.79)	(2.31)	(1.26)	(0.76)				
R^2	0.020	0.005	0.023	0.016	0.023	0.008	0.025	0.019	0.436	0.446	0.497	0.406
R^2 (FEs only)	N/A	N/A	N/A	N/A	0.009	0.003	0.004	0.003	0.432	0.444	0.496	0.406
p (Inst. types equal)	0.000	0.122	0.000	0.004	0.000	0.122	0.000	0.004	N/A	N/A	N/A	N/A

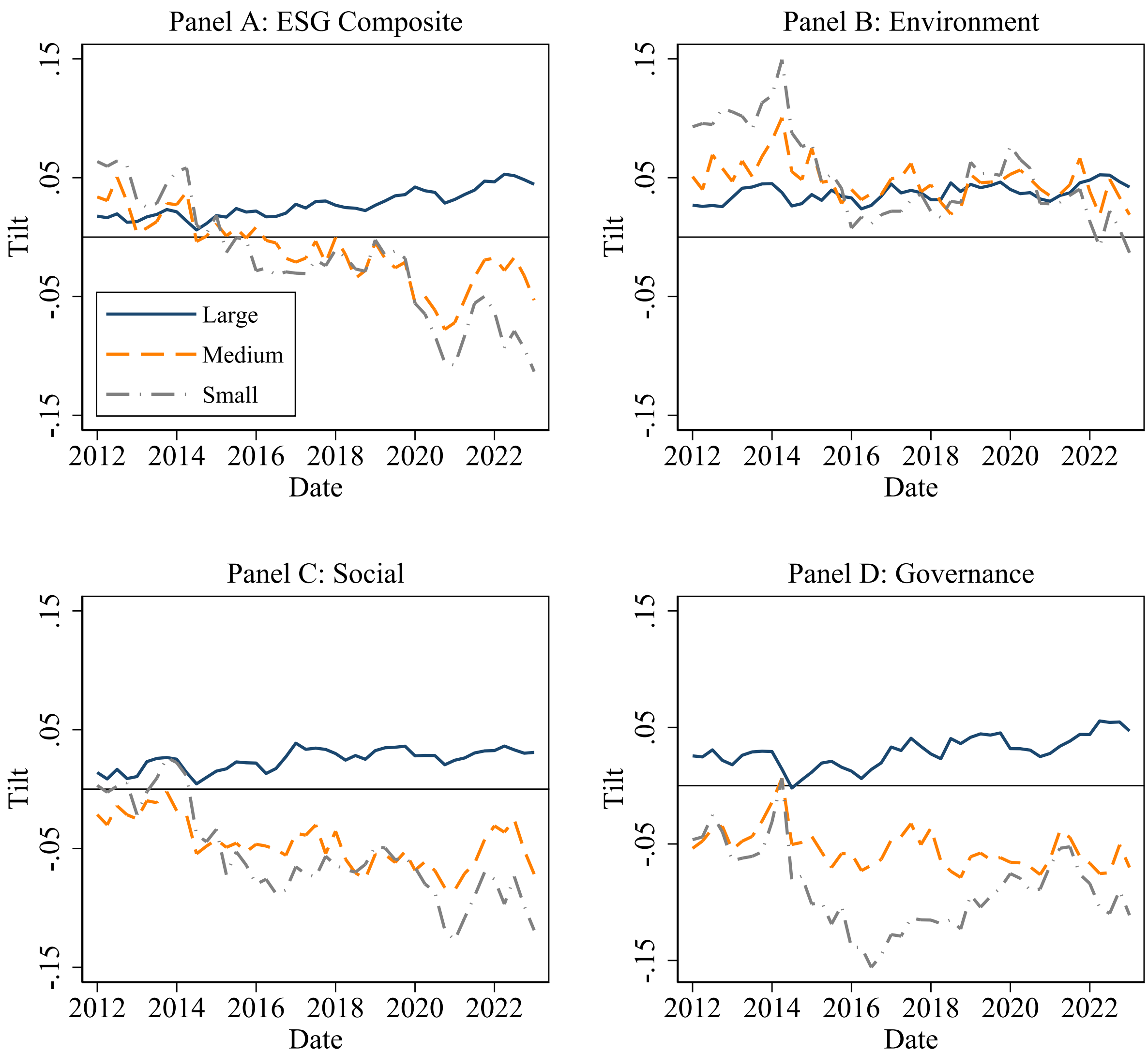

Fig. 6. Institution size and greenness. This figure compares GMB tilts across subsamples formed based on quarterly AUM terciles. Each line shows the subsample's AUM-weighted average GMB tilt.

on the specification, European institutions' GMB tilts are 3.5–5.2 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 et al. (2024) 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. (2023) 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 3 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}.[20] We see that both green and brown tilts drive the positive relation between AUM and greenness, but brown tilts matter much more. At the end of our sample period, larger institutions are both slightly greener and much less brown. Both legs, green and brown, 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 strong, positive relation to both green and brown tilts. The GMB tilt exhibits no relation to active share, however, as the positive effects in the green and brown legs largely offset each other (Table 2).

4.5. Industry adjustment

Our ESG characteristics are based on MSCI ESG ratings, which are not industry-adjusted. ESG ratings vary across industries—for example, E ratings tend to be higher in finance, health care, and technology, and lower in chemicals, steel, and mining (see Table 2 in (Pástor et al., 2022)). We focus on unadjusted ratings because they are widely used and reflect how many investors approach ESG, particularly those who exclude entire industries, such as oil and gas, from their portfolios. That said, some investors assess ESG performance relative to industry peers. In this section, we examine portfolio tilts based on industry-adjusted ESG scores.

We classify each firm into one of 94 industries, quarter by quarter, using MSCI's industry classification. For each of E, S, G, and the composite ESG score, we compute the average greenness of each industry

[20] Table 3 reports results from regressions without fixed effects. Results with fixed effects are in the Internet Appendix. Results with time fixed effects are very similar to those reported in Table 3.

Table 3
Institutions' 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 2.

	Green tilts				Brown tilts			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	0.0025	−0.0024	0.0037	0.0038	−0.0204	−0.0067	−0.0208	−0.0140
	(1.84)	(−1.22)	(2.13)	(3.08)	(−11.46)	(−4.13)	(−9.69)	(−7.84)
log(AUM) × trend	0.0230	0.0270	0.0156	0.0029	−0.0550	−0.0160	−0.0356	−0.0002
	(4.33)	(3.71)	(2.52)	(0.63)	(−9.39)	(−2.73)	(−5.19)	(−0.03)
Trend	0.2431	0.2653	0.2078	0.0564	−0.3912	−0.0944	−0.2233	0.0288
	(4.45)	(3.57)	(3.22)	(1.17)	(−6.62)	(−1.58)	(−3.24)	(0.45)
Active share	0.0904	0.1439	0.1283	0.0939	0.0916	0.1552	0.1143	0.1396
	(10.01)	(11.03)	(11.38)	(10.45)	(8.52)	(13.34)	(7.77)	(11.24)
1(UNPRI)	0.0230	0.0225	0.0122	0.0020	−0.0223	−0.0229	−0.0350	−0.0176
	(3.74)	(2.95)	(1.81)	(0.43)	(−4.09)	(−4.29)	(−5.47)	(−3.08)
1(Inv. advisor)	−0.0030	0.0063	0.0048	−0.0163	0.0215	0.0045	0.0107	0.0052
	(−0.33)	(0.43)	(0.48)	(−1.58)	(2.79)	(0.52)	(0.60)	(0.33)
1(Bank)	−0.0171	−0.0121	−0.0303	−0.0298	0.0685	0.0171	0.1095	0.0325
	(−1.72)	(−0.77)	(−2.71)	(−2.59)	(5.16)	(1.57)	(4.45)	(1.79)
1(Pension/endowment)	−0.0055	−0.0077	0.0104	−0.0054	0.0073	0.0057	−0.0108	−0.0113
	(−0.57)	(−0.47)	(0.86)	(−0.46)	(0.74)	(0.47)	(−0.58)	(−0.65)
1(Europe)	0.0272	0.0388	0.0281	0.0271	−0.0072	−0.0114	−0.0233	−0.0105
	(2.87)	(3.55)	(2.61)	(3.57)	(−0.97)	(−1.45)	(−2.70)	(−1.32)
1(Rest of world)	0.0097	0.0258	0.0151	0.0139	−0.0016	−0.0124	−0.0074	0.0026
	(1.08)	(2.19)	(1.40)	(1.56)	(−0.19)	(−1.43)	(−0.68)	(0.25)
R^2	0.017	0.024	0.023	0.014	0.043	0.030	0.043	0.037
p (Inst. types equal)	0.085	0.060	0.000	0.013	0.000	0.389	0.000	0.014

in each quarter by computing the value-weighted average of g_n across all firms in that industry and quarter. We then compute each firm n's industry-adjusted score in each quarter as g_n minus the corresponding industry average. We convert both the industry-adjusted values and the industry average to percentiles in the full cross section of stocks, analogous to our main analysis. Finally, we treat the industry-adjusted ESG scores' percentiles as our ESG characteristics ($\mathcal{G}$), and we add the industry-average ESG scores' percentiles to the set of controls ($\mathcal{C}$).

Fig. 7 is the counterpart of Fig. 1 using industry-adjusted ESG scores. The resulting total ESG tilt, T, remains fairly stable over time, ranging mostly from 4% to 5%. This range is below that of the unadjusted T (5.2% to 6.9%; see Fig. 1), suggesting that more investors use raw scores than industry-adjusted scores when forming portfolios. Apart from their lower levels, the adjusted tilts closely resemble the unadjusted ones: in both figures, T^{int} far exceeds T^{ext}, with the former trending slightly upward and the latter downward. The key takeaway from both figures is the same: ESG tilts account for a modest share of AUM and are much larger on the intensive margin.

Fig. 8 mirrors Fig. 3 but uses industry-adjusted green and brown tilts. Again, the levels are lower compared to the unadjusted tilts, but the overall patterns remain similar. In both figures, green tilts exceed brown, green tilts trend upward while brown tilts are flat, and these patterns hold across the four greenness measures. Industry-adjusted or not, institutions collectively tilt green, and increasingly so. In the Internet Appendix, we show the industry-adjusted versions of the other previous figures and tables.

4.6. Sustainalytics ratings

While MSCI is the leading global provider of ESG ratings (see Section 4.1), investors have access to multiple data sources. In this section, we assess the robustness of our results by using ESG scores from one of MSCI's main competitors: Sustainalytics.

Our Sustainalytics sample is smaller than our MSCI sample, for two reasons. First, MSCI covers more than twice as many firms. Second, we use Sustainalytics data only from December 2018 onward, following a major methodology overhaul that year. ESG ratings from the two providers are positively correlated, with correlations ranging from 0.17 for G scores to 0.78 for E scores. For a detailed description of the Sustainalytics data, including data coverage and summary statistics, see the Internet Appendix.

We use Sustainalytics' ESG scores to re-estimate all portfolio tilts for our institutional sample. We report all of our main results — the counterparts of Figs. 1 through 6 and Tables 1 through 3 — in the Internet Appendix. These results are remarkably similar to those based on MSCI scores. For example, the aggregate tilt is stable over time, ranging from 5.9% to 6.7%. The aggregate intensive-margin tilt remains much larger than the extensive-margin tilt. Green tilts exceed brown, indicating that institutions as a whole tilt green. Divestment from brown stocks still occurs primarily at the intensive margin. Larger institutions tilt greener for three of the four greenness measures. UNPRI signatories and European institutions are also greener, significantly so for the ESG composite and E measures. To summarize, all of our main conclusions hold also when using Sustainalytics' ESG scores.

5. Estimates of ESG tilts: Mutual funds

In this section, we estimate ESG-related portfolio tilts for U.S. equity mutual funds. Looking at mutual funds is useful for several reasons. First, some of the institutions analyzed in Section 4 are mutual fund families. In their 13F filings, fund families aggregate the portfolio holdings of their individual funds. This aggregation could mask fund-level ESG tilts that offset within families, understating the extent of overall tilting. It could also understate extensive-margin tilts, because a stock excluded by some funds will still appear in family-level holdings if held by any fund of the same family. Analyzing fund-level holdings allows us to address both issues and assess their importance. It also enables us to examine the tilts of ESG-labeled funds, which cannot be identified in 13F filings.

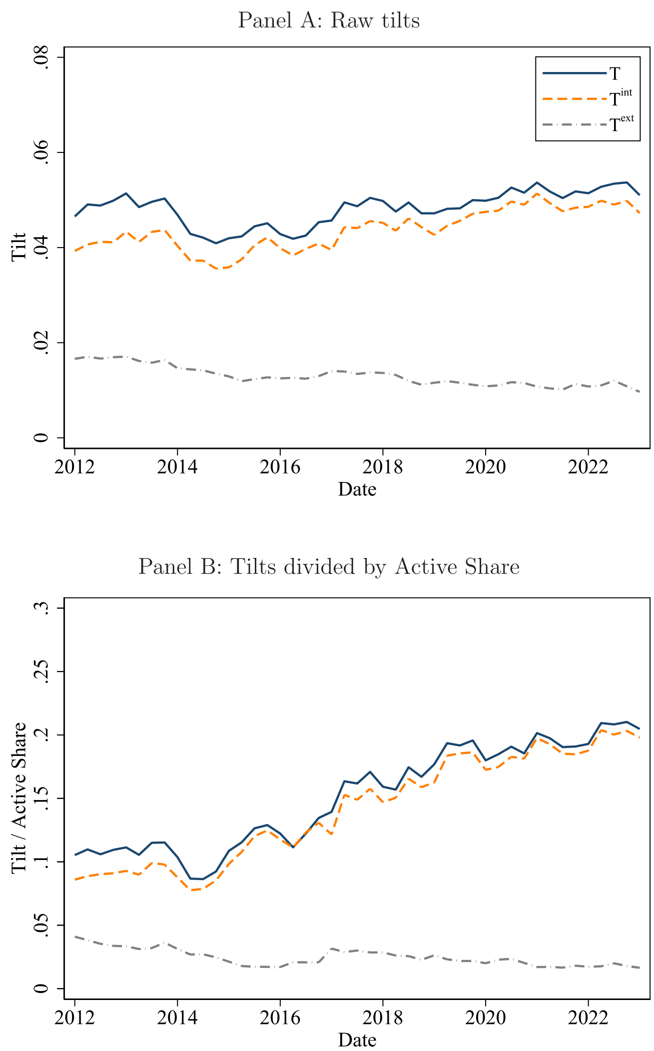

Fig. 7. Industry-adjusted tilts. This figure plots versions of the tilts from Fig. 1 estimated using stocks' industry-adjusted ESG scores. For each of E, S, and G, we compute stocks' industry-adjusted scores as g_n minus the value-weighted average of g_n across stocks in the same industry and quarter. We convert the industry average and industry-adjusted values to percentiles in the full cross section of stocks, similar to our main analysis. We include in $\mathcal{G}$ the industry-adjusted E, S, and G scores' percentiles, and we add the three industry-average E, S, and G scores' percentiles to the set of exogenous controls. Otherwise, the method and data are the same as in our main analysis.

A key limitation of the mutual fund universe is that it is much smaller than financial institutions in aggregate, covering only about a quarter of the 13F sample's AUM. The mutual fund sample excludes significant holdings, especially of banks, insurers, pension funds, endowments, hedge funds, and sovereign wealth funds. As a result, mutual fund evidence cannot fully capture the extent of ESG-related tilting in the investment industry. We view the results presented in this section as complementary to our main findings in Section 4, which draw on a broader and more comprehensive institutional sample.

5.1. Data

Starting with the Thomson Reuters Mutual Fund Holdings (S12) dataset, we compute funds' quarterly portfolio weights w_{in} among the subset of covered stocks. We take data on funds' characteristics from CRSP and Morningstar Direct.

We construct the fund sample as follows. Starting from all funds in the S12 dataset, we exclude bond funds, international funds, funds of funds, real estate funds, target retirement funds, and other non-equity funds based on keywords in the Morningstar Category variable. We also exclude variable annuity funds using the CRSP flag. We include index funds, labeled as "index" or "enhanced index" by CRSP or Morningstar. We aggregate multiple share classes of the same fund and drop funds with less than \$10 million in AUM. As in the previous section, we require funds to have at least 50% of their assets in covered stocks and at least 30 holdings, and we define a fund's AUM as the total value of its covered holdings. We clean the mutual fund data following Pástor et al. (2020).[21]

The number of funds in our sample ranges from 1,506 in 2012 to 1,221 in 2023. Funds' combined AUM grows from \$2.5 trillion to \$8.3 trillion during that period. For comparison, the 13F sample studied earlier contains roughly four times as much AUM. As of 2023, index funds make up 15% of the fund sample by count and 58% by AUM.

5.2. Total ESG tilts

Fig. 9 plots aggregate ESG tilts — T, T^{int}, and T^{ext} from Eqs. (10) through (12) — based on three mutual fund samples. The first sample includes only active funds, excluding index funds. The second sample includes all funds, active and passive. The third sample includes mutual fund families, which we create by grouping funds into families based on family names obtained from Morningstar (or CRSP if unavailable). For each family, we combine the holdings of member funds into a single "quasi-fund" and estimate its tilt.

Panel A of Fig. 9 shows total ESG tilts, T, across the three samples. For active funds, T is stable, ranging from 10% to 13%. Including passive funds lowers T to 6%–10%, reflecting their much smaller tilts. Fund-family tilts are lower still, between 3.5% and 6%. The gap between the T values for all funds and for fund families, which ranges from 1.6 to 4.2 percentage points, captures the extent of within-family offsetting. These offsets modestly reduce overall tilts. For example, at the end of our sample, T is 6.5% for all funds and 4.7% for fund families, so that offsetting tilts account for 1.8% of mutual fund families' AUM. Multiplying this share by the fraction of institutional AUM held by mutual fund families implies that adjusting for within-family offsets would increase the aggregate tilt in Fig. 1 by just under 0.5% in 2023.[22] This adjustment, from 6.5% to 7%, is fairly small.

Panels B and C of Fig. 9 plot intensive- and extensive-margin tilts, T^{int} and T^{ext}. The values of T^{ext} for the all-fund sample are about three times larger than those for the fund-family sample, and they also exceed their counterparts for the broader institutional sample (see Fig. 1). This is expected, as stock exclusions are more common at the fund level than at the family level, as explained earlier. More importantly, for each sample and each point in time, $T^{ext} < T^{int}$, just like in Fig. 1. In other words, our finding that $T^{ext} < T^{int}$ obtains not only at the institution level but also at the fund level.

[21] During the cleaning process, we correct one additional, notable, recently-introduced error in the S12 dataset. One data-cleaning step involves excluding funds whose total holdings exceed twice their fund-level assets. This step mistakenly drops the world's largest mutual fund, Vanguard's Total Stock Market Index Fund, starting in 2020q4. In the S12 data, this fund's reported asset values are misreported by a factor of ten from 2020q4 onward. After we correct this data error, the fund is restored to our sample.

[22] Mutual fund families manage \$8.3 trillion in 2023, which represents 26.3% of the AUM of all institutions in our 13F sample. Multiplying 26.3% by 1.8% gives 0.47%.

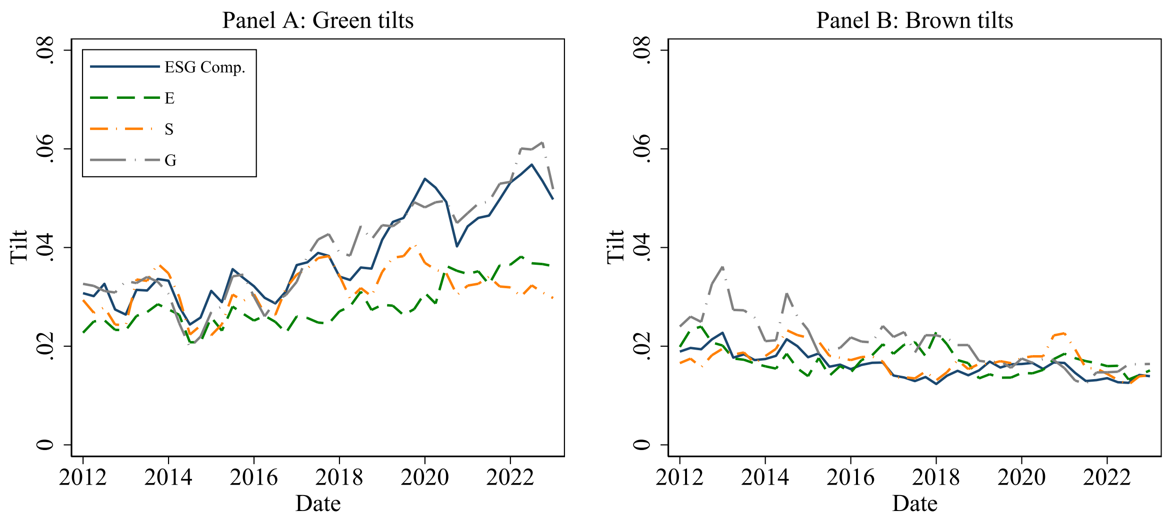

Fig. 8. Industry-adjusted green and brown tilts. This figure plots versions of the tilts from Fig. 3 estimated using stocks' industry-adjusted ESG scores. Details on the method are the same as in Fig. 7.

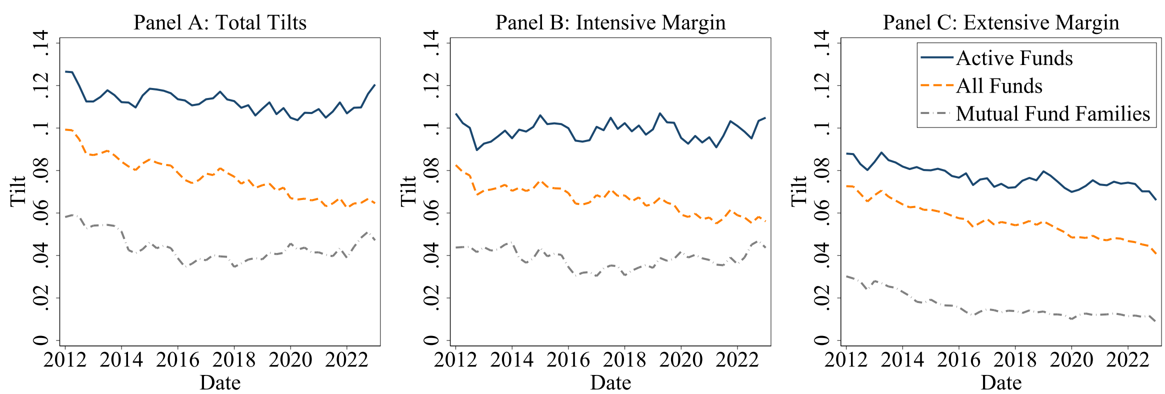

Fig. 9. Mutual funds' ESG tilts. Panels A, B, and C plot the aggregate ESG-related tilt (T), intensive-margin tilt (T^{int}), and extensive-margin tilt (T^{ext}), respectively, estimated in mutual-fund samples indicated in the legend. The sample of all funds includes both active and passive funds. We create the sample of mutual fund families as follows. For each family, we construct a "quasi-fund" by aggregating all funds (active and passive) within each family into a single portfolio, and we estimate that quasi-fund's tilts. All lines show AUM-weighted averages of tilts within the given sample of mutual funds. Tilt estimates are from the specification in which $\mathcal{G}$ contains three ESG characteristics (E, S, and G) per stock.

5.3. Green and brown portfolio tilts

Fig. 10 plots green and brown tilts, T^G and T^B, for the all-fund sample. The figure mirrors Fig. 3, but with tilts estimated at the mutual fund level rather than the institution level. As in Fig. 3, though to a lesser extent, we observe $T^G > T^B$, indicating that mutual funds collectively tilt green. Unlike in Fig. 3, there is no upward trend in T^G (or T^B), suggesting that the gradual increase in green tilting is driven by non-mutual-fund institutions. Green tilts range from 3% to 8%; brown tilts from 2% to 6%. All patterns in Fig. 10 look similar across the four greenness measures.

Fig. 11 examines mutual funds' divestment from brown stocks, paralleling Fig. 5 but using the all-fund sample instead of the full institutional sample. Extensive-margin divestment is larger for funds — ranging mostly from 0.5% to 1.5%, compared to 0.1% to 1.3% for institutions — reflecting the greater prevalence of full divestment at the fund level. More notably, as in the institutional sample, intensive-margin divestment remains consistently larger, typically from 1.5% to 3%, and it exceeds extensive-margin divestment throughout. Intensive- exceeds extensive-margin divestment even for active funds, where one might expect the latter divestment to be largest, as active funds typically hold fewer stocks than passive funds (see the Internet Appendix). Thus, even for individual mutual funds, brown divestment is primarily partial rather than full.

5.4. Which funds are greener?

Table 4 reports results from panel regressions of mutual funds' green and brown tilts on three fund characteristics — AUM, active share, and an ESG-label dummy — along with a time trend and its interaction with AUM. These regressions are analogous to those in Table 3, but they exclude institution-level regressors and include a fund-specific ESG dummy. This indicator, sourced from Morningstar, equals one if the fund is described in its prospectus or other regulatory filings as focusing on ESG, sustainability, or impact investing. We estimate the regressions separately for all mutual funds (Panel A) and for active funds only (Panel B). As the results are similar across panels, we discuss them jointly.

Table 4 shows that both green and brown tilts are strongly and positively related to active share, echoing the institution-level results in Table 3. Green tilts are also positively related to the time trend and its interaction with AUM, though these effects are somewhat weaker than in Table 3. Unlike in Table 3, the negative relations between brown tilts and both AUM and its interaction with the time trend are not statistically significant.

The most novel findings in Table 4, with no counterpart in Table 3, concern the ESG dummy. Compared to non-ESG funds, ESG-labeled funds' green tilts are substantially larger, by 9–16 pp of AUM, and

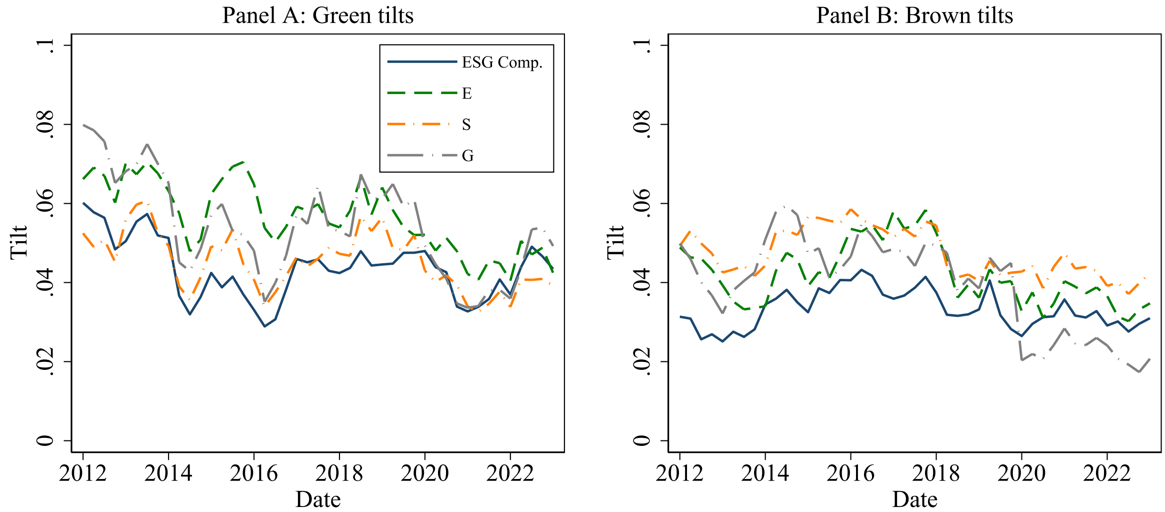

Fig. 10. Mutual funds' green and brown tilts. This figure plots the same quantities as Fig. 3, but tilts are estimated at the level of individual mutual funds (both active and passive).

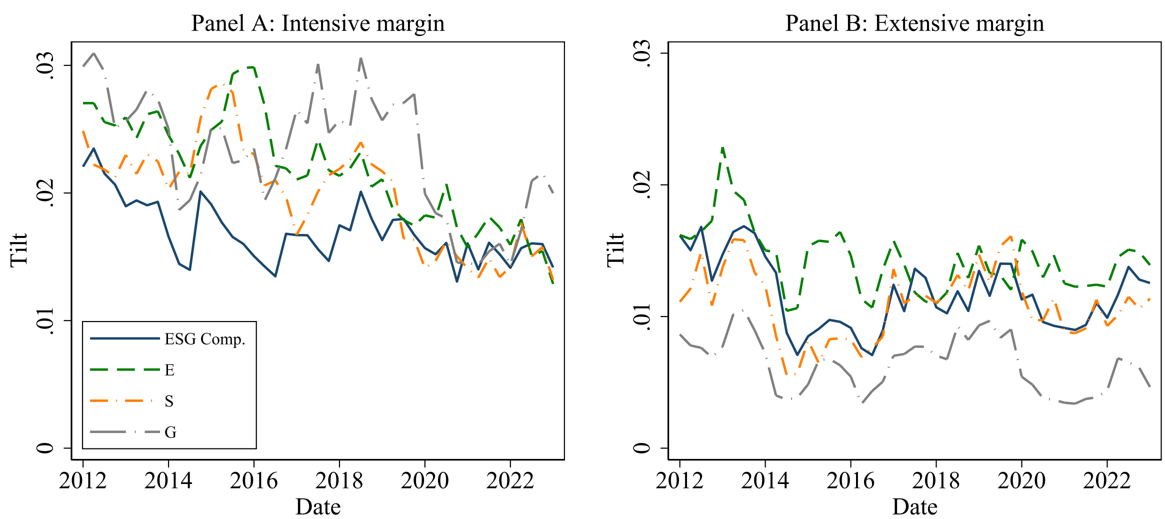

Fig. 11. Mutual funds' divestment from brown stocks. This figure plots the same quantities as Fig. 5, but tilts are estimated at the level of individual mutual funds (both active and passive).

their brown tilts are 2–5 pp smaller. Both of these relations are highly statistically significant across all four greenness measures. The relations are economically large relative to funds' aggregate green tilts (3%–8%) and brown tilts (2%–6%), plotted in Fig. 10. These results indicate that tilting, as captured by our methodology, is an important feature of mutual funds' ESG investment strategies.

6. Comparing measures of green portfolio tilts

How do other potential measures of green tilts differ from ours? In this section, we contrast our measure, T_i^{GMB} from Eq. (20), with several alternatives. We perform two comparisons at the end of our sample (2023q4): one across 13F institutions and another across mutual funds.

A key feature of T_i^{GMB} is that it controls for non-ESG stock characteristics, listed in Section 4.1. The first alternative we consider is a modified version of T_i^{GMB} that drops these controls. The second, even simpler alternative is the difference between the portfolio's weights in green and brown stocks: $\sum_{n\in Green} w_{in} - \sum_{n\in Brown} w_{in}$, where *Green* (*Brown*) denotes covered stocks whose ESG composite score is in the highest (lowest) quintile. This measure does not control for non-ESG characteristics, nor does it separate holdings at the extensive versus intensive margin—another key feature of our measure.

The third alternative, computed for the 13F sample, is an indicator for whether the institution signed the UNPRI by 2023q4. The fourth and fifth, computed for the mutual-fund sample, are the ESG-fund indicator from Section 5.4 and the fund's Morningstar Sustainability Rating, or the "globe rating". To compute this rating, Morningstar uses firm-level data from Sustainalytics to calculate the ESG risk of a fund's holdings. Funds receive 1 to 5 globes, with 5 indicating the lowest ESG risk relative to peer funds. Peers are funds in the same Morningstar Global Category, based on asset class and investment style (e.g., U.S. large-cap growth equity). Because the globe rating is relative, it implicitly controls for some non-ESG stock characteristics, such as size and book-to-market.

6.1. 13F institutions

Table 5 compares the green tilt measures at the 13F institution level. Column 1 reports each measure's AUM-weighted mean across institutions in 2023q4. For T_i^{GMB}, this average is 4.2%, indicating an aggregate net green tilt (see also Panel A of Fig. 4). Without controlling for non-ESG characteristics, the average rises to 11.2%, nearly three times larger. The even higher average of 27.6% for $\sum_{n\in G} w_{in} - \sum_{n\in B} w_{in}$

Table 4
Mutual funds' green and brown tilts.
This table shows results from panel regressions with dependent variable equal to the mutual fund's green tilt (T_{it}^{G}, columns 1–4) or brown tilt (T_{it}^{B}, columns 5–8). Variable 1(ESG-labeled fund), obtained from Morningstar, is an indicator for whether the fund is described in the prospectus or other regulatory filings as focusing on sustainability, impact investing, or ESG factors. Panel A shows results using all mutual funds (passive and active); this sample includes 28,789 fund×quarter non-missing observations from 2018q4–2023q4. (We begin the sample in 2018q4 because this is the first quarter that 1(ESG-labeled fund) is available.) Panel B shows results using active mutual funds only; this sample includes 24,788 fund×quarter non-missing observations from 2018q4–2023q4. Other details are the same as in Table 3.

	Green tilts				Brown tilts			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
Panel A: All funds								
log(AUM)	−0.0002	−0.0028	−0.0010	0.0011	−0.0019	−0.0000	−0.0011	−0.0031
	(−0.09)	(−1.14)	(−0.49)	(0.71)	(−1.24)	(−0.02)	(−0.57)	(−1.94)
log(AUM) × trend	0.0252	0.0412	0.0339	0.0282	−0.0048	−0.0161	−0.0034	−0.0079
	(1.90)	(2.31)	(2.25)	(2.10)	(−0.45)	(−1.24)	(−0.27)	(−0.60)
Trend	0.3598	0.5525	0.4306	0.2055	−0.0057	−0.2302	−0.0761	−0.2480
	(2.48)	(2.93)	(2.62)	(1.40)	(−0.05)	(−1.62)	(−0.54)	(−1.70)
Active share	0.0862	0.0642	0.1108	0.1011	0.0269	0.1362	0.0722	0.0584
	(10.58)	(5.56)	(10.59)	(13.08)	(3.87)	(12.90)	(7.85)	(7.38)
1(ESG-labeled fund)	0.1395	0.1581	0.1118	0.0896	−0.0203	−0.0437	−0.0385	−0.0193
	(9.78)	(9.49)	(7.62)	(7.55)	(−3.43)	(−8.13)	(−6.21)	(−2.77)
R^2	0.075	0.054	0.051	0.050	0.006	0.039	0.014	0.015
Panel B: Active funds								
log(AUM)	0.0006	−0.0012	−0.0005	0.0018	−0.0016	−0.0007	−0.0012	−0.0033
	(0.31)	(−0.41)	(−0.21)	(0.99)	(−0.88)	(−0.31)	(−0.52)	(−1.70)
log(AUM) × trend	0.0365	0.0618	0.0464	0.0385	−0.0054	−0.0238	−0.0074	−0.0137
	(2.23)	(2.85)	(2.51)	(2.36)	(−0.41)	(−1.49)	(−0.47)	(−0.85)
Trend	0.4914	0.8119	0.5789	0.3182	−0.0021	−0.3374	−0.1109	−0.3271
	(2.70)	(3.46)	(2.80)	(1.74)	(−0.01)	(−1.89)	(−0.64)	(−1.78)
Active share	0.0968	0.0311	0.1272	0.1214	−0.0103	0.1543	0.0449	0.0318
	(8.04)	(1.75)	(8.43)	(10.43)	(−0.89)	(10.02)	(3.16)	(2.52)
1(ESG-labeled fund)	0.1453	0.1678	0.1170	0.0956	−0.0233	−0.0475	−0.0415	−0.0208
	(9.31)	(9.62)	(7.16)	(7.21)	(−3.42)	(−7.85)	(−5.91)	(−2.60)
R^2	0.070	0.049	0.047	0.046	0.003	0.031	0.006	0.007

Table 5
Comparing measures of institutions' green tilts.
This table describes 13F institutions' green tilt measures in 2023q4. The two T_i^{GMB} measures are from our specifications in which $\mathcal{G}$ contains only the ESG composite score. The first of those specifications includes the non-ESG controls, as in our main analysis, and the second specification excludes those controls. To compute the third measure below, given by $\sum_{n\in Green} w_{in} - \sum_{n\in Brown} w_{in}$, we define *Green* (*Brown*) to be the set of covered stocks whose ESG composite score is in the highest (lowest) quintile. 1(UNPRI$_i$) is an indicator for whether institution i signed the UNPRI on or before 2023q4.

Green tilt measure	AUM-weighted average	Correlations (1)	(2)	(3)	(4)
(1) T_i^{GMB}, with controls	0.042	1			
(2) T_i^{GMB}, without controls	0.112	0.352	1		
(3) $\sum_{n\in Green} w_{in} - \sum_{n\in Brown} w_{in}$	0.276	0.342	0.569	1	
(4) $1(UNPRI_i)$	0.761	0.118	0.017	0.056	1

Table 6
Comparing measures of mutual funds' green tilts.
This table describes mutual funds' green tilt measures in 2023q4. Details are as in the previous table. MS Globe Rating$_i$ is fund i's Morningstar Sustainability Rating. 1(ESG-labeled fund$_i$) is defined in Table 4.

Green tilt measure	AUM-weighted average	Correlations (1)	(2)	(3)	(4)	(5)
Panel A: All funds						
(1) T_i^{GMB}, with controls	0.012	1				
(2) T_i^{GMB}, without controls	0.233	0.164	1			
(3) $\sum_{n\in Green} w_{in} - \sum_{n\in Brown} w_{in}$	0.269	0.325	0.759	1		
(4) MS Globe Rating$_i$	2.902	0.236	0.173	0.357	1	
(5) 1(ESG-labeled fund$_i$)	0.014	0.162	0.159	0.255	0.355	1
Panel B: Active funds						
(1) T_i^{GMB}, with controls	−0.001	1				
(2) T_i^{GMB}, without controls	0.229	0.156	1			
(3) $\sum_{n\in Green} w_{in} - \sum_{n\in Brown} w_{in}$	0.255	0.314	0.752	1		
(4) MS Globe Rating$_i$	2.684	0.229	0.171	0.367	1	
(5) 1(ESG-labeled fund$_i$)	0.026	0.159	0.169	0.271	0.362	1

underscores the importance of controlling for firm size, as larger firms tend to score higher on ESG. Finally, the 76.1% average for the UNPRI indicator reflects the share of U.S. equity AUM managed by UNPRI signatories, as mentioned in the introduction.

The remainder of Table 5 reports pairwise correlations across institutions among the four measures. The correlation between T_i^{GMB} with and without controls is only 35.2%, again underscoring the importance of controls (if the controls had no effect, the correlation would be 100%). The correlation between our measure (T_i^{GMB} with controls) and the simple difference $\sum_{n\in G} w_{in} - \sum_{n\in B} w_{in}$ is 34.2%. The fact that this correlation is positive is essentially a sanity check, as both measures aim to capture portfolio tilts toward green stocks; that this correlation is low shows that our measure is quite different from the simple one. The simple measure correlates more strongly (56.9%) with T_i^{GMB} without controls, which is consistent with both ignoring non-ESG characteristics. Finally, the UNPRI indicator has positive but low correlations with T_i^{GMB}, both with and without controls.

6.2. Mutual funds

Table 6 mirrors Table 5, but at the mutual fund level. Panel A covers all funds; Panel B focuses on active funds. The results in both panels are similar, and they lead to the same conclusions as in Table 5.

The AUM-weighted means show that omitting controls for non-ESG characteristics substantially inflates aggregate green tilt estimates. For example, in Panel A, the tilt is 23.3% without controls but only 1.2% with controls. The correlation between T_i^{GMB} with and without controls is only 16% in both panels — less than half its 13F-level counterpart in Table 5 — indicating that controlling for non-ESG characteristics is even more important at the mutual fund level. This makes sense, as individual mutual funds often follow more focused investment styles (e.g., size or value/growth), whereas styles tend to blend together within 13F institutions. The correlation between T_i^{GMB} and the simple difference $\sum_{n \in G} w_{in} - \sum_{n \in B} w_{in}$ is about 32% in both panels, similar to its equivalent in Table 5, but it rises to about 75%, much more sharply than in Table 5, when T_i^{GMB} is computed without controls. Again, controlling for non-ESG characteristics is even more critical for funds than for 13F institutions.

Our measure is also positively correlated with the two remaining measures: about 23% with Morningstar's globe rating and 16% with the ESG-fund indicator, passing two additional sanity checks.[23] The ESG-fund indicator's correlation with T_i^{GMB} is about the same whether or not controls are applied. In contrast, the globe rating is more strongly correlated with T_i^{GMB} with controls, which is consistent with its peer-adjusted design that effectively controls for some non-ESG characteristics, as explained earlier.

7. ESG investing versus index investing

We distinguish ESG investing from index investing. The rationale follows Pástor et al. (2021): when all investors value ESG equally, they all hold the market portfolio, as their preferences are fully reflected in market weights through 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 all investors hold the market portfolio, even though they have a preference for low-beta stocks. In that setting, low-beta stocks have low expected returns, so they have high prices and thus large market weights, all else equal. Yet the CAPM is generally characterized as a world of index investing, not "low-beta" investing. The same logic applies when ESG preferences are fully embedded in market prices.

The market portfolio's weights depend on the average strength of ESG preferences, but without heterogeneity in those preferences, there is no ESG investing. The latter arises from differences in ESG preferences across investors. To simplify their model, Pástor et al. (2021) assume that ESG is the only reason 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.

[23] The latter positive correlation is expected, given the evidence from Table 4 that ESG-labeled funds tend to have larger green tilts and smaller brown tilts than non-ESG funds.

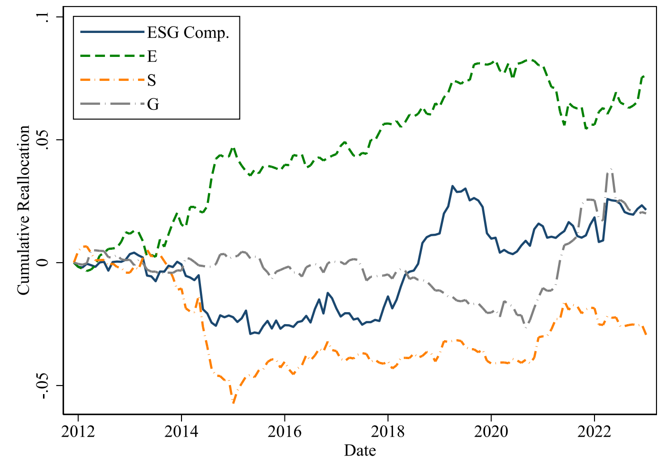

Fig. 12. Market reallocation to green stocks. This figure plots the cumulative sum of κ_t, defined in Eq. (33). Equivalently, it plots the cumulative change in the fraction of stocks whose greenness, g_n, is less than the value-weighted mean of g_n across all stocks. A positive (negative) change corresponds 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.

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

$$\kappa_t = \sum_{n=1}^{N_{t-1}} (w_{mn,t} - w_{mn,t-1}) g_{n,t-1}\,, \tag{33}$$

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.

Fig. 12 plots the cumulative sum of κ_t for each of our four greenness measures. For the ESG composite, the cumulative reallocation falls during the first half of the sample period, but then it rises sharply, by 5.5 percentage points, between mid-2018 and mid-2020. By the end of the sample period, the cumulative reallocation reaches 2.1%. The end-of-sample value is very similar when we measure greenness by the G score, although the reallocation to G-friendly stocks follows a different path. In contrast, the market reallocates away from S-friendly stocks over the full sample period, despite a steady reallocation toward them between 2015 and 2021. Finally, the reallocation to E-friendly stocks increases steadily between 2012 and 2020, before pulling back slightly at the end. Overall, for greenness measured by E, the market portfolio's allocation to green stocks increases substantially, by 7.6 percentage points, during the sample period.

8. Conclusion

From 2012 to 2023, ESG-related tilts in institutional U.S. equity portfolios consistently account for about 6% of the institutions' aggregate U.S. equity AUM. Over the same period, institutions' overall portfolio tilts in U.S. stocks, as measured by active share, have declined. When scaled by active share, the typical institution's ESG tilt has grown from 17% to 27%. So, while ESG tilts are a modest and steady fraction of total AUM, they represent a substantial and growing fraction of total portfolio tilts.

Our approach to estimating ESG tilts has several advantages. First, it isolates ESG tilts by controlling for non-ESG characteristics, which is valuable because stocks' ESG and non-ESG characteristics are correlated. For example, an institution may hold Tesla's stock either for its environmental profile or because it likes holding large-cap growth stocks. Our approach separates the two motives. We show that failing to control for non-ESG characteristics would overstate institutions' overall ESG tilt by more than three-fourths. 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. 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 four times larger.

Our approach also allows us to separate green tilts from brown. We find that institutions as a whole tilt more green than brown, and increasingly so. The rise in net green tilting occurs primarily at the intensive margin; for example, institutions divest from brown stocks mostly by reducing positions rather than eliminating them. In contrast, non-13F institutions and households tilt more brown than green, and increasingly so. Greenness also varies across institutions. Larger institutions are greener, and the rise in net green tilting is fully driven by the largest third of institutions. Those institutions are increasingly green, whereas smaller institutions are increasingly brown. UNPRI signatories and European institutions are also greener in terms of their U.S. stock holdings, while banks are the least green institutional type. Our results are similar across four different ESG-related measures of greenness. These results are important because green tilts could come with lower expected returns, as noted at the outset.

We also estimate the ESG-related tilts of U.S. equity mutual funds. We find only small offsetting ESG tilts within fund families. Mutual funds' aggregate ESG tilts range from 6% to 10%, and up to 13% for active funds. Extensive-margin tilts are larger than for 13F institutions but remain smaller than intensive-margin tilts. Divestment of brown stocks also remains smaller at the extensive margin, indicating that even at the fund level, brown divestment is more partial than full. Mutual funds collectively tilt green, though less so than institutions. Finally, funds with ESG labels or more Morningstar globes tilt greener.

Our study opens many avenues for future research. For example, do institutions substitute voting green for tilting green, or are those actions complementary?[24] What are the financial implications of institutions' green tilts? Could one compute stock-level ESG tilts and relate them to stocks' expected returns? 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.

CRediT authorship contribution statement

Lubos Pastor: Writing – original draft. **Robert F. Stambaugh:** Writing – original draft. **Lucian A. Taylor:** Writing – original draft.

Declaration of competing interest

We have no conflicts of interest to disclose.

[24] A 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).

Appendix A

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

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

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

$$\sum_i \phi_i w_{in} = \sum_i \frac{A_i}{A}\frac{M_{in}}{A_i} = \sum_i \frac{M_{in}}{A} = \sum_i \frac{M_{in}}{M} = \frac{M_n}{M} = w_{mn}, \tag{A.1}$$

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

$$\sum_i \phi_i \mathrm{E}\{w_{in}|\mathcal{G},\mathcal{C}\} = \sum_i \phi_i \mathrm{E}\{w_{in}|\mathcal{G}_0,\mathcal{C}\} = w_{mn}, \tag{A.2}$$

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

$$\sum_i \phi_i \Delta_{in} = 0 \tag{A.3}$$

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

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

implying

$$T^{OG} = T^{UG}, \tag{A.4}$$

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

$$T^{OB} = T^{UB}, \tag{A.5}$$

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

$$T^G = T^B, \tag{A.6}$$

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

A.2. Estimating the intensive-margin model

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

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

That is, w_{in}^+ is linear in the K values of $w_{mn}x_{nj}$. If a given stock n is held, its expected weight could in principle depend not only on the stock's own value of $w_{mn}x_{nj}$ but also on the values of that quantity for other stocks the investor may hold. Recognizing that potential dependence, we allow c_{ij} to depend on the portfolio's expected sum across stocks of $w_{mn}x_{nj}$ (i.e., $\pi_i' h_j$, where h_j denotes the $N\times 1$ vector whose nth 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:

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

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

$$c_{ij} = b_{ij} \Big/ \sum_{n=1}^{N} \pi_{in} w_{mn} x_{nj}, \quad j = 1, \ldots, K, \tag{A.9}$$

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

$$\sum_{j=1}^{K} b_{ij} = 1. \tag{A.10}$$

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

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

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

$$w_{in} = w_{in}^+ + \epsilon_{in}, \tag{A.12}$$

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

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

where the jth independent variable is

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

The quantity $e_{in} \equiv \epsilon_{in}/w_{mn}$ satisfies the property required of a regression disturbance, i.e., that it has zero expectation conditional on the $\tilde{x}_{nj}$'s, because the nth row of X includes w_{mn} (as noted earlier).

We estimate the regression in (A.13) 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 Eq. (A.14). For that purpose we set $\pi_i = \hat{\pi}_i$, the estimate of π_i from our model of the extensive margin. We also allow for the possible correlation between e_{in} and the probability that stock n is held. Specifically, we apply a correction following Heckman (1979). The first step is to estimate the probit model,

$$y_{in} = \gamma_i' z_{in} + u_{in}, \tag{A.15}$$

where u_{in} is a standard normal variate, and investor i holds stock n if $y_{in} > 0$. We specify z_{in} as a two-element vector, with the first element equal to 1 and the second element equal to an indicator variable set to 1 if investor i held stock n during any of the previous 11 quarters (and set to 0 otherwise). The probit model is estimated via maximum likelihood using all stocks with non-missing data. The second step is to estimate the regression in Eq. (A.13) with the quantity $\phi(\hat{\gamma}_i' z_{in})/\Phi(\hat{\gamma}_i' z_{in})$ included as an additional independent variable, where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the standard normal density and distribution functions.[25] This regression is estimated for each institution and quarter subject to the linear coefficient restriction in Eq. (A.10). We find that the regressions fit the data quite well, delivering an average R^2 of 0.41 (Internet Appendix). Finally, we plug the estimated b_{ij}'s into Eq. (A.11) to obtain expected weights for all assets, $n = 1, \ldots, N$.

The resulting values of w_{in}^+ contain some estimation error. This error causes some estimates of w_{in}^+ to be negative or exceed 1. We remove these implausible values by truncating w_{in}^+ to be in [0,1]. The rate of truncation is low. Roughly 5% of w_{in}^+ values are truncated at 0, and less than 0.5% are truncated at 1. The rate of truncation is not concentrated in any particular set of institutions (e.g., large versus small, investment advisors vs. insurance companies), nor is it concentrated in any particular industry. To show this, we regress an indicator for whether w_{in}^+ is truncated on dummy variables for institution categories and stock industries. We find an R^2 of only 0.003, and few dummies enter significantly (Internet Appendix).

After the truncation of w_{in}^+, 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. In 2023, this truncation affects only 0.9% of institutions that represent around 0.1% of covered AUM. No values of T_i or T_i^{GMB} exceed 1 in 2023.

A.3. Bias adjustment and standard errors

This section describes the bootstrap procedure that we use to de-bias the raw estimates of T_i and obtain their standard errors, extending the discussion from Section 3.4. 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 (Eq. (A.13)), to which we have added the additional Heckman regressor, $\phi(\hat{\gamma}_i' z_{in})/\Phi(\hat{\gamma}_i' z_{in})$ (see previous section for details). Since the intensive-margin regression is estimated with a constraint, 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.

[25] The use of lagged holdings in the probit model is consistent with the finding by Koijen and Yogo (2019) that an institution does not often hold a stock currently if the stock was not held within the past 11 quarters. This persistence in holdings conveniently allows us to have the probit model rely on a variable different from the x_{nj}'s used in the intensive-margin model, thereby satisfying the recommended exclusion restriction for the successful application of the Heckman correction (e.g., (Puhani, 2000)). If instead we were simply to specify z_{in} as containing those same x_{nj}'s, then $\phi(\hat{\gamma}_i' z_{in})/\Phi(\hat{\gamma}_i' z_{in})$ could possess strong collinearity with the x_{nj}'s, making it difficult to separate any selection effect from the primary roles of the x_{nj}'s in the intensive-margin model. We do not include lagged holdings in our extensive-margin model, because the objective of that model is to infer how stock characteristics predict the set of stocks the institution currently holds, regardless of how long the institution has held those stocks.

(c) Let $\hat{b}_i$ denote the intensive-margin model's estimated coefficient vector, and let $\widehat{[\rho\sigma_u]}_i$ denote the estimated coefficient on $\phi(\hat{\gamma}_i' z_{in})/\Phi(\hat{\gamma}_i' z_{in})$.

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 $M_n^{\lambda_i}$. We estimate λ_i as the coefficient on $\log(M_n)$ from an institution-specific regression of $\log(|e_{in}|)$ on $\log(M_n)$.[26] Let $\delta_{in} \equiv e_{in}/M_n^{\lambda_i}$ 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 Eq. (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 Eq. (A.11) while using the estimates of $\hat{b}_i$ and $\hat{\pi}_{in}$ from step 1. Following Eqs. (A.11) and (A.13), compute a draw of $\tilde{w}_{in}/w_{mn}$ by adding two terms to w_{in}^+/w_{mn}. The first term is a random draw of e, which we compute as the product of $M_n^{\lambda_i}$ and a random draw (with replacement) of an element of δ_i. Multiplying by $M_n^{\lambda_i}$ performs a heteroskedasticity adjustment to e. The second term, from the Heckman adjustment, is $\widehat{[\rho\sigma_u]}_i$ times $\phi(\hat{\gamma}_i' z_{in})/\Phi(\hat{\gamma}_i' z_{in})$. Adding this second term allows a correlation between the error term in the intensive-margin model and the probability that the stock is held.
   (d) With this new sample of size L_i, estimate the intensive-margin model as in Eq. (A.13), replacing π_{in} with $\tilde{\pi}_{in}$ and w_{in} with $\tilde{w}_{in}$, and performing the Heckman adjustment. Denote the new intensive-margin model coefficients by $\tilde{b}_{ij}$. Substitute $\tilde{b}_{ij}$ and $\tilde{\pi}_{in}$ into Eq. (A.11) to obtain $\tilde{w}_{in}^+$, also denoted $\tilde{w}^+[\mathcal{G}, \tilde{\pi}_i(\mathcal{G})]$. Similarly, compute $\tilde{w}^+[\mathcal{G}_0, \tilde{\pi}_i(\mathcal{G}_0)]$.
   (e) Replacing variables with their tilde counterparts, compute $\tilde{\Delta}_{in}$ in Eq. (1).
   (f) Compute $\tilde{T}_i$ from Eq. (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:

$$\hat{T}_i = T_i^{raw} - TBias_i. \tag{A.16}$$

8. Compute the standard error of $\hat{T}_i$ as follows. Let V_T denote the variance of $\tilde{T}_i$ across the $NSim$ trials. The standard error of $\hat{T}_i$ is $[V_T + V_T/NSim]^{1/2}$. We need to add $V_T/NSim$ because $TBias_i$, an average across $NSim$ trials, is itself estimated with error. The variance of the $TBias_i$ estimate is $V_T/NSim$.
9. We compute a 95% confidence interval for T_i as follows.

   (a) The lower end of this interval equals $\hat{T}_i - \text{Gap}_{2.5}$, where $\text{Gap}_{2.5} = \bar{\tilde{T}}_i - \tilde{T}_i^{2.5}$ 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.

[26] In 2023, the mean and median of estimated λ_i are −0.258 and −0.270, respectively. Estimated λ_i is negative for more than 95% of institutions and significantly negative at the 5% level for more than 75% of institutions.

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