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Dissecting green returns[☆]

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ABSTRACT

Green assets delivered high returns in recent years. This performance reflects unexpectedly strong increases in environmental concerns, not high expected returns. German green bonds outperformed their higher-yielding non-green twins as the “greenium” widened, and U.S. green stocks outperformed brown as climate concerns strengthened. Despite that outperformance, we estimate lower expected returns for green stocks than for brown, consistent with theory. We estimate expected returns in two ways: ex ante, using implied costs of capital, and ex post, using realized returns purged of shocks from climate concerns and earnings. A theoretically motivated green factor explains much of value stocks' recent underperformance.

1. Introduction

The growth of sustainable investing is a leading trend in the investment industry over the past decade. Sustainable investing applies environmental, social, and governance (ESG) criteria, with environmental concerns playing the leading role. For example, 88% of the clients of BlackRock, the world's largest asset manager, rank environment as “the priority most in focus” among ESG criteria (BlackRock, 2020). Investments considered environmentally friendly are often referred to as “green,” with “brown” denoting the opposite.

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Investors often cite improved returns as a top motivation for applying ESG criteria.[1] Moreover, asset managers often market sustainable investment products as offering superior risk-adjusted returns.[2] Past performance is a popular marketing tool, and indeed a number of studies report superior historical returns to sustainable strategies (e.g., Edmans, 2011; Nagy et al., 2016; In et al., 2019). Of course, as the SEC generally requires of all marketed funds, managers must warn that past performance does not necessarily predict future performance. In this study we show why investors would be especially well advised to heed that warning when investing in green assets.

What does the past performance of green assets imply about their future performance? We address this question empirically, guided by the equilibrium model of Pástor et al. (2021, henceforth PST). The PST model predicts that green assets have lower *expected* returns than brown, for two reasons: investors have green tastes, and greener assets are a better hedge against climate risk. Greener assets' lower expected returns thus reflect both a taste premium and a risk premium. PST also explain, however, that green assets can have higher *realized* returns while agents' demands shift unexpectedly in the green direction. This wedge between expected and realized returns is central to our paper. PST identify two ways green demands can shift. First, investors' demand for green assets can increase, directly driving up green asset prices. Second, consumers' demand for green products can strengthen—for example, due to environmental regulations—driving up green firms' profits and thus their stock prices. Similarly, investors' demand for brown assets or consumers' demand for brown products can decrease, again making green stocks outperform.

Our analysis focuses primarily on the U.S. stock market. Using environmental ratings from MSCI, a leading provider of ESG ratings, we assign greenness measures to individual stocks. Our sample begins in November 2012, when MSCI's data coverage increased sharply, and ends in December 2020. Over this period, the value-weighted portfolio of stocks in the top third of greenness outperformed the bottom third by a cumulative return difference of 174%. This return spread, which we denote as GMB (green-minus-brown), has a monthly Sharpe ratio of 0.33, larger than the stock market's Sharpe ratio during this bull-market period. In short, green stocks strongly outperformed brown in recent years.

Should green stocks' recent outperformance lead one to expect high green returns going forward? No, we argue. That outperformance likely reflects an unanticipated increase in environmental concerns. We reach this conclusion after computing a measure of concerns about climate change, using the media index constructed by Ardia et al. (2021). We observe a strong increase in climate concerns during the last decade, with the level of our measure nearly doubling. We find that shocks to climate concerns exhibit a significant positive relation to GMB. Green stocks thus tend to outperform brown when there is bad news about climate change, consistent with green stocks being better hedges against climate shocks.

We compute an ex post estimate of GMB's expected return by purging unanticipated shocks from its average realized return. If we set the climate shocks to zero, GMB's counterfactual performance becomes essentially flat. That is, green stocks would not have outperformed brown without strengthened climate concerns. In fact, they would have underperformed had there been no surprises to either climate concerns or earnings of green versus brown firms. If we zero out both climate and earnings shocks, GMB's counterfactual performance becomes slightly negative, indicating a negative expected return for GMB.

Our empirical explanation of green stocks' outperformance accords with the PST model. During a period when climate concerns strengthen sufficiently and unexpectedly, GMB delivers a positive return, as investors demand greener stocks or customers demand greener products. Outperformance caused by the strengthening of investor concerns is followed by lower expected performance of GMB going forward. That is, a shift in GMB's expected future performance relates inversely to its realized performance.

An inverse relation between realized returns and shifts in expected returns is not new in the stock return literature.[3] With stocks, a challenge to documenting this relation is that expected stock returns are generally hard to estimate. With bonds, however, we can see the relation more clearly. The inverse relation between a bond's realized return and the change in its yield to maturity is well understood, and the yield provides direct information about expected return, especially for buy-and-hold investors.

The case of German "twin" bonds illustrates this inverse relation in the context of climate concerns. Since 2020, the German government has issued green bonds, along with virtually identical non-green twins. The green bonds trade at lower yields, indicating lower expected returns compared to non-green bonds. The yield spread between the green and non-green twins, known as the "greenium," reflects investors' willingness to accept a lower return in exchange for holding assets more aligned with their environmental values. Since issuance, the 10-year greenium experienced almost a four-fold widening, possibly due to growing climate concerns. As a result, the green bond outperformed its non-green twin by a significant margin over the same period. However, this outperformance does not imply green outperformance going forward. Rather the opposite is clearly true, given the now wider greenium.

We define an equity analogue to the greenium, the "equity greenium," as the difference between the expected returns of green and brown stocks, i.e., GMB's expected re-

[1] Improved returns is the first- or second-ranked motivation for ESG investing in surveys of investors by BlackRock (2020), BNP Paribas (2019), and Schroders (2020). In addition, in the BNP Paribas survey, 60% of respondents expect their ESG portfolios to outperform over the next five years.

[2] For example, BlackRock believes that "integrating sustainability can help investors build more resilient portfolios and achieve better long-term, risk-adjusted returns" (Fink, 2021). According to State Street, "ESG is a source of alpha that leads to positive portfolio performance" (Lester and He, 2018).

[3] For example, this inverse relation figures prominently in empirical analyses of the equity premium by Fama and French (2002) and Pástor and Stambaugh (2001, 2009).

turn. Given the difficulty in estimating expected stock returns, the equity greenium cannot be measured as precisely as the greenium for bonds. Complementing our ex post approach, we estimate the equity greenium ex ante by the difference between the implied costs of capital of green and brown stocks. We find a consistently negative equity greenium throughout our sample. This evidence lends further support to our argument that the outperformance of green stocks in our sample period was unexpected. The equity greenium widens in the second half of our sample, consistent with strengthening investor demands for green assets.

Our main results relating climate shocks to stock returns rely on the time series of GMB. We also conduct a parallel analysis by running panel regressions on individual stocks, leading to several findings. First, there is a positive cross-sectional relation between a stock's greenness and its return. Second, that relation disappears when we interact greenness with climate-concern shocks, revealing that these shocks fully account for the superior performance of green stocks during the sample period. In fact, the relation becomes slightly negative when we add earnings shocks as controls. These results echo our time-series evidence: despite having lower expected returns, green stocks outperform brown due to positive surprises over the sample period. Finally, industry-level greenness, as opposed to within-industry differences in greenness, largely accounts for the superior performance of green stocks as well as the importance of climate shocks in explaining that performance.

We find that small stocks react to climate news with a delay. In panel regressions of individual stock returns on greenness interacted with climate shocks, previous-month shocks enter more strongly than current-month shocks, indicating a delayed reaction for some stocks. There is no significant delay in the response of GMB, whose long and short legs are value-weighted, to climate shocks. But when we replicate GMB's construction separately within the large- and small-cap segments, we find that small-cap GMB responds mostly to previous-month climate shocks, whereas large-cap GMB responds mostly to same-month shocks. At a weekly frequency, large-cap GMB reacts more strongly than small-cap GMB to climate shocks in the current and previous week, whereas small-cap GMB reacts more strongly to shocks at longer lags, especially the three-week lag. This evidence suggests that smaller stocks react more slowly to climate news, consistent with prior evidence that small stocks react more slowly to news in general (Lo and MacKinlay, 1990). Our evidence of a delay complements that of Hong et al. (2019). They also find that stock prices are slow to react to climate-change risks, but they look at different assets (stocks in food industries across countries) and different climate shocks (trends in the risks of drought).

Green stocks' recent outperformance helps us understand the poor performance of value stocks in the 2010s, the worst decade on record for the HML factor of Fama and French (1993). We leverage PST's theoretical result that assets are priced by a two-factor model, where the factors are the market portfolio and the ESG factor. Focusing on the "E" part of ESG, we construct a "green factor" by following PST's procedure. The green factor is the return on a portfolio that goes long green and short brown stocks, where the stocks are weighted by their greenness. We find that the two-factor model explains much of HML's recent underperformance. From November 2012 through December 2020, HML's monthly CAPM alpha is a marginally significant −71 bps, whereas HML's two-factor alpha is an insignificant −15 bps. In contrast, the green factor's alpha with respect to the Fama-French three-factor model is a significant 38 bps. The green factor and HML are negatively correlated, as value stocks are more often brown than green. Insofar as recent average performance, however, the two-factor model explains HML's underperformance better than the three-factor model explains the green factor's outperformance. The two-factor model can also explain the momentum strategy's positive performance over the same period: momentum's monthly CAPM alpha is 66 bps, whereas its two-factor alpha is −6 bps.

Our study relates to a large empirical literature investigating returns on green versus brown assets. One set of studies examine returns on an ex ante basis, using proxies for expected future returns. In the bond market, for example, Baker et al. (2018), Zerbib (2019), and Larcker and Watts (2020) analyze yields on green bonds versus brown. In the stock market, Chava (2014) and El Ghoul et al. (2011) compare implied costs of capital estimated for green firms versus brown. Most of these studies find lower ex ante returns on green assets, consistent with theory. A second, larger set of studies examine returns on an ex post basis, measuring realized green-versus-brown returns, generally for stocks. Examples include Garvey et al. (2018), In et al. (2019), Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2022), Görgen et al. (2020), Hsu et al. (2022), and Aswani et al. (2021). We examine returns both ex ante and ex post, focusing on the distinction between expected and realized returns, in the spirit of Elton (1999). We show why high green returns realized in recent years are likely to be misleading predictors of the future.

Our evidence on how climate shocks affect realized returns also relates to studies investigating the pricing of climate risk. Recent work examines that pricing in equities (e.g., Bolton and Kacperczyk, 2021; Bolton and Kacperczyk, 2022; Hsu et al., 2022; Faccini et al., 2021), corporate bonds (Huynh and Xia, 2021; Seltzer et al., 2021), municipal bonds (Painter, 2020; Pinkham et al., 2021), options (Ilhan et al., 2021), and real estate (Bernstein et al., 2019; Baldauf et al., 2020; Giglio et al., 2021b). Engle et al. (2020) develop a procedure to dynamically hedge climate risk with the help of mimicking portfolios and textual analysis of news sources. Krueger et al. (2020) document the importance of climate risk in a survey of institutional investors. For a survey of the climate finance literature, see Giglio et al. (2021a).

Our empirical analysis is guided by the theoretical model of PST, in which investors' tastes for green assets play a key role. Other models featuring tastes for green assets can be found in Fama and French (2007), Baker et al. (2018), Pedersen et al. (2021), Avramov et al. (2022), and Zerbib (2022). PST's model assumes that markets are efficient, so that if green firms are expected to be more profitable than brown in the future, this difference is reflected in current prices. Pedersen et al. show that if some investors anticipate this greater profitability before market prices respond, those investors expect higher returns on green assets. While our analysis is motivated primarily by PST's efficient-market perspective, we do find some evidence of slow price response, as noted earlier.

Our results have important implications for research and practice. They underline the danger in using recent average returns to estimate expected returns. In particular, the recent outperformance of green assets does not imply high green returns going forward. In fact, if the outperformance resulted from increased demands by ESG investors, then green assets' expected returns are lower today than a decade ago. In the same spirit, value stocks' recent underperformance is less likely to continue, because value stocks tend to be brown and growth stocks green. From the corporate finance perspective, our findings imply that greener firms have lower costs of capital than their recent stock performance might suggest. This is good news for ESG investors, because one way they exert social impact is by decreasing green firms' cost of capital (e.g., Heinkel et al., 2001; PST).

This paper is organized as follows. Section 2 highlights the gap between expected and realized returns in the context of German twin bonds. Section 3 describes how we measure greenness for U.S. stocks. Section 4 compares the realized performance of green versus brown stocks. Section 5 implements two approaches to estimating the expected return on the green-minus-brown stock portfolio. Section 6 documents the delayed reaction of stock prices to climate news. Section 7 discusses how we construct the green factor and explore its role in pricing value and momentum. Section 8 concludes.

2. German twin bonds

This paper emphasizes the difference between expected and realized returns on green assets. In this section, we illustrate this difference for bonds. Bonds' expected returns are tightly linked to yields to maturity, which are easily observable.

Since 2020, the government of Germany, the largest European economy, has been issuing green securities to finance its transition towards a low-carbon, sustainable economy.[4] The first green security, a 10-year bond, was issued in September 2020 in the amount of 6.5 billion euros. The second green security, a 5-year note, followed two months later in the amount of 5 billion euros. Both securities have zero coupon rates. Germany plans to issue at least one green security per year. We refer to these securities as "green bonds."

Each green bond is issued with the same characteristics as an existing conventional bond issued by the German government. Besides having the same issuer, the two bonds have the same maturity date, the same coupon rate, and the same coupon payment dates. This pairing creates "twin" bonds, which offer identical streams of cash flows with identical credit risk but different greenness. This clean twin pairing makes German government bonds uniquely well suited for our purposes. By comparing the prices of twin bonds, we can gain some insight into the value assigned to greenness by bond market investors.

Table 1
German government bond yields and returns.
Panel A reports the yields to maturity of the 10-year German government green bond (column 1), 10-year German government conventional bond (column 2), and their difference (column 3), all in basis points per year. Average yields are computed over the full sample period of September 8, 2020 to November 17, 2021. The yields on the first and last days of this period are also reported. Panel B reports the realized returns on the same green bond (column 1), same conventional bond (column 2), and their difference (column 3). Average returns are in basis points per day. Cumulative returns are in percent over the full sample period. The t-statistics, which are shown in parentheses, are adjusted for any statistically significant autocorrelation in the underlying series.

	Green bond	Non-green bond	Difference
Panel A. Yields to maturity (basis points per year)			
Average	-46.72	-42.09	-4.63
	(-13.53)	(-10.90)	(-6.19)
First day	-51.20	-49.60	-1.60
Last day	-40.60	-34.40	-6.20
Panel B. Realized returns			
Average	-0.47	-0.59	0.12
	(-0.35)	(-0.44)	(2.19)
Cumulative	-1.53	-1.90	0.37

Even though the twin bonds are paired very carefully, some differences between them remain. First, the issuance date of the green bond always comes after the initial issuance date of the conventional bond. For example, the green bond issued in September 2020 has a conventional twin issued in June 2020. Second, conventional bonds tend to be issued at larger volumes than their green twins. For example, in 2020, the issuance of conventional bonds was almost five times larger than that of the corresponding green bonds. Conventional bonds could thus in principle be more liquid than their green twins. However, the German Finance Agency has committed to play an active role in the secondary market for green bonds to make their liquidity comparable to that of conventional bonds.

We obtain daily data on the first pair of twin bonds, downloading the end-of-day bond prices and mid-yields to maturity for the 10-year green bond (ISIN DE0001030708) and the 10-year non-green bond (DE0001102507) from Bloomberg. We download data since the first date of trading for the green bond, which is September 8, 2020, through November 17, 2021. Over this time period, the two bonds' annual yields fluctuate between −67 and −15 bps. We plot these yields in Panel A of Fig. 1 and show their means in Panel A of Table 1.[5]

[4] For more details, see https://www.deutsche-finanzagentur.de/en/institutional-investors/federal-securities/green-federal-securities/.

[5] In the Appendix, we plot the counterpart of Fig. 1 for the second pair of twin bonds (five-year bonds), which was first issued in November 2020. The results are similar to those presented in Fig. 1. We prioritize the first twin pair due to its longer history. The Appendix is on the authors' websites.

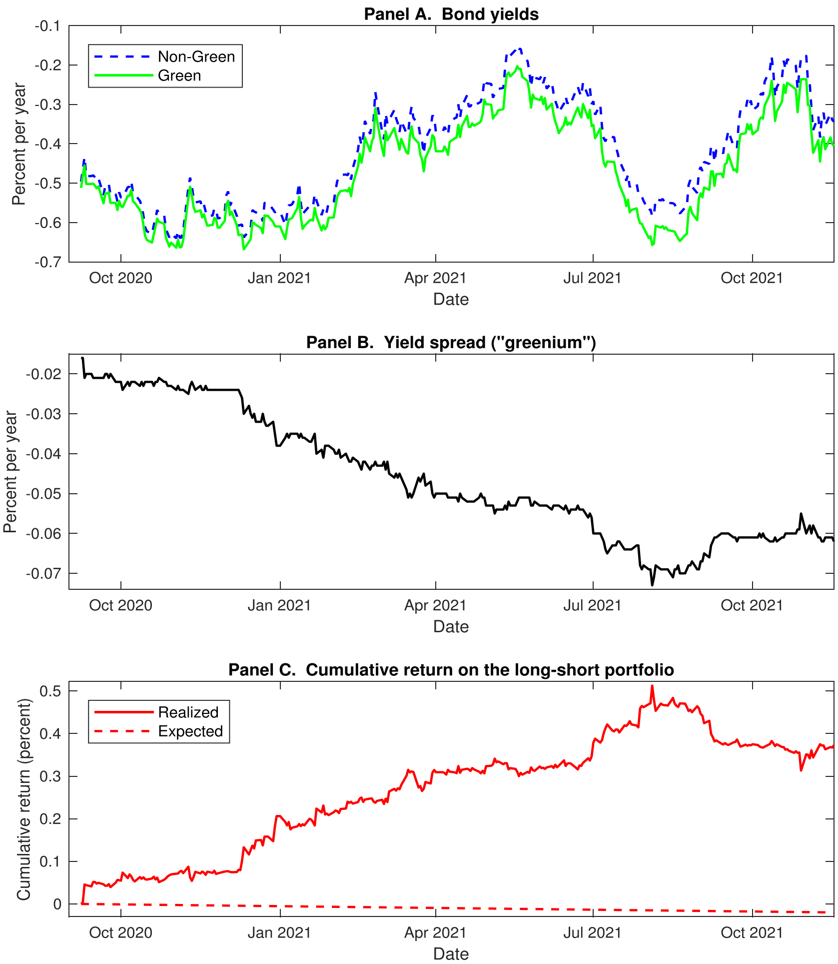

Fig. 1. German twin bonds. Panel A plots the daily time series of annual yields on the German government's 10-year green bond and its non-green twin. Panel B plots the "greenium," the yield difference between the green bond and its non-green twin. Panel C plots the performance of a portfolio that goes long the 10-year green bond and short its non-green twin. The solid line plots this long-short portfolio's daily cumulative realized return. The dashed line plots the expected cumulative return as of the first day of trading of the green bond (September 8, 2020), absent a subsequent change in the greenium, which was −1.6 bps on that day.

Panel B of Fig. 1 plots the difference between the yields of green and non-green bonds, also known as the greenium (e.g., Larcker and Watts, 2020). The greenium is always negative, averaging −4.6 bps and ranging mostly between −7 and −2 bps per year.[6] Therefore, for investors holding the bonds to maturity, the green bond always has a lower expected return than the non-green bond. This evidence is in line with theories predicting that green assets offer lower expected returns than non-green assets (e.g., PST).[7]

Given the lower yield of the green bond, one would expect it to deliver a lower return than its conventional twin. Instead, the green bond delivered a higher return in our sample. We calculate bond returns as daily percentage changes in bond prices and report them in Panel B of Table 1. The full-sample cumulative returns are negative, −1.53% for the green bond and −1.90% for the non-green bond, due to a rise in yields between September 2020 and November 2021. More interesting, the green bond outperforms its non-green twin over this time period, as shown by Panel C of Fig. 1. The figure plots cumulative returns on a long-short portfolio, which goes long the green bond and short the non-green bond. The portfolio's average daily return of 0.12 bps is statistically significant ($t = 2.19$), and its cumulative return of 37 bps is substantial relative to German government bond yields.

[6] These greenium values are close to those estimated by prior studies in different settings. For example, Baker et al. (2018) estimate a greenium of about −6 bps in a sample of over 2,000 U.S. municipal and corporate green bonds, whereas Zerbib (2019) estimates −2 bps in a sample of over 1000 supranational, sub-sovereign and agency, municipal, corporate, financial, and covered green bonds.

[7] This conclusion is reinforced by liquidity considerations. As noted earlier, the non-green bond has been issued at larger volume than its green twin. If this volume difference makes the conventional bond more liquid despite the aforementioned efforts of the German Finance Agency, then the resulting liquidity premium pushes the greenium up, and the expected return penalty associated with greenness is even larger.

Importantly, the positive average return of the long-short portfolio does not imply that the portfolio's expected return is positive. On the contrary, we know with certainty that the portfolio's expected return is negative if the bonds are held to maturity. For example, on September 8, 2020, the green bond's yield was −51.2 bps per year, whereas the non-green bond's yield was −49.6 bps. Therefore, if both bonds are held to maturity, the green bond delivers a return 1.6 bps lower than the non-green bond. The green bond's expected return is lower also if the bonds are not held to maturity under a variety of plausible conditions, such as changes in the greenium being unpredictable. That condition is likely to hold, especially in efficient, or near-efficient, markets. Under that condition, the green bond's expected return is lower at the beginning of the sample, and the expected return of the long-short portfolio is negative. The cumulative value of this expected return is plotted by the dashed line in Panel C of Fig. 1, which is gently downward-sloping.

How can we reconcile the higher realized return of the green bond with its lower expected return? The answer is that that the greenium in Panel B grows increasingly negative between September 2020 and November 2021, deepening from −1.6 to −6.2 bps. This deepening is responsible for the outperformance of the long-short portfolio in Panel C. In the language of PST, if investors' tastes shift toward green assets, they push up the price of the green bond relative to the non-green bond. However, the green bond's outperformance is temporary, as it comes entirely at the expense of the bond's future return. Investors buying the bonds on September 8, 2020 and holding them to maturity expected to earn 1.6 bps less from the green bond, but those buying on November 17, 2021 expected to earn 6.2 bps less.

Investors' tastes for green assets could plausibly have shifted unexpectedly due to heightened concerns about climate change. Those concerns are likely to have risen in July 2021 when Germany, along with several other European countries, experienced catastrophic floods caused by heavy rainfall that followed unprecedented heat waves. Germany experienced around 200 fatalities in those floods, which were the deadliest natural disaster in the country in almost six decades. Consistent with a shift in investors' tastes toward green German bonds, the greenium widened from −5.5 bps on June 29, to −7.3 bps on August 4, before easing back to −6 bps by mid-September. These changes suggest a possible link between investors' tastes and climate concerns.[8] We further explore this link later in the paper.

The case study of German twin bonds illustrates how shifts in expected return drive a wedge between returns expected ex ante and those realized ex post. Even though the green bond's realized return is higher than that of the non-green bond, the green bond's expected long-term return is demonstrably lower. In other words, the expected return of the long-short portfolio is negative even though the portfolio's average realized return is positive and significant. Unexpected events often happen, and one of them was likely the outperformance of the German green bond in the first 14 months of its existence.

3. Measuring stocks' greenness

While the German bond example is clean, it is essentially a case study. In this section, we begin our main analysis, which examines U.S. stocks. Focusing on stocks allows us to examine the role of greenness in a larger asset universe over a longer time period.

We compute stock-level environmental scores based on MSCI ESG Ratings data, a successor to the MSCI KLD data used in many academic studies. Our data have a number of advantages. According to Eccles and Stroehle (2018), MSCI is the world's largest provider of ESG ratings. The MSCI ESG Ratings data are used by more than 1700 clients, including pension funds, asset managers, consultants, advisers, banks, and insurers.[9] MSCI covers more firms than other ESG raters, such as Asset4, KLD, RobecoSAM, Sustainalytics, and Vigeo Eiris (Berg et al., 2019). Berg et al. (2021) find that MSCI's ESG scores are the least noisy among the eight ESG data vendors they consider. MSCI generates its ratings based on a variety of sources and updates those ratings at least annually. MSCI's ESG research unit employs more than 200 analysts and incorporates artificial intelligence, machine learning, and natural language processing into its methodology.

The availability of industry-unadjusted granular data is another advantage of the MSCI data. With industry adjustment, a heavily polluting firm is classified as green if it pollutes less than other firms in its heavily polluting industry. Without industry adjustment, such a firm is classified as very brown. In principle, either classification could be more relevant for green-versus-brown effects on investor and consumer demands. The MSCI data allow us to explore that issue. MSCI's composite ESG rating is industry-adjusted, as are ratings from other leading providers, whereas MSCI's granular data allow us to compute a greenness measure that is not industry adjusted. We conduct our primary analyses using the latter all-in measure. This approach seems reasonable, as we later show that the effects we identify are strongly associated with industry-level greenness.

We use the MSCI variables "Environmental pillar score" (*E_score*) and "Environmental pillar weight" (*E_weight*). *E_score* is a number between 0 and 10 measuring the firm's weighted-average score across 13 environmental issues related to climate change, natural resources, pollution and waste, and environmental opportunities. These scores are designed to measure a company's resilience to long-term environmental risks. *E_weight*, which is typically con-

[8] According to the September 2021 ARD-DeutschlandTREND survey, 33% of Germans view climate as the first or second most important problem facing Germany, ahead of immigration (22%), the coronavirus (18%), and social injustice (16%). In the pre-flood June 2021 survey, the proportion favoring climate was lower, 28%, indicating a substantial shift in Germans' climate concerns in the summer of 2021.

[9] See https://www.msci.com/our-solutions/esg-investing, as of May 2021. In addition, MSCI has been voted 'Best firm for SRI research' in the Extel & SRI Connect Independent Research in Responsible Investment Survey in each year from 2015 through 2019 (https://www.msci.com/zh/esg-ratings).

stant across firms in the same industry, is a number between 0 and 100 measuring the importance of environmental issues relative to social and governance issues.[10]

We compute the unadjusted greenness score of firm i at the beginning of month t as

$$G_{i,t-1} = -(10 - E\_score_{i,t-1}) \times E\_weight_{i,t-1}/100, \quad (1)$$

where $E\_score_{i,t-1}$ and $E\_weight_{i,t-1}$ are from company i's most recent MSCI ratings date before month t, looking back no more than 12 months. The quantity $10 - E\_score_{i,t-1}$ measures how far the company is from a perfect environment score of 10. The product $(10 - E\_score_{i,t-1}) \times E\_weight_{i,t-1}$ measures how brown the firm is, specifically, the interaction of how badly the firm scores on environmental issues and how large the environmental impacts are for the industry's typical firm (i.e., $E\_weight_{i,t-1}$). The initial minus sign converts the measure from brownness to greenness.

Including *E_weight* in Eq. (1) is important for capturing a company's greenness. For example, in 2019, Exxon Mobil and Best Buy had similar *E_score* values: 4.2 and 4.1, respectively. If we used only *E_score*, we would judge these companies to be similarly green. But *E_weight* is 48 for Exxon and only 11 for Best Buy, reflecting that oil and gas companies have larger environmental impacts than consumer retail companies. Exxon and Best Buy end up with $G_{i,t} = -2.78$ and -0.65, respectively, indicating that Best Buy is much greener than Exxon. Similar to us, MSCI uses the interaction of *E_score* and *E_weight* when computing firms' composite ESG ratings.[11]

The environmental score we use in our analysis is

$$g_{i,t} = G_{i,t} - \bar{G}_t, \quad (2)$$

where $\bar{G}_t$ is the value-weighted average of $G_{i,t}$ across all firms i. Since we subtract $\bar{G}_t$, $g_{i,t}$ measures the company's greenness relative to the market portfolio, as in PST. If w_t and g_t denote the vectors containing stocks' market weights and $g_{i,t}$ values in month t, then

$$w_t' g_t = 0, \quad (3)$$

a condition imposed by PST.

We compute $g_{i,t}$ in the sample of stocks with non-missing MSCI data and CRSP share codes of 10 or 11. We merge CRSP and MSCI by using a combination of CUSIP, ticker, and company name. Our sample extends from November 2012 to December 2020. We begin in November 2012 because MSCI's coverage increases dramatically in October 2012, when MSCI began covering small U.S. stocks.[12] Figure 2 plots the number of U.S. stocks with non-missing lagged MSCI ratings. This number increases sharply in November 2012, from roughly 500 to over 2,000. Our purchased MSCI data end in March 2020, but we extend our sample through December 2020 by looking back up to 12 months when computing $G_{i,t-1}$.

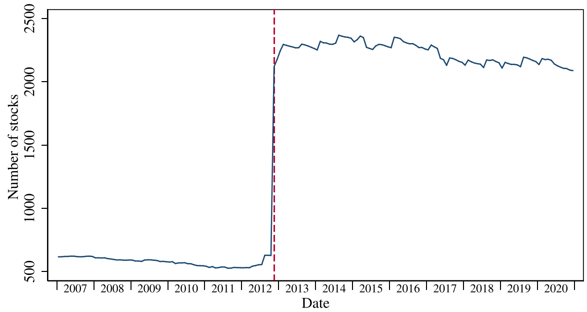

Fig. 2. MSCI coverage. The figure plots the number of stocks in our sample with non-missing MSCI environmental scores at the beginning of the month. The dashed red line is at November 2012, where our sample begins. MSCI expanded its coverage in October 2012. We begin our sample in November 2012, as we require lagged environmental scores.

Table 2 shows industries ranked by their equal-weighted average $g_{i,t}$ scores at the end of 2019. The lowest-ranked industries include chemicals, oil and gas exploration and production, steel, mining (including coal), paper and forest products, and marine transport. It is reassuring that these industries, which are generally viewed as having negative environmental impacts, appear at the bottom of our ranking.

Among the 64 industries considered in Table 2, only 20 have positive values of average $g_{i,t}$ at the end of 2019. This fact may appear at odds with our assumption that the average value of $g_{i,t}$ across all stocks is zero. However, our assumption pertains to the market-value-weighted average (see Eq. (3)). While the equal-weighted average of $g_{i,t}$ at the end of 2019 is -0.33, the value-weighted average is indeed zero, by construction. The value-weighted average exceeds the equal-weighted one because greener firms tend to be larger.

4. Realized green stock returns

Green stocks strongly outperformed brown in recent years. Figure 3 displays the performance of green and brown stocks from November 2012 to December 2020. The solid line, representing green stocks, plots the cumulative value-weighted return on the portfolio of stocks with greenness scores in the top third. The dashed line, representing brown stocks, plots the corresponding return for stocks with scores in the bottom third. We see that green stocks strongly outperformed brown in the 2010s, with a cumulative return difference of 174% over our 8.2-year

[10] MSCI's E, S, and G weights sum to 100. According to MSCI, "The weightings take into account both the contribution of the industry, relative to all other industries, to the negative or positive impact on the environment or society; and the timeline within which we expect that risk or opportunity for companies in the industry to materialize...." We follow MSCI in using the GICS sub-industry classification.

[11] MSCI's composite ESG rating is based on their "Weighted Average Key Issue" score, which equals $[E\_score \times E\_weight + S\_score \times S\_weight + G\_score \times G\_weight]/100$, where S and G refer to social and governance. So if MSCI used a formula like Eq. (1) to compute greenness not just on environmental but also on social and governance dimensions, then we could express MSCI's composite ESG score as 10 plus the sum of E, S, and G greenness.

[12] Before October 2012, MSCI covered only the largest 1500 companies in the MSCI World Index, plus large companies in the UK and Australia MSCI indexes. In October 2012 MSCI added many smaller U.S. firms when it began covering also the MSCI U.S. Investible Market Index.

Table 2
Industries ranked by environmental scores.
Average *g* is the environmental score averaged across firms within each MSCI industry at the end of 2019. MSCI uses the GICS sub-industry classification.

Rank	MSCI Industry	Avg. *g*	Rank	MSCI Industry	Avg. *g*
1	Asset Management & Custody Banks	0.87	33	Textiles, Apparel & Luxury Goods	-0.50
2	Professional Services	0.85	34	Auto Components	-0.51
3	Telecommunication Services	0.84	35	Property & Casualty Insurance	-0.51
4	Consumer Finance	0.84	36	Casinos & Gaming	-0.54
5	Health Care Equipment & Supplies	0.84	37	Real Estate Development	-0.55
6	Health Care Providers & Services	0.83	38	Semiconductors	-0.66
7	Life & Health Insurance	0.76	39	Electrical Equipment	-0.75
8	Interactive Media & Services	0.74	40	Construction & Farm Machinery	-0.76
9	Diversified Financials	0.73	41	Tobacco	-0.89
10	Media & Entertainment	0.70	42	Trading Companies & Distributors	-0.99
11	Diversified Consumer Services	0.61	43	Industrial Machinery	-1.04
12	Biotechnology	0.57	44	Containers & Packaging	-1.09
13	Pharmaceuticals	0.49	45	Energy Equipment & Services	-1.16
14	Multi-Line Insurance & Brokerage	0.40	46	Real Estate Management & Services	-1.20
15	Investment Banking & Brokerage	0.39	47	Airlines	-1.21
16	Banks	0.35	48	Hotels & Travel	-1.57
17	Restaurants	0.31	49	Building Products	-1.62
18	Construction & Engineering	0.13	50	Utilities	-1.90
19	Aerospace & Defense	0.10	51	Integrated Oil & Gas	-2.01
20	Commercial Services & Supplies	0.07	52	Food Products	-2.02
21	Air Freight & Logistics	-0.06	53	Beverages	-2.04
22	Household Durables	-0.12	54	Metals and Mining, Precious	-2.19
23	Software & Services	-0.13	55	Oil & Gas Refining, Marketing	-2.52
24	Electronic Equipment, Instruments	-0.17	56	Construction Materials	-2.56
25	Leisure Products	-0.17	57	Specialty Chemicals	-2.82
26	Automobiles	-0.22	58	Marine Transport	-2.83
27	Retail - Food & Staples	-0.25	59	Paper & Forest Products	-2.93
28	Retail - Consumer Discretionary	-0.27	60	Metals and Mining, Non-Precious	-2.95
29	Road & Rail Transport	-0.30	61	Steel	-2.96
30	Household & Personal Products	-0.30	62	Oil & Gas Exploration & Production	-3.01
31	Industrial Conglomerates	-0.36	63	Diversified Chemicals	-3.21
32	Technology Hardware, Storage	-0.39	64	Commodity Chemicals	-3.78

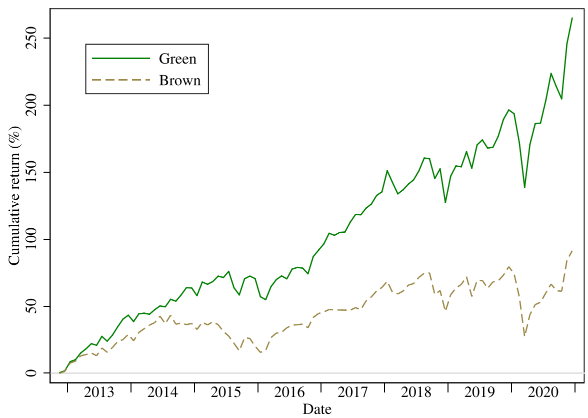

Fig. 3. Returns on value-weighted green and brown portfolios. This figure plots the green and brown portfolios' cumulative returns. The values of the green and brown lines at the end of 2020 are 264.9 and 91.3, implying green stocks outperformed brown by 264.9 – 91.3 = 174 percentage points over this period.

sample period. The monthly return difference, which we denote GMB (green-minus-brown), averaged 65 bps per month (t-statistic: 3.23), as reported in the first column of Table 3. The monthly Sharpe ratio of GMB is 0.33, larger than even the market portfolio's Sharpe ratio of 0.30 over the same period.

This strong performance of GMB cannot be explained by exposures to return factors prominent in the asset pricing literature. The remaining columns of Table 3 report results of regressing GMB on various factors, including those in the three- and five-factor models of Fama and French (1993, 2015), the momentum factor (UMD) as constructed by those authors, the traded liquidity factor of Pástor and Stambaugh (2003), and the factors of Hou et al. (2015) and Hou et al. (2021). In all cases, GMB's alpha (regression constant) is economically and statistically significant, ranging from 47 to 71 bps per month, with t-statistics between 1.99 and 2.91.

GMB's lowest alpha in Table 3 occurs in column 4, where we adjust for the three Fama-French factors and momentum. Its exposures to SMB, HML, and UMD indicate that GMB tilts toward large stocks, growth stocks, and recent winners. Net of those exposures, the alpha of GMB is 47 bps per month ($t = 2.14$).

At first sight, these results appear at odds with those of Bolton and Kacperczyk (2021), who find that stocks of firms with higher carbon emissions earn higher risk-adjusted returns. However, Bolton and Kacperczyk's sample period, 2005 to 2017, is substantially different from ours. Moreover, the sign of the carbon premium depends

Table 3
GMB performance.
We estimate monthly time-series regressions using data from November 2012 to December 2020. The dependent variable is the difference between the returns on the green and brown portfolios (GMB). Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French (1993). UMD is the momentum factor of Carhart (1997). LIQ is the traded liquidity factor of Pástor and Stambaugh (2003). RMW and CMA are the profitability and investment factors of Fama and French (2015). ME, I/A, and Roe are the size, investment, and profitability factors of Hou et al. (2015). Eg is the expected-growth factor of Hou et al. (2021). Returns are in percent per month. Robust *t*-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.65	0.71	0.50	0.47	0.50	0.50	0.55	0.49
	(3.23)	(2.91)	(2.23)	(2.14)	(2.25)	(2.38)	(2.28)	(1.99)
Mkt-RF		-0.05	0.02	0.05	0.01	0.04	-0.00	0.01
		(-0.78)	(0.32)	(0.87)	(0.21)	(0.77)	(-0.05)	(0.23)
SMB			-0.14	-0.11	-0.16	-0.26		
			(-1.49)	(-1.23)	(-1.56)	(-2.59)		
HML			-0.26	-0.18	-0.26	-0.21		
			(-3.36)	(-1.99)	(-3.26)	(-2.60)		
UMD				0.13				
				(2.00)				
LIQ					0.04			
					(0.60)			
RMW						-0.39		
						(-2.90)		
CMA						-0.10		
						(-0.60)		
ME							-0.15	-0.13
							(-1.48)	(-1.28)
I/A							-0.30	-0.25
							(-2.21)	(-1.59)
Roe							0.09	0.02
							(0.99)	(0.20)
Eg								0.12
								(0.67)
Observations	98	98	98	98	98	98	98	98
R^2	0.00	0.01	0.19	0.22	0.19	0.26	0.13	0.14

on how exactly carbon emissions are measured. Bolton and Kacperczyk find a positive carbon premium associated with total emissions, but not with emission intensity (i.e., emissions per unit of sales). Görgen et al. (2020) find an insignificantly negative carbon premium when they combine multiple carbon-emission-related measures and use a sample period closer to ours, 2010 to 2017. Finally, carbon emissions are only one of 13 firm characteristics that enter MSCI's environmental scores, which we use to determine firm greenness. For example, MSCI also considers the firm's handling of land use, water stress, raw material sourcing, toxic waste, and opportunities in clean tech, green building, and renewable energy.

5. The equity greenium

We next explore the equity analog to the bond greenium analyzed in Section 2. The equity greenium captures the difference in expected returns on green versus brown stocks. For concreteness, we define the equity greenium as the expected return on the GMB spread. Expected stock returns are not directly observable, so the equity greenium must be estimated. This section presents two approaches to the estimation.

One approach uses ex ante data while the other uses ex post data. The first approach estimates each stock's expected return as its implied cost of capital (ICC), which is the discount rate that equates the stock's current price to the present value of expected future cash flows, with the latter estimated using data available when the price is observed. With this ex ante approach, we construct the expected GMB return from the underlying stocks' ICCs. The second approach estimates the expected GMB return as the average ex post return purged of unanticipated shocks to quantities affecting the return. To identify those shocks, we follow PST in noting that GMB's realized performance can be positive in periods of unanticipated increases in demands for green firms' products and stocks (or decreases in demands for brown firms' products and stocks). These demands can change for various reasons, but a likely leading source is increased concerns about climate change. We use climate-concern shocks and earnings-news shocks when pursuing the second approach.

As we detail below, the ex ante and ex post approaches deliver similar negative estimates of the expected GMB return. These estimates contrast sharply with GMB's strongly positive realized performance. Later in the section we show that our main conclusions about expected versus realized returns are robust along various dimensions, such as including additional shocks and examining returns at the individual stock level. We also show that our results are driven more by industry-level greenness than within-industry greenness.

5.1. ICC estimates of the equity greenium

Our first approach to estimating the equity greenium, using ex ante data, computes the ICC for each stock-month. The ICC combines data on market prices and forecasted cash flows to infer a discount rate using the standard discounted-cash-flow formula. We follow the approach of Hou et al. (2012), which builds on the classic framework of Gebhardt et al. (2001) but replaces analysts' earnings forecasts with regression-based forecasts. Lee et al. (2021) compare ICC methods used in a number of finance studies. We choose the method they find produces the most precise expected return estimates in the cross section. The Appendix provides further details.

Panel A of Fig. 4 plots the time series of the ICCs of the green and brown portfolios, the long and short legs of GMB. Each portfolio's ICC is the value-weighted average of its stocks' ICCs. During our sample period, the green portfolio's ICC declines from 7.6% to 4.9% per year, whereas the brown portfolio's ICC falls from 8.8% to 6.8% per year. Importantly, at each point in time, the green portfolio's ICC is below that of the brown portfolio, indicating a consistently negative equity greenium, i.e., lower expected return on green stocks versus brown. Panel B plots the difference between the two ICCs. This difference, which is the GMB portfolio's ICC, ranges from −0.4% to −2.4%, with an average of −1.4% per year. To the extent that the ICC is a good proxy for expected stock return, this evidence of a consistently negative equity greenium supports our argument that GMB's strong performance in our sample period was unexpected.

Additional insight into the equity greenium comes from a panel regression of a stock's ICC on the stock's greenness, with month fixed effects. This regression produces a highly significant negative slope estimate ($t = -11.90$), again consistent with a negative equity greenium. When we add the interaction of greenness with a time trend to the right-hand side of the regression, both greenness and this interaction command highly significant slope estimates, with t-statistics of about −5.5. (We tabulate the results in the Appendix.) These estimates imply not only that the equity greenium is negative but also that it widened over our sample period. Consistent with the latter, in Panel B of Fig. 4 the ICC of GMB declines from −1.2% to −1.9% per year during our sample period, albeit far from monotonically. The greenium's decline is especially steep from 2017 to 2020. This evidence of a widening equity greenium is consistent with investors' demand for green assets strengthening during our sample period.

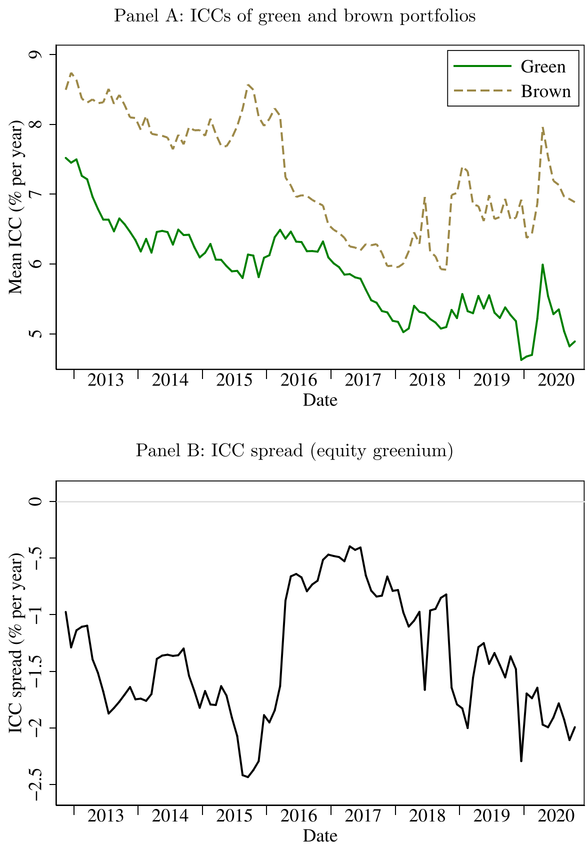

Fig. 4. Implied costs of capital. Panel A plots the ICCs of green and brown portfolios, computed as value-weighted averages of annual ICCs of stocks within each portfolio. Panel B plots the green-minus-brown difference between the ICCs from Panel A.

5.2. Inferring expected return from past realizations

Our second approach to estimating the equity greenium addresses the general problem of inferring an asset's unconditional expected return, $\mu = E\{r_t\}$, using ex post data. One option is to use the asset's sample average return, $\bar{r}$, as the estimate of μ. Another approach, which we follow, is to exploit the additional information in the contemporaneous history of another variable, x_t, that is correlated with the return and for which $E\{x_t\} = 0$. For example, as in our setting, x_t can be an unanticipated change in climate concerns. In the regression,

$$r_t = a + bx_t + \epsilon_t \,, \tag{4}$$

$a = \mu$ because x_t has zero mean ex ante. Therefore, we can estimate μ by the sample estimate of a. This estimate is given by the OLS intercept $\hat{a} = \bar{r} - \hat{b}\bar{x}$, where $\hat{b}$ is the OLS slope and $\bar{x}$ is the sample average of x_t. We thus have two alternative estimators of μ:

$$\text{Estimator 1:}\, \bar{r} \tag{5}$$

$$\text{Estimator 2:}\, \hat{a} = \bar{r} - \hat{b}\bar{x} \,. \tag{6}$$

To obtain more insight into the second estimator, let x_t be signed such that $b > 0$. Suppose the realizations of x_t exceed their expectation on average, so that $\bar{x} > 0$. As a result, $\bar{r}$ overstates μ by $b\bar{x}$ on average. This overstatement is essentially removed by the second estimator, $\hat{a}$, which reduces $\bar{r}$ by $\hat{b}\bar{x}$. Similarly, when instead $\bar{x} < 0$, one expects $\bar{r}$ to understate μ, and $\hat{a}$ essentially adds back the understatement. In general, with $\bar{x} \neq 0$, the regression intercept removes the associated ex post distortion in $\bar{r}$. The same argument applies if x_t is a vector of variables whose sample means differ from their zero ex ante means.

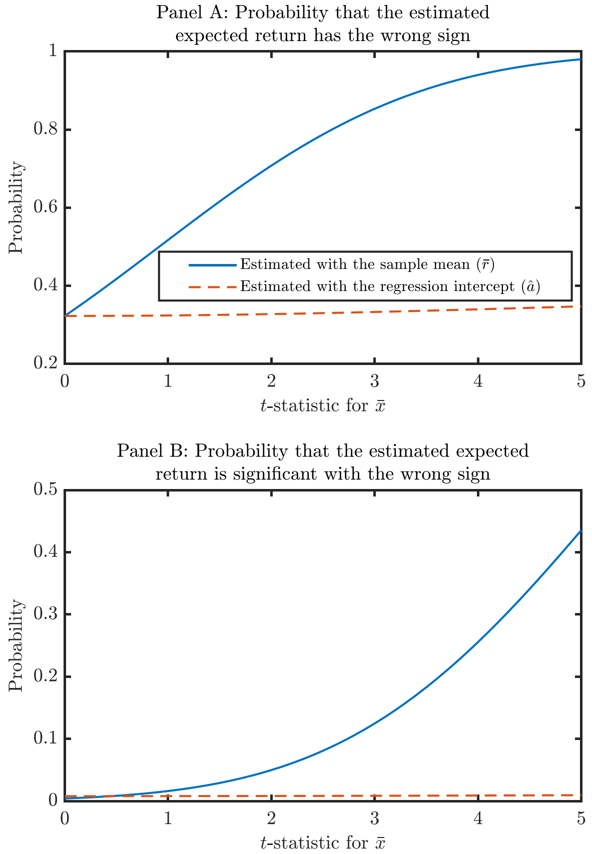

Fig. 5. Comparing estimators of expected return. The figure displays the indicated probabilities when the number of observations equals 68, the regression R-squared is 20%, and the monthly return has a true mean (μ) of −10 basis points and a standard deviation of 2%. In Panel B, statistical significance is at the two-tailed 5% level.

To illustrate quantitatively how $\bar{r}$ and $\hat{a}$ can provide different inferences, we analyze a setting that corresponds roughly to our regressions presented later, just simplified to the above case of one explanatory variable, x_t. Specifically, we set T equal to 68 months, the sample length in our regressions, and we assume that the regression in Eq. (4) has an R-squared of 20%, which is broadly representative of our estimated regressions. We also assume that the ϵ_t's are normally distributed, independently and identically across months, and that the monthly return, r_t, has a standard deviation of 2%, matching that of GMB. Finally, we set that spread's expected return, μ, equal to −10 bps per month, which is representative of both the −11.6 bps implied by the earlier ICC estimate (−1.4% per year on average) as well as the estimates we obtain later using $\hat{a}$.

Figure 5 displays comparisons of $\bar{r}$ and $\hat{a}$ as estimators of μ. Panel A shows the probability that an estimate of μ is positive, i.e., has the wrong sign. The probability is conditioned on the magnitude of $\bar{x}$, which we express on the horizontal axis in terms of $t_{\bar{x}}$, the t-statistic for $\bar{x}$.[13] Regardless of $t_{\bar{x}}$, if μ is estimated by $\hat{a}$, the probability of getting the wrong sign is about 0.33. For $t_{\bar{x}} = 0$, that value is also the probability of getting the wrong sign when estimating μ by $\bar{r}$, but the probability in this latter case rises quickly as $t_{\bar{x}}$ increases, to the extent that getting the wrong sign becomes very likely when $\bar{x}$ is strongly significant. Panel B shows the probability that each estimate of μ not only gets the wrong sign but is also statistically significant at the two-tailed 5% level. If μ is estimated by $\hat{a}$, this probability is consistently less than 1%. If μ is instead estimated by $\bar{r}$, the probability grows quickly as $t_{\bar{x}}$ increases. For example, if $t_{\bar{x}} = 4$, there is a 25% probability of having $\bar{r}$ be statistically significant with the wrong sign. Overall, for samples in which $\bar{x}$ departs significantly from its zero mean, the advantage of using $\hat{a}$ rather than $\bar{r}$ to estimate μ seems clear.

5.3. Measuring shocks to climate concerns and earnings

To implement the above approach that uses $\hat{a}$, we must specify x_t. We generalize the latter to be a vector of shocks having two sources. First, climate concerns are likely to play a key role in boosting demands by consumers for green firms' products as well as demands by investors for green firms' stocks (and reducing demands for brown firms' products and stocks). Therefore, news regarding climate concerns serves as one source of return shocks in x_t.[14] Second, while the product-demand channel for climate news impacts returns via expectations of firms' earnings, non-climate information also impacts earnings expectations and thus returns. We therefore include earnings news directly as another source of return shocks in x_t. Next, we describe how we measure both sources of shocks.

5.3.1. Climate concerns

We measure concerns about climate change with the Media Climate Change Concerns index (MCCC) of Ardia et al. (2021). This index, which is available from January 2003 through June 2018, is constructed by using data from eight major U.S. newspapers. It captures the number of climate news stories each day as well as their negativity and focus on risk. For each news article discussing climate change, Ardia et al. compute a "concern" measure that interacts two quantities: the fraction of total words related to risk and the scaled difference between negative and positive words. They aggregate this measure to the newspaper-day level by adding the concern values across stories. Next, they aggregate to the day level by averaging across newspapers, after adjusting for heterogeneity across newspapers. Finally, they take the square root of this daily measure because, as they put it, "One concerning article about climate change may increase concerns, but 20 concerning articles are unlikely to increase concerns 20 times more."

Following Ardia et al. (2021), we measure shocks to climate concerns as prediction errors from AR(1) models applied to the underlying MCCC index. To compute the prediction error in month t, we estimate an AR(1) model using the 36 months of MCCC data ending in month $t-1$

[13] The probabilities in Fig. 5 are derived in the Appendix.

[14] We do not take a stand on whether customers' and investors' responses to climate news reflect genuine concerns about climate or just virtue signaling. Either way, asset prices can be affected.

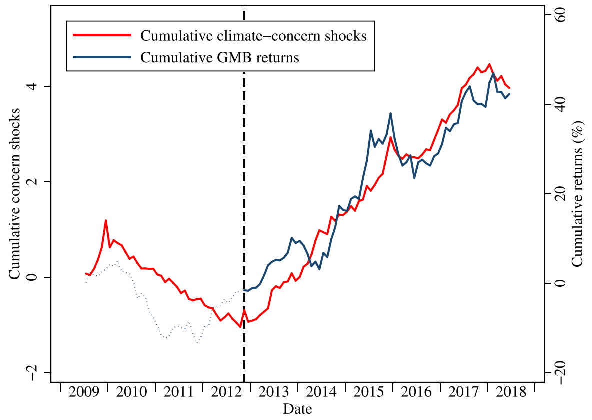

Fig. 6. Climate concerns and GMB. Climate-concern shocks are prediction errors from rolling AR(1) models fitted to the monthly MCCC index. The dashed vertical line is at November 2012, where our sample begins. Before November 2012, the GMB return, shown as a dotted line, is constructed using a much smaller number of stocks (recall Fig. 2). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(including data before November 2012), and we set the prediction error to month t's realization of MCCC minus the AR(1) model's prediction.

Figure 6 plots the cumulative shocks to climate concerns over the ten-year period between July 2009 and June 2018. We begin the plot immediately after the financial-crisis-induced recession, which ended in June 2009. The cumulative shocks trend down initially but then trend up sharply from 2013 through 2017, before dipping slightly in 2018.[15] GMB's performance, also plotted in Fig. 6, looks strikingly similar. It performs strongly in 2013 through 2018, cumulatively returning over 40%, whereas its pre-2013 performance is negative. Of course, GMB's performance before November 2012 is only approximate because it is computed based on a sample of firms that is much smaller and biased toward large-capitalization firms (recall Fig. 2). We plot GMB's imprecise earlier performance for comparison purposes, but we do not use it in any of our analysis.

We include month t's climate-concern shock, which we denote as ΔC_t, in x_t. We also include in x_t the previous month's shock, ΔC_{t-1}, given our evidence of delayed stock price reactions to climate news. (That evidence is analyzed later in Section 6.)

5.3.2. Earnings news

Next, we include in x_t two measures of earnings news constructed using data from CRSP and I/B/E/S. The first measure is based on the idea that a large portion of earnings news occurs on days when firms make earnings-related announcements (Beyer et al., 2010). We consider two types of announcements: those of quarterly earnings and voluntary forward guidance regarding future earnings. We compute stock returns in excess of the market during the three-trading-day windows centered on these announcement dates. We add the excess returns across unique events within a given stock-quarter. For about 70% of observations, no summation is required because the forward-guidance date coincides with the earnings-announcement date. We find that our announcement-return measure explains about 20% of the variance of quarterly stock-level returns (see the Appendix).

Our second measure captures news about long-term earnings. Such news can arrive gradually over time, in between the quarterly announcements. This second measure uses data on analysts' forecasts of each firm's long-run earnings growth rate. For firm i and quarter t, the measure equals the earliest mean analyst forecast in quarter $t+1$ minus the latest mean forecast in quarter $t-1$. Using forecasts from quarters $t-1$ and $t+1$ helps to capture all news arriving in quarter t. The measure may also include a small amount of information that arrives in quarters $t-1$ or $t+1$, but those inclusions are innocuous since they should not help explain returns in quarter t. We winsorize this measure at the 1% level. We find that this measure is significantly related to quarterly stock-level returns but explains less than 1% of their variance (see the Appendix).

Since GMB is a spread between portfolio returns, we need to convert our firm-level earnings measures into the appropriate portfolio-level quantities to be included in x_t. We do so following GMB's construction, each month computing value-weighted averages of the firm-level measures within GMB's green and brown legs and then taking the difference.

Measuring the part of returns coming from earnings news is known to be difficult, and our measures surely miss important earnings news. Our first measure misses short-term news that arrives outside the three-day announcement windows. One limitation of our second measure is that analysts' forecasts can differ from investors' forecasts. In addition, analysts' long-term forecasts are only three- to five-year forecasts, so the second measure also misses changes in expectations of earnings that lie more than five years in the future.

Changes in expectations of distant future earnings seem especially likely to arise from shocks to climate concerns. For example, the meteoric rise of Tesla's stock price in 2020 may have been caused in part by climate-driven revisions to forecasts of electric vehicle sales at horizons longer than five years. Such climate-driven shocks to earnings, and thus to returns, can nevertheless be captured by our climate news measure, ΔC_t, which is included in x_t. In general, the return shocks captured by our specification of x_t can reflect changes in earnings expectations, either climate-driven, and thus captured by ΔC_t, or non-climate-driven, and thus captured by the earnings news measures.

5.4. Estimates of the equity greenium using past realizations

The first two columns of Table 4 report results from regressions of GMB returns on x_t, both with and without the earnings variables included in x_t. Including those vari-

[15] Sautner et al. (2021) provide independent evidence that climate concerns strengthen after 2012. They measure firms' climate change exposures by the extent to which climate change topics are discussed in firms' earnings calls, finding a sharp increase in climate change exposure between 2013 and 2018.

Table 4
Sources of GMB performance.
We estimate monthly time-series regressions using data from November 2012 through June 2018. The dependent variable is the GMB return in columns 1–2 and GMB's Fama-French three-factor alpha in columns 3–4. We estimate alphas in a time-series regression of GMB on the Fama-French factors. We set each month's alpha equal to the regression's intercept plus residual. Both returns are in percent per month. "Δ Climate concerns" is the prediction error from rolling AR(1) models applied to the MCCC index. The two earnings news measures, "Earnings announcement returns" and "Δ Earnings forecasts," are described in Section 5.5. They correspond to the quarter that contains the given month. Robust t-statistics are in parentheses.

	Dependent variable			
Independent variable	GMB return		GMB alpha	
Δ Climate concerns (same month)	4.08	3.75	3.95	3.44
	(2.70)	(2.69)	(2.79)	(2.70)
Δ Climate concerns (prev. month)	2.98	2.86	2.64	2.33
	(1.86)	(1.77)	(1.97)	(1.82)
Earnings announcement returns		0.77		0.63
		(2.64)		(2.31)
Δ Earnings forecasts		6.93		14.16
		(0.44)		(0.96)
Constant	0.05	-0.04	-0.10	-0.15
	(0.20)	(-0.15)	(-0.41)	(-0.66)
Observations	68	68	68	68
R^2	0.14	0.25	0.14	0.26

ables raises the R-squared from 0.14 to 0.25. The same-month climate shock, ΔC_t, and the earnings announcement return both enter significantly with their expected positive signs (t-statistics: 2.69 and 2.64). The positive ΔC_t coefficient supports the prediction that an increase in climate concerns is worse news for brown stocks than green stocks. This conclusion, based on monthly returns, echoes the conclusion reached by Ardia et al. (2021) at the daily frequency. The previous month's climate shock, ΔC_{t-1} also enters positively and is marginally significant (t-statistic: 1.77). This result, which suggests delayed stock price response to climate news, emerges more strongly among smaller stocks, as we show in Section 6. The only variable falling well short of statistical significance is the change in analysts' long-term forecasts, although its coefficient does have the expected positive sign.

The key quantity of interest, the equity greenium, is estimated by the regression intercept $\hat{a}$. With the earnings variables included in x_t, the estimated equity greenium is −4 bps per month. Recall that the ICC estimate is about −12 bps per month. Both the ex ante and ex post approaches thus suggest a negative equity greenium whose magnitude is modest, at least in comparison to the 65 bps for GMB's realized average return.

As noted earlier, GMB tilts toward large growth stocks. Size and growth effects are not driving our results, however. The remaining columns of Table 4, labeled "GMB alpha," repeat the above regressions with the dependent variable redefined as the GMB return adjusted by the three factors of Fama and French (1993). To construct that return, we take the intercept plus the residual from the time-series regression of GMB on the factors. The resulting slope coefficients are all quite similar to their counterparts in the first two columns. The intercept when the earnings variables are included shifts downward somewhat, from −4 bps to −15 bps.

What if there had been no climate-concern shocks or other shocks to green-versus-brown earnings? Panel A of Fig. 7 compares GMB's realized performance to its counterfactual performance in the absence of climate and earnings shocks. Using the regression estimated in column 2 of Table 4, we compute the counterfactual monthly GMB return as the regression intercept, $\hat{a}$, plus the estimated residual. (Equivalently, the counterfactual equals the realized value minus the regressors times their respective coefficients.) The dashed line plots the cumulative counterfactual return, and the solid line shows the cumulative realized return. We also plot a 95% confidence interval around the counterfactual, recognizing that the regression coefficients are estimated with error. To compute this interval, we repeatedly draw regression coefficients from their estimated sampling distribution, use those coefficients to compute simulated counterfactual returns, and plot the simulated returns' 95% confidence intervals. Panel B of Fig. 7 repeats the same analysis using the GMB alpha and the regression estimated in column 4 of Table 4.

Both panels of Fig. 7 deliver the striking message that, absent shocks to climate concerns and earnings, GMB's performance is slightly downward-trending, reflecting the negative intercepts in the second and fourth columns of Table 4. Moreover, GMB's counterfactual performance is reliably below its realized performance, as the latter lies well outside the 95% confidence interval in both panels.

The sharp contrast between the realized and counterfactual performance in Fig. 7 reflects the difference between $\bar{r}$ and $\hat{a}$, the two estimators in Eqs. (5) and (6). The main source of this difference is that the climate-concern shock, ΔC_t, had average realizations that were unexpectedly high during the sample period. Note in column 1 of Table 4 that when controlling for just climate-concern shocks, $\hat{a}$ is merely 5 bps, compared to 65 bps for GMB's average return, $\bar{r}$. The t-statistic for the average of ΔC_t is

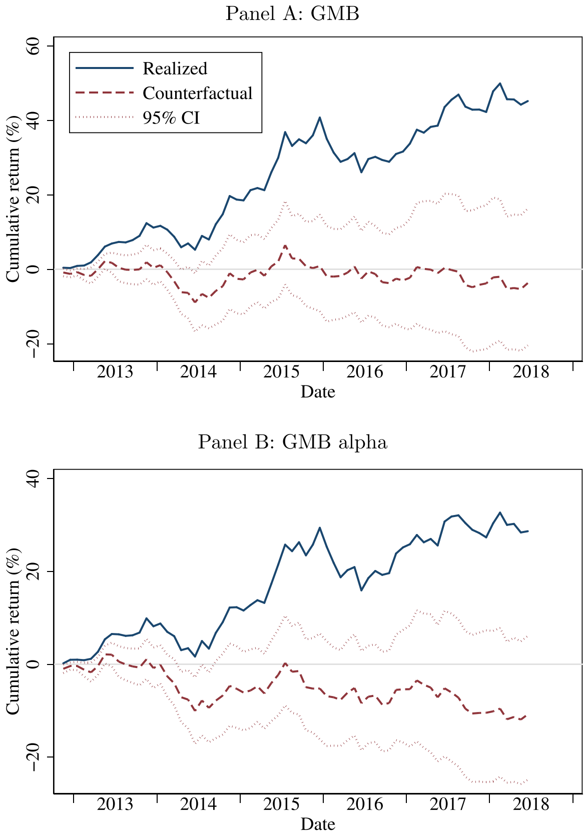

Fig. 7. Counterfactual GMB performance. The solid line shows realized cumulative, compounded returns on GMB (Panel A) and GMB's Fama-French three-factor alpha (Panel B). Alphas are computed as in Table 4. The dashed line shows the returns' counterfactual counterparts computed from columns 2 and 4, respectively, of Table 4. The counterfactual monthly return equals the realized return minus the regressors times their respective regression slopes. Dotted lines indicate the counterfactual's 95% confidence interval. We compute confidence intervals using the following steps: (1) Estimate the regression from column 2 of Table 4 and store the estimated coefficients and their covariance matrix. (2) Repeat the following steps (2a)–(2c) 500 times: (2a) draw a new coefficient vector from a normal distribution with mean and variance saved in step (1); (2b) use the new coefficient to compute each period's counterfactual return; (2c) compute and store cumulative counterfactual returns. (3) Each month, compute the 2.5th and 97.5th percentiles of the counterfactual cumulative returns stored in step (2c).

4.01. Recall from Fig. 5 that with such an outcome in the single-variable version of x_t, getting a misleading estimate of the equity greenium is much more likely when using the average realized performance, $\bar{r}$, than when using the average counterfactual performance, $\hat{a}$. In essence, given that a substantial portion of the increase in climate concerns was unanticipated, so too was GMB's significant positive performance. Accordingly, that performance should not lead one to infer that the expected return on green stocks is higher than brown.

Given the high realized average of ΔC_t, one might question whether its non-zero values were truly unanticipated. An alternative story could be that positive shocks early in the sample period led investors to anticipate subsequent increases in the climate-concern index. In considering that story, first recall that we use a moving 36-month estimation window when computing ΔC_t as the prediction error from an AR(1) model. The AR(1) model's intercept absorbs the recent level and trend in the climate index. Second, an equal split of the sample period gives results contrary to the above anticipation story. When we estimate the regressions in Table 4 separately in both subperiods, the climate-concern shocks actually enter somewhat more strongly in the second half (results are in the Appendix). If ΔC_t had become anticipated later in the sample period, then returns should have reacted to ΔC_t less strongly in the second subperiod, not more strongly.

5.5. ESG flows and assets

Increased climate concerns can impact green-versus-brown stock returns not only through expected earnings (via product demands) but also by impacting investors' desires to hold green stocks rather than brown. As perhaps the most prominent recent trend in the investment management industry, sustainable investing has experienced rapid growth. At the same time, however, the dollar amounts reallocated by sustainable investing thus far, especially in the U.S., appear to be fairly small relative to aggregates. Consider the universe of U.S. mutual funds and ETFs, for example. In 2020 its assets totaled about \$29 trillion, but sustainable funds' assets accounted for only \$230 billion, less than 1% of the total.[16]

When sustainable investing's asset share is small, so too is the likely effect of that investment on expected stock returns. In PST's calibrated version of their model, a small value for the fraction of the market's total assets owned by ESG-conscious investors (λ in their setting) implies a small effect on expected return. Berk and Binsbergen (2021) show that the effects of ESG divestment on expected return are quite small in both theoretical and empirical settings where the fraction of assets being divested is small.

Important to remember, though, is that the magnitude of the equity greenium does not depend only on such taste-related investment effects. Green stocks' expected returns can also reflect those stocks' greater ability to hedge against adverse climate news. Evidence of such ability appears in our Table 4 in the form of a significantly positive relation between GMB and ΔC_t, as well as in prior studies mentioned earlier. All investors can be willing to pay for that climate-hedging property of green stocks, whether or not some investors reallocate due to the warm glow (anguish) they get from holding green (brown) stocks. If climate-hedging demand increased during our sample period, this is yet another source of increased investor demand, and hence unexpected returns, for green assets.

Given that the asset footprint of ESG investing is still fairly small, one might reasonably surmise that ESG investing did not exert significant effects on GMB's realized returns. Nevertheless, some exploration of such potential effects seems warranted, especially given evidence that stock

[16] Sources: Morningstar's *2021 Sustainable Funds U.S. Landscape Report* and the Investment Company Institute's *2021 Investment Company Fact Book*.

prices can respond significantly to seemingly small demand shifts (e.g., Koijen and Yogo, 2019; Gabaix and Koijen, 2021). In looking for ESG investing effects, we also examine green and brown returns separately, because such effects are more likely to be evident in brown stocks. For example, Nofsinger et al. (2019) find that institutions are more likely to underweight stocks with negative environmental and social indicators than they are to overweight stocks scoring positively on those dimensions. The experimental evidence of Humphrey et al. (2020) shows the strengths of green versus brown preferences exhibit a similar asymmetry.

We construct two variables to investigate effects of ESG investing. The first uses flows into sustainable funds as a proxy for shifts in investor demand for green assets. From Morningstar's *2021 Sustainable Funds U.S. Landscape Report*, we obtain data on quarterly total flows into U.S. sustainable funds.[17] We scale these flows, which we refer to as "ESG flows," by the average total market capitalization of CRSP stocks during the quarter. ESG flows increased dramatically in 2013–2020, especially beginning in 2019.

The second investing variable uses sustainable funds' lagged total assets (AUM) as a proxy for the level of investors' ESG tastes. This variable is motivated by PST's theoretical result that expected green-minus-brown returns depend negatively on the average strength of ESG tastes (see Eq. (33) in PST), and the size of the ESG industry depends positively on those tastes (see Fig. 5 in PST). We compute sustainable fund AUM from the previously mentioned Morningstar report, as detailed in the Appendix. We scale ESG AUM by the total market capitalization of CRSP stocks.

Columns 1 and 2 of Table 5 report results from regressions of GMB returns on the two investing variables and the previous climate and earnings variables. In columns 3 and 4, the dependent variable is the return on the green leg, and in columns 5 and 6, the brown leg of the GMB spread. Reverse causation is a potential concern when regressing returns on contemporaneous flows. Instead of flows (or shifts in investors' ESG demands) causing returns, flows could be chasing recent returns within the same period. We address this potential endogeneity by instrumenting for same-quarter ESG flow using its previous-quarter value and estimating the regression by two-stage least squares. The exclusion restriction plausibly holds, because flows cannot chase future realized returns. We find large first-stage t-statistics, indicating that the relevance condition holds and there is no problem with weak instruments.

The coefficients on ESG flows and assets in Table 5 all have their predicted signs, whether or not climate concerns are included in the regression. That is, ESG flows enter positively for the GMB spread and its green leg but negatively for the brown leg, whereas ESG assets enter negatively for the GMB spread and its green leg but positively for the brown leg. For the GMB spread and its green leg, none of the above coefficients are statistically significant. This insignificance could be related to the fact, noted above, that ESG investment during this period is still relatively small. For the brown leg, however, when climate concerns are excluded from the regression, ESG flows enter with a t-statistic of -2.55, and ESG assets get a marginally significant t-statistic of 1.78. These stronger effects of ESG investing on the brown leg are consistent with the asymmetry noted earlier. When climate concerns are included in the regression, though, the brown leg's coefficients on ESG flows and assets also become insignificant.[18] A reasonable interpretation is that the effects of ESG investing on brown stocks' returns are driven largely by climate concerns. Overall, the results in Table 5 justify having excluded ESG flows and assets from our primary regression analyses in Table 4.

5.6. Adding other shocks

As explained earlier, our measure of climate concerns builds on that of Ardia et al. (2021). Those authors in turn acknowledge the prior work of Engle et al. (2020), who construct two media-based measures of climate concerns. Ardia et al. discuss those alternative measures and explain that their measure adds risk as another component of climate concerns. We rely on that more recent measure, but we also examine the robustness of our results to including the Engle et al. measures. We find that doing so does not change our conclusions. We augment the independent variables in column 2 of Table 4 by including climate-concern shocks based on both Engle et al. measures. One of their measures enters significantly, whereas the Ardia et al. measure always enters positively and significantly, either for the current or previous month. When we add the one significant measure from Engle et al. to the right-hand side of the regression in column 2 of Table 4, we obtain the same conclusions: the counterfactual GMB return slopes down slightly. The plot is in the Appendix.

Besides their MCCC index, Ardia et al. (2021) also construct sub-indices capturing eight themes related to climate change: agreement and summit, agricultural impact, disaster, environmental impact, financial and regulation, research, societal impact, and "other." To see which themes correlate most closely with GMB returns, we first compute the ΔC_t series for each of the eight sub-indices and then regress GMB on both ΔC_t and its lag, analogous to our analysis for the MCCC index. For each of the eight themes, we find positive slope estimates on both ΔC_t and its lag. At least one of those measures is statistically significant for five of the eight themes. (We tabulate the results in the Appendix.) Therefore, the results in Table 4 are not driven by any single type of climate concerns.

The three themes that deliver the largest R-squareds in the above regressions are agreement and summit ($R^2 =$

[17] The data combine active and passive funds, equity and bond funds, open-end funds, and ETFs. Morningstar defines a sustainable fund as follows: "For a fund to be included in the sustainable funds universe, it must hold itself out to be a sustainable investment. In other words, ESG concerns must be central to its investment process and the fund's intent should be apparent from a simple reading of its prospectus…."

[18] When we adjust the GMB spread for the three Fama-French factors, all the coefficients on ESG flows and assets retain the same signs, but none of them are statistically significant. See the Appendix for details.

Table 5
The roles of ESG flows and assets.
This table builds on Table 4 by adding controls for ESG flows and assets. "ESG flows" equals the quarter's dollar flow into ESG funds scaled by the average total CRSP market capitalization during the quarter that contains the given month, times 1000. In the specifications that drop Δ Climate concerns, the sample extends through September 2020. We instrument for contemporaneous ESG flow by using its previous-quarter value. The first-stage t-statistic for lagged flows is 3.50 in the shorter samples and 5.68 in the longer samples. We do not tabulate R^2 because it is difficult to interpret in an IV setting. "ESG assets" equals total AUM in ESG funds scaled by the total CRSP market capitalization and measured at the beginning of the quarter containing the given month, times 1000. The dependent variable is the GMB return in columns 1–2 and the market-hedged return on GMB's green (brown) leg in columns 3–4 (5–6), all in percent per month. We compute the market-hedged portfolio returns by replacing individual stock returns with $\tilde{r}^e_t$, the market-adjusted return defined in Section 7.1. Remaining details are the same as in Table 4.

	Dependent variable					
Independent variable	GMB return		Green leg		Brown leg	
Δ Climate concerns (same month)	4.02		1.93		-1.90	
	(2.74)		(2.78)		(-1.69)	
Δ Climate concerns (prev. month)	3.30		0.42		-3.04	
	(2.13)		(0.67)		(-2.62)	
Earnings announcement returns	0.84	0.88	0.20	0.22	-0.63	-0.60
	(3.06)	(2.69)	(1.61)	(1.54)	(-2.88)	(-2.51)
Δ Earnings forecasts	9.97	2.00	4.56	5.20	-6.70	3.23
	(0.70)	(0.15)	(0.82)	(1.06)	(-0.59)	(0.31)
ESG flows	32.96	9.00	7.30	1.91	-29.69	-11.99
	(1.51)	(1.42)	(0.95)	(0.54)	(-1.60)	(-2.55)
ESG assets	-0.56	-0.74	-0.27	-0.27	0.61	0.84
	(-0.82)	(-1.13)	(-0.89)	(-0.81)	(1.08)	(1.78)
Constant	-0.34	1.80	0.18	0.64	0.03	-1.75
	(-0.28)	(1.37)	(0.28)	(1.02)	(0.03)	(-1.80)
Observations	68	95	68	95	68	95

0.15), societal impact ($R^2 = 0.12$), and financial and regulation ($R^2 = 0.12$). Ardia et al. (2021) find these three themes are also closely related to the returns on their green-minus-brown portfolio, which is constructed differently from ours. Moreover, these are the three most discussed themes in the media, according to Ardia et al. The theme that delivers the lowest R-squared is disaster ($R^2 = 0.02$). GMB returns are thus more closely associated with climate-related policy news than with news about disasters.

We also examine the robustness of our results to the inclusion of oil price shocks, which have clear environmental relevance, and long-term bond returns, which could be related to differences in duration between green and brown stocks. We measure oil price shocks as the monthly change in the expected "front month" value of oil, derived from oil futures contracts.[19] We take the long-term bond return to be the return on the 30-year U.S. Treasury bond. When we add both variables to the right-hand side of the regression in column 2 of Table 4, the counterfactual performance of GMB is again essentially flat. See the Appendix.

5.7. Greenness and individual stock returns

All of our empirical analysis thus far is based on the time series of green-versus-brown portfolio returns. To show that our conclusions do not hinge solely on portfolio returns, we next run panel regressions using individual stocks.

Table 6 reports regressions of individual stock returns in month t on various regressors. All regressions include time fixed effects and therefore capture cross-sectional variation in returns. We begin in column 1 with a single regressor, the stock's greenness, $g_{i,t-1}$. The remaining columns add regressors that capture shocks to climate concerns and earnings. The climate-concern shocks are interacted with the stock's greenness, and the earnings variables are the firm-level constituents of the earlier portfolio-level versions used in Table 4. The last column includes additional stock-specific variables as controls: log of market equity, log of book-to-market, and return from months $t-12$ through $t-2$.

When greenness is the only regressor, it has a significantly positive relation to return (column 1), consistent with the outperformance of green stocks reflected in GMB. The coefficient on greenness becomes negative when the regressors include the climate-concern and earnings variables (columns 3 and 4), consistent with GMB's negative expected return estimate given by the intercept in column 2 of Table 4. Thus, consistent with the GMB results, the relation between greenness and return flips from strongly positive to modestly negative when controlling for shocks to returns from climate concerns and earnings.

The coefficients on the climate-concern variables indicate that green stocks outperform when climate concerns increase, consistent with that same conclusion delivered by the regressions for GMB in Table 4. The timing is somewhat different, however, in that the lagged climate-concern shock now enters more strongly than the contemporaneous shock. In Table 6 the coefficient on $g_{i,t-1}$ interacted with ΔC_t is positive but insignificant, while the coefficient

[19] We thank Erik Gilje for providing these data.

Table 6
Greenness and individual stock returns.
This table shows results from panel regressions in which the dependent variable is stock i's percent return in month t. $g_{i,t-1}$ is the stock's lagged greenness. ΔC_t is month t's change in aggregate climate concerns, computed as the prediction error from a rolling AR(1) model applied to the MCCC index. "[Earnings announcement ret.]$_{i,t}$" is the stock's sum of the three-trading-day excess percent returns (stock minus market) around earnings announcements and management earnings forecasts (if available) during the quarter containing month t. "[Δ Earnings forecast]$_{i,t}$" is the change in analysts' mean long-term earnings growth rate forecast for stock i during the quarter containing month t. The last column adds controls (untabulated) for the log of lagged market equity, log of lagged book-to-market ratio, and the stock's return from months $t-12$ through $t-2$, following Lewellen (2015). The sample begins in November 2012. All regressions include month fixed effects, cluster by month, and use robust standard errors.

	(1)	(2)	(3)	(4)
$g_{i,t-1}$	0.21	0.00	-0.02	-0.04
	(2.24)	(0.02)	(-0.23)	(-0.41)
$g_{i,t-1} \times \Delta C_t$		0.83	0.81	0.72
		(1.42)	(1.59)	(1.28)
$g_{i,t-1} \times \Delta C_{t-1}$		1.70	1.54	1.65
		(2.66)	(2.78)	(2.68)
[Earnings announcement ret.]$_{i,t}$			0.32	0.32
			(13.28)	(12.38)
[Δ Earnings forecast]$_{i,t}$			5.89	5.91
			(5.02)	(4.58)
Observations	218,208	153,884	133,290	114,355
R^2	0.18	0.11	0.18	0.19
Additional controls	No	No	No	Yes

on the interaction with ΔC_{t-1} is larger and significant. In Section 6 we further analyze the delayed reaction of stock prices to climate news.

5.8. Industry greenness

Our analysis thus far is based on $g_{i,t}$, a measure of the firm's total greenness that reflects two components: the greenness of the firm's industry and the relative greenness of the firm within its industry. How do each of those components contribute to our results? To investigate this question, we decompose $g_{i,t}$ as

$$g_{i,t} = gAcross_{i,t} + gWithin_{i,t}, \tag{7}$$

with $gAcross_{i,t}$ equal to the average $g_{i,t}$ of all firms within the same industry as stock i in month t, and $gWithin_{i,t} = g_{i,t} - gAcross_{i,t}$.

Figure 8 displays the original GMB analyzed earlier as well as an alternative GMB series constructed the same way but with $gWithin_{i,t}$ replacing $g_{i,t-1}$. We see that the cumulative performance of this alternative, industry-adjusted GMB is much weaker than the original. While the original GMB's average return is positive and highly significant ($t = 3.23$; see column 1 of Table 3), the average return of the industry-adjusted GMB is four times smaller and insignificant ($t = 0.99$; see the Appendix). Therefore, the original GMB's performance owes much to industry-level greenness.

The technology industry, especially "big tech," has delivered high stock returns in recent years. However, our results are not driven by big tech. To show this, we compute monthly returns on the value-weighted portfolio of "FAANG" stocks, which include Meta (formerly Facebook), Amazon, Apple, Netflix, and Alphabet (formerly Google).

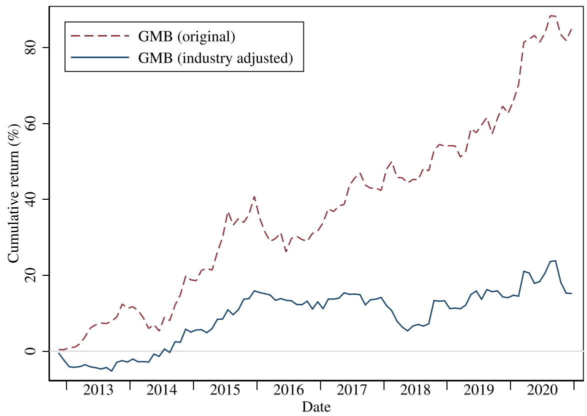

Fig. 8. Effect of industry adjustment. The dashed line plots the cumulative return on the original GMB (green-minus-brown) portfolio constructed with firms' total greenness (i.e., not industry-adjusted). The solid line plots the cumulative return on an industry-adjusted GMB portfolio, which is constructed using g scores demeaned at the industry × month level.

The FAANG portfolio's return is not significantly related to either the original GMB or changes in climate concerns. The Appendix shows the details.

The importance of industry greenness is also evident in individual stock returns. Table 7 reports the same regressions as Table 6, except that each independent variable containing $g_{i,t}$ is replaced by two variables, one for each component in Eq. (7). We first see that, as with GMB, the superior performance of green stocks relative to brown is largely attributable to industry greenness. In column 1 of Table 7, the coefficient on $gAcross_{i,t}$, industry greenness, is 3.6 times the coefficient on $gWithin_{i,t}$, within-industry

Table 7
Greenness and individual stock returns: Effects within and across industries.
This table repeats the regressions in Table 6, except that we decompose g into $gAcross$ and $gWithin$, representing across- and within-industry variation. We define $gAcross$ as the average of g within the industry×month, and $gWithin = g - gAcross$, so that $g = gAcross + gWithin$.

	(1)	(2)	(3)	(4)
$gAcross_{i,t-1}$	0.25	-0.00	-0.02	-0.05
	(2.14)	(-0.01)	(-0.18)	(-0.39)
$gWithin_{i,t-1}$	0.07	0.02	-0.02	-0.01
	(1.11)	(0.28)	(-0.27)	(-0.11)
$gAcross_{i,t-1} \times \Delta C_t$		1.08	1.05	0.94
		(1.49)	(1.66)	(1.33)
$gWithin_{i,t-1} \times \Delta C_t$		-0.13	-0.08	-0.09
		(-0.28)	(-0.17)	(-0.16)
$gAcross_{i,t-1} \times \Delta C_{t-1}$		2.01	1.86	1.94
		(2.58)	(2.74)	(2.57)
$gWithin_{i,t-1} \times \Delta C_{t-1}$		0.49	0.34	0.56
		(1.05)	(0.70)	(1.00)
[Earnings announcement ret.]$_{i,t}$			0.32	0.32
			(13.28)	(12.38)
[Δ Earnings forecast]$_{i,t}$			5.85	5.88
			(5.01)	(4.57)
Observations	218,208	153,884	133,290	114,355
R^2	0.18	0.11	0.18	0.19
Additional contrls	No	No	No	Yes

greenness; the former coefficient is statistically significant ($t = 2.14$), whereas the latter is not ($t = 1.11$).

Industry greenness continues to play the dominant role in Table 7's remaining columns, which analyze the sources of green stocks' outperformance. Recall that a key result in Table 6 is the significantly positive coefficient on $g_{i,t-1}$ interacted with month $t-1$'s climate-concern shock. When the latter shock is instead interacted with industry greenness ($gAcross_{i,t}$), the coefficient on that variable is significantly positive in each of columns 2 through 4. In contrast, when the same climate shock is interacted with within-industry greenness ($gWithin_{i,t}$), the coefficient is insignificant throughout. Therefore, we conclude that industry greenness is the key component of a firm's greenness, capturing both the superior past performance of green stocks as well as the climate-shock source of that performance.

6. Delayed stock price reaction to climate news

In this section, we take a closer look at the timing of the strong positive relation between green-versus-brown returns and the shock to climate concerns, ΔC. As shown in the previous section, the GMB return is strongly related to ΔC in the current month, whereas ΔC in the previous month enters more strongly in the panel regression using individual stocks. We conjecture this difference relates to stocks' market capitalization. The long- and short-leg portfolios of GMB are value-weighted, making GMB most representative of the largest stocks. The panel regression is instead representative of a typical stock, which is substantially smaller than the largest stocks.

To investigate the role of size, we replicate GMB's construction separately within the large- and small-cap segments. Small (large) stocks are those in the bottom (top) quartile of market capitalization based on NYSE breakpoints. As in the original GMB, we continue value-weighting stocks within each GMB spread's green and brown legs. We then regress these GMB returns on the current and lagged month's ΔC. The first row of Table 8 reports the results. For large-cap GMB, same-month ΔC is significant ($t = 2.46$), whereas previous-month ΔC is not ($t = 1.74$). In contrast, for small-cap GMB, same-month ΔC is insignificant ($t = 1.23$), whereas previous-month ΔC is strongly significant ($t = 2.99$), and its coefficient significantly exceeds its large-cap counterpart ($t = 2.35$). In sum, while both large-cap and small-cap GMB exhibit strong positive reactions to ΔC, the reaction is significantly more delayed in the small-cap segment.

We bring sharper focus to the timing of this size-related difference in reactions by looking at a weekly frequency. We construct the weekly ΔC as the prediction error from an AR(1) model estimated using the previous three years of observations of the weekly $MCCC$, computed as the within-week average of the daily $MCCC$ values. We also compute the weekly difference in returns between large-cap and small-cap GMB. Then we regress that return difference on ΔC lagged each of τ weeks, for $\tau = 0, \ldots, 7$. Fig. 9 displays the estimated coefficients along with their 95% confidence intervals. The plot reveals that large-cap GMB reacts more strongly than small-cap GMB to ΔC in the current and most recent week, with the difference being statistically significant for the current week. In contrast, small-cap GMB reacts more strongly at longer lags, significantly so at the three-week lag.

The apparent slower reaction of small stocks to climate news is consistent with prior evidence that small stocks react more slowly in general. For example, Lo and MacKinlay (1990) show that returns on small stocks generally lag those of large stocks. Also, it is well known that small stocks are less liquid and less covered by analysts and media, potentially making them more susceptible to underreaction. A large literature attributes numerous return anomalies to underreaction, and Chen et al. (2021) find

Table 8
Stock size and the response to climate news.
This table shows results from six time-series regressions of monthly portfolio percent returns on ΔC, the change in climate concerns, from the same and previous months. The first row shows results for two value-weighted GMB portfolios, the second shows results for two green portfolios, and the third shows results for two brown portfolios. The green and brown portfolios form the two legs of GMB. For each portfolio, we form one version using small-cap stocks and a second version using large-cap stocks. Small (large) stocks are those in the bottom (top) quartile of market capitalization, using monthly unconditional NYSE breakpoints. The column "Lg. - Sm." shows the difference between the large- and small-cap portfolios' coefficients. The green and brown portfolios' returns are market-adjusted, meaning we subtract from each stock's excess return the stock's estimated market beta times the excess market return. Each regression has 68 observations and uses data from November 2012 through June 2018. Robust t-statistics are in parentheses.

	ΔC (same month)			ΔC (prev. month)		
Portfolio	Small	Large	Lg. - Sm.	Small	Large	Lg. - Sm.
GMB	2.83	3.91	1.08	7.49	2.79	-4.70
	(1.23)	(2.46)	(0.56)	(2.99)	(1.74)	(-2.35)
Green	0.03	2.27	2.24	-0.14	0.62	0.75
	(0.01)	(3.19)	(0.75)	(-0.06)	(0.83)	(0.28)
Brown	-1.81	-1.39	0.42	-8.49	-2.35	6.14
	(-0.61)	(-1.26)	(0.15)	(-2.71)	(-2.10)	(2.29)

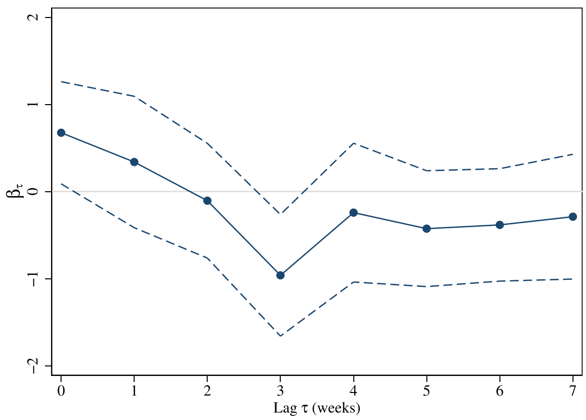

Fig. 9. Weekly response of GMB to climate news: Large versus small stocks. This figure plots the coefficients β_τ from a regression of large-minus-small GMB weekly percent returns on weekly shocks to climate concerns lagged by τ weeks, for $\tau = 0, \ldots, 7$ weeks. The large-minus-small GMB portfolio is defined in Table 8. Weekly shocks to climate concerns are prediction errors from rolling AR(1) models fitted to the weekly MCCC index. Dashed lines indicate 95% confidence intervals.

those anomalies are stronger among firms with lower media coverage.

Underreaction of stock prices to climate news may not be limited to small stocks. Recall from the first row of Table 8 that large-cap GMB's coefficient on the previous month's ΔC borders on significance ($t = 1.74$). Stronger evidence of large-cap underreaction emerges when we examine GMB's green and brown legs separately in the remaining rows of Table 8. For large stocks, both the green and brown legs exhibit significant reactions to ΔC in the expected directions, i.e., positive for green and negative for brown. However, the green leg's significant reaction occurs for the same month ($t = 3.19$), whereas the brown leg's significant reaction occurs for the previous month ($t = -2.10$). The other t-statistics for the large-cap legs are insignificant.

Separating the green and brown legs also reveals that the effect of climate news on small stocks is limited to brown stocks. The green leg's coefficients on both the same-month and previous-month ΔC are virtually zero ($t = 0.01$ and -0.06, respectively), whereas the brown leg exhibits negative reactions to both ΔC's. Only the previous-month ΔC is statistically significant, not surprisingly, given the similar result for the small-cap GMB spread.

7. The green factor

PST introduce an ESG factor and show that, along with the market factor, the ESG factor prices assets in equilibrium. Motivated by that insight, we use stocks' greenness scores to construct a green factor, thereby continuing our focus on the prominent role of "E" in ESG investing. In this section, we explain the green factor's construction and show that it helps explain the recent underperformance of value stocks. We also find that the green factor, appropriately scaled, is empirically similar to GMB analyzed above.

7.1. Constructing the green factor

We apply the PST methodology to construct the green factor. PST show that the factor's realizations can be estimated month by month by running cross-sectional regressions of market-adjusted excess stock returns on the stocks' greenness, with no intercept. The slope from one such regression, which represents the green factor's realization in month t, is given in Eq. (34) of PST as

$$\hat{f}_{gt} = \frac{g_{t-1}' \tilde{r}_t^e}{g_{t-1}' g_{t-1}} \tag{8}$$

where $\tilde{r}_t^e \equiv \tilde{r}_t - \beta_{m,t-1}\tilde{r}_{mt}$ is the vector of stocks' market-adjusted excess returns. Specifically, $\tilde{r}_t$ is the vector of stocks' returns in excess of the risk-free rate, $\tilde{r}_{mt}$ is the market return in excess of the risk-free rate, and $\beta_{m,t-1}$ is the vector of stocks' market betas, which we estimate from rolling monthly regressions of individual stocks' excess returns on excess market returns using up to 60 months (and no less than 36 months) of data ending in month t.

Equation (8) implies that $\hat{f}_{gt}$, a linear combination of the elements of $\tilde{r}_t^e$, is the market-hedged excess return on a portfolio containing long positions in green stocks (with positive $g_{i,t-1}$'s) and short positions in brown stocks (with negative $g_{i,t-1}$'s). In common terminology, the green factor is therefore the return on a "zero-cost" long-short factor. The green factor, however, differs in both motivation and construction from typical zero-cost factors in the finance literature. Motivation for the latter factors is often empirical, whereas PST derive the green factor theoretically, showing that assets are priced in equilibrium by two factors, the market portfolio and the green factor. The construction of many zero-cost factors can be somewhat arbitrary, with stocks in the long and short legs often weighted by market cap (e.g., Fama and French, 1993; Fama and French, 2015). In contrast, the analytically derived green factor weights each stock by its greenness, with green stocks receiving positive weights and brown stocks negative weights. Also, the typical factor's long and short returns are not market-hedged, whereas the green factor is constructed with market-hedged excess returns.

In addition to market hedging and weighting stocks by greenness, the green factor's construction differs from that of the typical zero-cost factor in another technical respect. The typical factor is a difference between two unlevered rates of return: the return on the long leg minus the return on the short leg. The green factor is generally not a return difference with the same simple form, at least not quite. Specifically, we can rewrite Eq. (8) as $\hat{f}_{gt} = \hat{f}_{green,t} - \hat{f}_{brown,t}$, with the contribution from green stocks being $\hat{f}_{green,t} = g_{t-1}^{\prime +}\tilde{r}_t^{e+}/(g_{t-1}^{\prime}g_{t-1})$, where g_{t-1}^{+} contains positive values of g_{t-1} and $\tilde{r}_t^{e+}$ contains those stocks' excess returns. Similarly, the contribution to $\hat{f}_{gt}$ from brown stocks is $\hat{f}_{brown,t} = -g_{t-1}^{\prime -}\tilde{r}_t^{e-}/(g_{t-1}^{\prime}g_{t-1})$, where g_{t-1}^{-} contains negative values of g_{t-1} and $\tilde{r}_t^{e-}$ contains those stocks' excess returns. Both $\hat{f}_{green,t}$ and $\hat{f}_{brown,t}$ are market-hedged excess returns on portfolios, but generally those portfolios have differing degrees of implied leverage, because the sum of the elements of $g_{t-1}^{\prime +}$ does not necessarily equal minus the sum of the elements of $g_{t-1}^{\prime -}$. In our data, for example, the latter sum's magnitude is about 1.9 times the former sum, on average. Moreover, neither of those sums generally equals $g_{t-1}^{\prime}g_{t-1}$ in magnitude, meaning that neither $\hat{f}_{green,t}$ nor $\hat{f}_{brown,t}$ is the unlevered excess return on the market-hedged portfolio of its underlying stocks. Note finally that g_{t-1} is meaningfully defined only up to multiplication by a positive scalar, whose value is irrelevant to satisfying the condition in Eq. (3). The right-hand side of Eq. (8) can be multiplied by any positive scalar without affecting the green factor's pricing ability. We choose the scalar to achieve a desired volatility of the green factor, as explained next.[20]

[20] Note that the green factor's greenness always equals one. Following PST, a portfolio with market-adjusted excess return $x_{t-1}^{\prime}\tilde{r}_t^e$ has greenness equal to $x_{t-1}^{\prime}g_{t-1}$. The green factor in Eq. (8) has $x_{t-1} = (1/g_{t-1}^{\prime}g_{t-1})g_{t-1}$, so the factor's greenness equals $(1/g_{t-1}^{\prime}g_{t-1})g_{t-1}^{\prime}g_{t-1} = 1$.

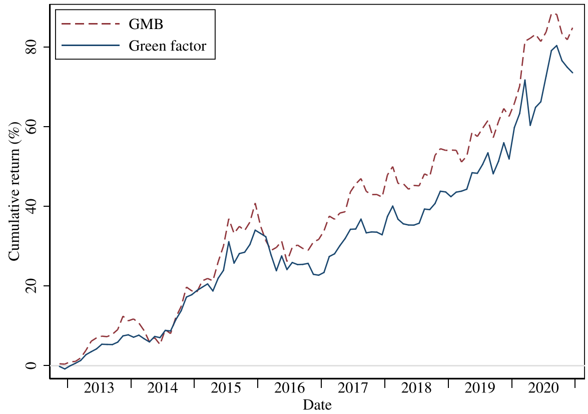

Fig. 10. Green factor. This figure compares the cumulative returns of the green factor (solid line) and GMB (dashed line).

Table 9
Explaining value and momentum with the green factor. We estimate monthly time-series regressions of either HML (in columns 1 and 2) or UMD (in columns 3 and 4) on the excess market return and the green factor by using data from November 2012 to December 2020. Returns are in percent per month. Robust t-statistics are in parentheses.

	Value		Momentum	
Constant	-0.71	-0.15	0.66	-0.06
	(-1.93)	(-0.50)	(1.92)	(-0.22)
Mkt-RF	0.14	0.07	-0.37	-0.27
	(1.18)	(0.70)	(-3.75)	(-3.14)
Green factor		-0.80		1.05
		(-4.55)		(6.18)
Observations	98	98	98	98
R^2	0.04	0.35	0.17	0.49

Recall that GMB is the green-versus-brown return spread analyzed earlier. We scale the green factor to have its monthly volatility match that of GMB over the sample period, 1.99%. Fig. 10 plots the green factor's cumulative return (solid line) along with that of the cumulative GMB return (dashed line). The plotted lines exhibit strong similarities in both cumulative performance and fluctuations. The monthly Sharpe ratios over the period are similar, 0.29 for the green factor versus 0.33 for GMB, and the monthly correlation between the green factor and GMB is 0.72. Therefore, despite the various differences in construction between GMB, a typical zero-cost return, and our green factor, the latter is well viewed empirically as a green-versus-brown return difference over the sample period.[21]

7.2. Value and momentum

During our sample period, the market-adjusted monthly alphas of HML and UMD are −71 bps and 66 bps, respectively, with t-statistics of −1.93 and 1.92, as shown in columns 1 and 3 of Table 9. GMB's significant exposures to value and momentum, noted earlier, prompt us to ask a performance question in the reverse direction: To what

[21] This result seems somewhat similar to an observation made independently by Lioui and Tarelli (2021).

extent can the strong performance of green stocks relative to brown account for the last decade's historic underperformance of value, or for the positive performance of momentum?

To address this question, we turn to PST's two-factor model, in which the factors are the market portfolio and the green factor. HML's and UMD's alphas with respect to the two-factor model, which are shown in columns 2 and 4 of Table 9, are much smaller in magnitude than with just market adjustment. HML's alpha becomes −15 bps instead of −71 bps; UMD's alpha becomes −6 bps instead of 66 bps. The t-statistics shrink to −0.50 and −0.22. These results show that nearly 80% of HML's negative alpha, and all of UMD's positive alpha, disappear after controlling for the green factor's strong performance. Recognizing the brown nature of value stocks, and the green nature of growth stocks, thus helps us understand why the value strategy experienced its worst decade ever in the 2010s.

The green factor also explains about two thirds of the underperformance of an industry-neutral HML factor.[22] This factor's monthly CAPM alpha in our sample period is −66 bps ($t = -2.69$), but the alpha drops to −23 bps ($t = -1.37$) when we add the green factor to the regression. As with the original HML, the industry-neutral HML has a significantly negative loading on the green factor. See the Appendix for details.

Recall that PST's two-factor model includes the green factor, not GMB, as the second factor alongside the market. When we depart from the model and replace the green factor with GMB, the two-factor alphas of both HML and UMD move farther away from zero: HML's alpha becomes −32 bps instead of −15 bps, and UMD's alpha becomes 21 bps instead of −6 bps. A full table is in the Appendix. The green factor thus performs better than GMB in explaining value and momentum over the past decade.

While exposure to the green factor explains most or all of HML and UMD, the reverse is not true. The green factor's strong performance over the last decade survives controlling for HML and UMD exposures. When we rerun the regression reported in column 4 of Table 3, replacing GMB with the green factor, $\hat{f}_{gt}$, we find a positive and significant alpha of 34 bps per month ($t = 2.46$). Details are in the Appendix.

8. Conclusion

Realized returns are a popular proxy for expected returns in the empirical asset pricing literature. However, high realized returns do not always indicate high expected returns, especially if realized over a relatively short period. We offer the salient example of high returns on green assets over the past decade. We show that these high returns were unexpected, reflecting news about environmental concerns rather than high expected returns. After constructing a green-minus-brown portfolio from U.S. stock data, we show that the portfolio's recent outperformance vanishes after removing the effects of unexpected increases in climate concerns. Another proxy for the portfolio's expected return, its implied cost of capital, is also consistently negative. A two-factor asset pricing model featuring a theoretically motivated green factor absorbs much of the historic underperformance of value stocks in the 2010s. Finally, our evidence suggests that small stocks underreact to climate news.

Our results contain a warning for investigations of the pricing of climate risk. We find that green stocks typically outperform brown when climate concerns increase. This result echoes similar findings by Choi et al. (2020), Engle et al. (2020), and Ardia et al. (2021). Equilibrium expected returns of stocks that are better hedges against adverse climate shocks include a negative hedging premium if the representative investor is averse to such shocks (e.g., PST). Empirically confirming a climate risk premium, however, must confront the large unanticipated positive component of green stock returns during the last decade. Without accounting for those unexpectedly high returns on stocks that appear to be good climate hedges, one could be led astray. That is, one could infer that stocks providing better climate hedging have higher expected returns, not lower as theory predicts.

We use two approaches to estimate the green-minus-brown portfolio's expected return, which we label the equity greenium. The first approach, the implied cost of capital, has been applied by prior studies to different data. The second approach, which removes unanticipated shocks from the realized average return, seems novel. Future research can apply this latter approach to estimate expected returns in other settings.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco.2022.07.007.

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