Are Hedge Funds Exploiting Climate Concerns?

George O. Aragon
Arizona State University

Yuxiang Jiang
Southwestern University of Finance and Economics

Juha Joenväärä
Aalto University

Cristian Ioan Tiu
University at Buffalo (SUNY)

December, 2023*

ABSTRACT

We measure a hedge fund's exposure to climate concerns using its return covariation with the returns on a green-minus-brown stock portfolio (GMB beta). Hedge funds in the top decile ranked by GMB beta outperform those in the bottom decile by 8% per year on a risk-adjusted basis. We provide evidence that these funds' managers are more skilled at exploiting the market's climate concerns. Hedge funds' aggregate portfolio of green stocks outperforms the market portfolio of green stocks, and their demand for put options on green stocks reliably anticipates lower stock returns. We also find that hedge funds tend to hold stocks with lower future carbon emissions, and investors reward high-GMB beta funds with greater flows.

Keywords: Hedge funds, climate risk, climate concerns, carbon emissions, arbitrage

JEL Classification: G20, G23, G24, G12

*Contact information: Aragon: george.aragon@asu.edu; Jiang: yuxiangj@swufe.edu.cn; Joenväärä: juha.joenvaara@aalto.fi; Tiu: ctiu@buffalo.edu. We thank the Nasdaq Nordic Foundation, OP Research Foundation, and the Foundation for Economic Education for supporting this research through their grants. We are grateful to Jaakko Ahdekivi, Elias Huttunen, Mikko Kauppila, and Joona Venviläinen for research assistance with data processing.

1. Introduction

Green assets delivered high returns in recent years due to unexpectedly strong increases in climate concerns[1]. We hypothesize that hedge fund managers possess skill in exploiting concerns about climate change and thus deliver superior future fund performance. Hedge funds are highly incentivized rational arbitrageurs that focus on financial performance without having nonpecuniary preferences or tastes. They are skillful at predicting sentiment and the continuation of asset pricing bubbles, take concentrated and leveraged bets, and earn high abnormal returns in the process.[2]

In this paper, we empirically examine whether hedge funds exploit climate concerns using a consolidated hedge fund database (BarclayHedge, Eurekahedge, Hedge Fund Management (HFM), Hedge Fund Research (HFR), Lipper TASS, and Morningstar). We find significant heterogeneity in their Pástor et al. (2022) GMB beta loadings at the individual hedge fund level. We then show, using portfolio sorts, that hedge funds with high GMB betas outperform those with low GMB betas by an economically significant 7.11% per year (t-statistic = 2.81). After adjusting for co-variation with the six-factor alphas based on the benchmark model containing the five Fama and French (2015) and Pástor and Stambaugh (2003) factors, the outperformance is 8.18% per year (t-statistic = 3.28). Our results also after controlling for other known predictors of hedge fund performance.

A potential concern is that the performance of high-GMB beta hedge funds is simply due to their greater exposure to green assets during a period where green assets outperform. This is not the case since hedge funds with high GMB betas continue to outperform after we add the GMB factor itself to the benchmark model. We also address concerns that our results are specific to GMB beta because of the assumptions about how it is built or are driven by

[1]See, e.g., Pástor, Stambaugh, and Taylor (2022) and Zhang (2023)

[2]See e.g., Abreu and Brunnermeier (2003), and Abreu and Brunnermeier (2002) Brunnermeier and Nagel (2004), Chen, Han, and Pan (2021), and Gao, Gao, and Song (2018).

the baseline time period we use. To address these issues, we re-run our portfolio sorts using the Pollutive-minus-Clean (PMC) factor of Huij, Laurs, Stork, and Zwinkels (2021) that is based on carbon emission intensity rather than MSCI environmental scores as in Pástor et al. (2022). Consistent with our results for GMB beta portfolios, hedge funds with high exposure to clean stock outperform those with high exposure to pollution stocks; the six-factor alpha is 6.46% per year (t-statistic = 3.23).

We next consider whether selectivity skill drives the superior performance of hedge funds with greater exposure to climate concerns. We form "copycat" portfolios that invest in aggregate hedge fund shareholdings obtained from 13F filings. We find consistently with our return-based analysis that hedge funds' green copycat portfolio outperforms the brown copycat portfolio by 5.11% per year in terms of the six-factor alpha. Moreover, green copycat portfolio delivers economically significantly larger risk-adjusted returns than the market portfolio of green stocks. Although the 1.05% per year difference is only marginally statistically significant, the six-factor alpha for the copycat portfolio is around one-third higher than those of the green market portfolio. We further find that hedge funds cannot pick brown stocks, which aligns with our return-based evidence, showing that the performance of brown top decile funds can be explained mainly by mechanical GMB exposure, not by brown stock selection skill.

To explore whether climate concerns relate to the underlying mechanism driving the outperformance of green copycat portfolios, we divide our sample into low and high climate concern periods based on the index developed by Ardia, Bluteau, Boudt, and Inghelbrecht (2023) As expected, in line with Pástor et al. (2022) and Zhang (2023), we document the risk-adjusted return difference between the green and brown copycat portfolios is more pronounced during times of high climate concerns. However, surprisingly, we show that hedge fund green copycat portfolio outperformance of green market benchmark is stronger during times of low climate concerns measured using the Ardia et al. (2023) index. Although hedge fund green copycat portfolio delivers a substantial six-factor alpha during times of high climate concerns, they do not beat the green market benchmark. In contrast, during the low climate concern state, the six-factor alpha for the green copycat portfolio's outperformance is economically large and statistically significant, being 2.25% per year, which is more than two times higher than the average outperformance. This finding suggests that hedge funds possess stock selection and hedging skills related to climate concerns in the green stock universe.

To explore further whether hedge funds' can anticipate the green stock market valuations, we examine the predictive power of hedge funds' option positions for future stock returns using an approach developed by Aragon and Martin (2012). Our analysis reveals that hedge funds' directional put option positions have significant predictive power for excess returns on green stocks. This finding is even stronger during low climate concerns measured using the Ardia et al. (2023) index. Our evidence also shows that during times of high climate concerns – when green stocks deliver high returns – hedge funds' bullish call option bets generate higher returns on green stocks. Our analysis indicates that hedge funds are skillful at anticipating the poor returns of green stocks and are able to exploit green firms' stock price fluctuations related to climate concerns in the options market.

To uncover why green copycat portfolios outperform, we decompose them into components related to their under- and overweighting of the green market portfolio. Our analysis reveals that the green copycat portfolio underweights a large set of total emission and emission intensity variables constructed in previous research. This finding indicates that the source of hedge fund outperformance is not the high exposure to carbon-transition risk (e.g., Bolton and Kacperczyk (2021)). In contrast, hedge funds' green copycat portfolio's superior performance is related to the underweighting of firms with a low emission intensity available for investors in real-time when they make decisions. The finding is consistent with Zhang (2023), and it helps to disentangle the fact that the positive carbon return found in earlier studies arises from the forward-looking emission information rather than the risk premium.

Another possible reason for the hedge funds' outperformance could be their ability to anticipate companies' environmental innovation capacity. However, we uncover that both green and brown copycat portfolios underweight stocks with the measures of green innovation (Cohen, Gurun, and Nguyen (2020), Hege, Pouget, and Zhang, 2022 and Bolton, Kacperczyk, and Wiedemann, 2022)). Although this may be surprising at first glance, our finding is consistent with recent working papers presenting evidence that green patent announcements (Andriosopoulos, Czarnowski, and Marshall (2022)) and sophisticated textual measures of green innovations (Leippold and Yu (2023)) are associated with lower risk-adjusted stock returns.

Having established that hedge funds are relatively overweighting stocks with past low carbon emission stocks, we next examine whether hedge funds decarbonize their future portfolios using the approach proposed by Atta-Darkua, Glossner, Krueger, and Matos (2023). Both theoretical work and anecdotal evidence would expect that hedge funds do not re-weight their future portfolios toward low carbon emission stocks. Nevertheless, we demonstrate that hedge fund portfolios tend to have lower future total emissions and emission intensities. However, we do not find a link between hedge fund future portfolio re-weighting and higher green innovation and green revenues. Overall, this evidence is consistent with the view that hedge funds are not always pure arbitrageurs like many theory models assume.

Finally, we examine whether the Pástor et al. (2022) GMB betas are related to capital flows from investors. Several papers examine mutual fund investors' preferences for sustainable investments (see., e.g., Riedl and Smeets (2017) and Hartzmark and Sussman (2019)), but the literature on hedge funds is scarce. Only Liang, Sun, and Teo (2022) provide evidence that hedge funds that are UNPRI signatories receive more flows than non-signatories. Using a revealed preferences approach introduced by Berk and van Binsbergen (2016) and Barber, Huang, and Odean (2016), we add to this literature by documenting strong evidence that GMB beta positively relates to fund flows even after controlling for UNPRI membership and self-reported intention to follow ESG strategy, as well as a host of other controls, such as past performance. We further divided our sample into the early and late periods to understand investors' preferences for green hedge funds. We document that GMB beta is essential in explaining fund flows for the later period. In contrast, the UNPRI signatories no longer receive significantly more flows, as they did during the early period (consistent with Gibson Brandon, Glossner, Krueger, Matos, and Steffen (2022) in their study for all types of institutional investors). These findings are stronger when we use a subset of 13F filers whose holdings investors can observe via holdings reports. Our results support the view that during the most recent period, truly green hedge funds received more flows than those who are saying or self-reporting to be green. Perhaps hedge fund investors are sophisticated enough to distinguish genuinely green funds from greenwashers compared to mutual fund investors (see, e.g., Andrikogiannopoulou, Krueger, Mitali, and Papakonstantinou (2022)).

Our paper relates to the ongoing climate finance debate to the potential magnitude of changes in the cost of capital related to the reduced overall emissions (see, for example, Pedersen, Fitzgibbons, and Pomorski (2021), Pástor, Stambaugh, and Taylor (2021), Goldstein, Kopytov, Shen, and Xiang (2022), Berk and Van Binsbergen (2021), Bolton and Kacperczyk (2023)). However, even the direction of the overall carbon-transition risk amount is unclear and depends on the way emission measures are constructed ((Aswani, Raghunandan, and Rajgopal (2023)) and real-time data availability (Zhang (2023)). Our paper contributes to this debate by showing that green hedge funds outperform brown hedge funds. To do so, we demonstrate that hedge funds prefer to hold low-emission intensity stocks and provide relatively high risk-adjusted during states with low climate concerns (Engle, Giglio, Kelly, Lee, and Stroebel (2020), Ardia et al. (2023)) when green stocks generally do not outperform brown stocks.

Our paper is closely related to Krueger, Sautner, and Starks (2020) documenting the top motivation for incorporating climate risk into investing decisions. According to their survey, institutional investors state, along with reputational risk, three other reasons why it would be beneficial to manage climate risk are potentially higher portfolio return and volatility and downside risk mitigation. In addition, Due to the increasing climate risks, investors may wish to hedge against such adverse outcomes. Engle et al. (2020) construct a dynamic hedging "mimicking" portfolio against news about climate change that is negatively exposed to climate risk and shows positive returns following negative innovations in the index. Alekseev, Giglio, Maingi, Selgrad, and Stroebel (2022) expand this approach by introducing a quantity-based approach for mutual funds. Our related findings reveal that hedge funds can hedge using bearish put options when green stock returns are low stock returns and exploit bullish calls, especially during high climate concern states. This indicates that green hedge funds are good candidates for delivering portfolios that both hedge climate risk but also generate relatively high risk-adjusted returns even during states of low climate concern when climate risk hedging is expensive (see, Ilhan, Sautner, and Vilkov (2020)).

Our paper adds to the hedge fund literature showing that hedge funds exposed to systematic risk (Bali, Brown, and Caglayan (2012)), macroeconomic risk (Bali, Brown, and Caglayan (2011), Bali, Brown, and Caglayan (2014)), liquidity risk (Sadka (2010)), tail risk (Bali, Gokcan, and Liang (2007) and Agarwal, Ruenzi, and Weigert (2017)) and crowded trades (Brown, Howard, and Lundblad (2022)), on average, deliver high returns. Regarding the above literature, it would have been natural for us to have found that hedge funds exposed to carbon transition risk would have produced high returns. However, our finding aligns more with Brunnermeier and Nagel (2004) and Chen et al. (2021), showing that hedge funds rode on the tech bubble and have exploited broad investor sentiment. The recent literature also documented that hedge funds with lower funding risk deliver higher returns (Klingler (2022) and, more closely to us, they exploited rare disaster concerns (Gao et al. (2018)). Our findings provide strong evidence that hedge funds can exploit investors' green tastes and, generally, climate concerns associated with higher realized returns.

2. Data

2.1. Commercial hedge fund databases

We examine hedge funds' green stock picking and timing skills using monthly returns and assets under management (henceforth AUM) data of live and dead hedge funds reported in the BarclayHedge, Eurekahedge, Hedge Fund Management (HFM), Hedge Fund Research (HFR), Lipper TASS, and Morningstar databases from January 1994 to December 2022. We merge these databases using the matching procedure outlined in the Data Appendix of Joenväärä, Kauppila, Kosowski, and Tolonen (2021). Over that period, there were 32,321 individual hedge funds, of which 7,593 are currently operating actively.

Following the SEC Form PF, we classify funds into eight investment styles: Credit, Equity, Event Driven, Relative Value, Macro, Managed Futures/CTA, Multi-strategy, and Others.[3] We collect fund variables related to compensation structure, share restrictions, leverage, domicile, and investment region for each fund. We require the sample hedge funds' primary investment region is North America and that they report their returns monthly with at least 24 monthly observations. This North American requirement allows us to link our fund return-based results to 13F holding-based firm-level results. We focus on data from November 2012 onward as the data on the Green-minus-Brown (GMB) portfolio of Pástor et al. (2022) becomes available. These rules yield 3,750 funds, of which 1,456 are live funds, and 2,294 are dead funds. Out of these funds, 556 are signed with UNPRI, and 80 are ESG-compliant.

Hedge fund data are susceptible to biases associated with voluntary reporting (e.g., Fung

[3]We exclude funds-of-funds and Macro and Futures/CTA funds since they do not focus on individual securities but instead aim to profit from the direction of various broad market prices and technical or fundamental-based strategies in commodity markets. Our results are, however, robust when we use all USD dollar-denominated funds.

and Hsieh (2000) and Liang (2000)). One concern is that a fund listed on a database often includes data before the listing date. Because successful funds have a strong incentive to report in order to attract capital, backfilled returns are often higher than non-backfilled returns. To mitigate these concerns, we remove all return observations that were backfilled before the fund listing date. We impute missing listing dates using the Jorion and Schwarz (2019) method and use the earliest possible listing date for funds reporting to multiple databases, increasing coverage (Joenväärä et al. (2021)). To eliminate duplicate share classes, we do not simply select a "representative" share class, such as the one with the longest return series and the largest assets. Instead, as in mutual fund literature, we aggregate the fund-level information across all duplicates. We create a "master" share class using information across databases and different share classes. To mitigate the impact of strategic delays in return reporting (Aragon and Nanda (2017)), while we download hedge fund data in mid-2023, we do not use the last few months of returns and instead focus on the period ending in December 2022.

We measure each hedge fund's exposure to climate concerns using its return covariation with the returns on a green-minus-brown (GMB) stock portfolio. Specifically, we follow Pástor et al. (2022) and sort publicly traded U.S. stocks based on their environmental scores provided by MSCI, a leading ESG rating provider. Each month, we divide stocks in terciles and classify the stocks in the top (best environmental score) as *green*, while the stocks in the bottom tercile are classified as *brown*. We then estimate a fund's GMB beta by regressing its monthly returns on the GMB portfolio and the Fama and French (2015) five-factor model augmented with Pástor and Stambaugh (2003) liquidity risk factor.[4] Funds with greater GMB betas ("green funds") generate higher returns during periods when green stocks outperform brown stocks and, in this sense, are more exposed to climate change

[4]Our results are robust when we use an alternative benchmark model containing the betting-against-beta and momentum factors.

concerns.

2.2. Hedge fund holdings data

Investment advisors such as hedge funds with assets under management (AUM) of at least $100 million in public companies must report their quarter-end long positions to the US Securities and Exchange Commission (SEC) on a form 13F-HR. We have downloaded and parsed these reports from 1999 (when the reports were first available electronically) through 2022. By parsing 13F filings ourselves instead of using commercial provider (i.e., ThomsonReuters) data, we obtain data on hedge funds' option holdings (Aragon and Martin (2012)).

Following Brunnermeier and Nagel (2004), we focus on pure hedge funds that can be considered arbitrageurs in practice and the sense of financial economics theory. We identify pure hedge fund firms by creating firm-level mapping between SEC filings (13F and Form ADV) and firm names obtained from commercial hedge fund databases. When a 13F filer reports to commercial databases or its Form ADV shows that a firm invests a significant portion of its regulatory assets in hedge funds, we classify it as a hedge fund. However, to be a "pure" hedge fund firm, we require that (i) at least 50% of its clients are "Other pooled investment vehicles" or "High net worth individuals," (ii) it charges performance-based fees, and (iii) it is not affiliated with a conglomerate or bank. These rules yield 1,938 pure hedge fund firms, of which 173 are signatories of UNPRI.

3. Return-based evidence of fund performance

This section examines, using an aggregated commercial hedge fund database, whether hedge funds exposed to Pástor et al. (2022)) Green-minus-Brown (GMB) portfolio and to Pollutive-minus-Clean factor of Huij et al. (2021) provide superior future risk-adjusted returns.

3.1. GMB beta sorts

To examine how GMB betas are related to fund performance, we sort each individual hedge fund returns into decile portfolios according to the fund's exposure to the GMB portfolio. Using the most recent 24 monthly observations, we estimate each fund's GMB exposure by running the regression in the Fama and French (2015) five-factor model augmented with Pástor and Stambaugh (2003) factor. At each month's end, funds are sorted into decile portfolios according to their historical GMB beta (or t-statistic of GMB beta). Portfolios of the sorted funds are equally weighted monthly and are reconstituted monthly. The out-of-sample performance of each portfolio is then estimated once over the concatenated holding period from November 2012 to December 2022.

Figure 1 presents monthly average GMB betas and their t-statistic for each decile portfolio. It shows that the average GMB is around zero. Nevertheless, more interestingly, the top green and bottom brown deciles show that some hedge funds are significantly positively or negatively exposed to the GMB portfolio. Indeed, Table 1 shows economically wide spreads of 1.89 and 4.03 between top green and brown GMB betas and t-statistics, respectively. This heterogeneity among funds indicates that performance differences may exist between funds related to their GMB loadings. To get a first impression of hedge fund managers' potential green stock selection skills, Figure 2 plots the monthly cumulative returns of the decile portfolios in Panel A of Table 1. It shows that the high-GMB portfolio outperforms the low-GMB portfolio over the entire sample period.

Panel A of Table 1 reveals that hedge funds with high exposure to green (Portfolio 10) outperform those with high loadings to brown (Portfolio 1) by an economically significant 7.11% per year (t-statistic = 2.81). After adjusting for co-variation with the five Fama and French (2015) and Pástor and Stambaugh (2003) factors, the outperformance is 8.18% per year (t-statistic = 3.28). Panel B shows that green funds also outperform by 4.92% per year (t-statistic = 2.61) when funds are sorted based on their t-statistics of GMB betac instead of

GMB betas. Regarding six-factor alphas, the green funds outperform brown ones by 5.79% per year (t-statistic = 3.57). The relationship between t-statistic of GMB beta and alphas is more monotonic when compared to the GMB sorts. This is consistent with the fact that the usage of t-statistic reduces noise in estimation.

Note that the superior performance of top-GMB beta hedge funds is not merely driven by their greater exposure to green assets and the fact that green assets realized higher returns over the sample period. This is not the case because the alpha spreads remain large and significant (6.06% vs. 8.18%) and significant (t-stat.=2.98 vs. 3.28) after adding GMB to the benchmark model for computing portfolio alphas.

3.2. Pollute-minus-Clean beta sorts

We allay concerns that our results are specific to our specific GMB proxy for climate concerns by repeating our portfolio sorts using the Pollutive-minus-Clean (PMC) betas of Huij et al. (2021). Instead of using MSCI environmental scores, Huij et al. (2021) use emission intensity (i.e., emissions scaled by revenues) to build their factor. Their climate transition risk exposures are priced in the cross-section of equity returns, and they are lower during months in which climate change is more frequently discussed in the news, in which temperatures are abnormally high, and during exceptionally dry months. If hedge funds understand the climate concerns and can profit from trading them, we should expect that funds with low PMC betas will deliver superior performance.

Panel A of Table 2 shows that hedge funds with high exposure to clean stocks with low emission intensity outperform those with high loadings to stocks with high exposure to emission intensity by an economically significant 6.63% per year (t-statistic = 3.11). After adjusting for co-variation with the six-factor benchmark model, the outperformance is 6.46% per year (t-statistic = 3.23). Using the t-statistic of PMC beta as a sorting variable, Panel B shows that funds exposed to clean stocks outperform those with high loadings to stocks with high exposure to emission intensity. In addition, as in the case of GMB beta, the alpha spreads remain large and significant (5.96% vs. 6.46%) and significant (t-stat.=3.17 vs. 3.23) after adding PMC to the benchmark model for computing portfolio alphas. Overall, our findings are not driven by the specific proxy for climate concerns.

3.3. UNPRI and ESG funds

So far, we have established a robust relationship between GMB betas and fund performance for the full sample of hedge funds. Next, we explore whether the relationship is stronger for funds that are signatories of the United National Principles for Responsible Investment (UNPRI funds) or self-report that they follow an ESG-compliant strategy (ESG funds). As shown in Panel A of Table 3, we do not find a meaningful pattern in alphas related to GMB betas for UNPRI signatories. However, for non-UNPRI funds, we find a positive and significant spread between top green and brown funds as in the baseline analysis of Table 1. This finding is consistent with Liang et al. (2022) who document that UNPRI funds deliver lower alphas than non-UNPRI funds at the aggregate level. We contribute by showing that UNPRI funds do not generate superior returns by taking exposure to green stocks.

Panel B of Table 3 shows the result for ESG funds. In contrast to UNPRI funds, GMB beta sorts of ESG funds deliver a large alpha spread between the top-beta and bottom-beta funds. In terms of six-factor alphas, the green ESG funds outperform ESG brown ones by 14.31% per year (t-statistic = 5.17). The respective alpha spread for non-ESG funds is similar to those for the baseline case. These results indicate that the relative performance of green versus brown funds is mainly present among funds that are not UNPRI signatories, and is particularly strong among funds that self-report as being ESG-focused.

3.4. Fama and MacBeth (1973) regressions

Next we use multivariate Fama and MacBeth (1973) regressions to examine whether GMB betas predict fund performance after controlling for other fund characteristics. In each month and for each hedge fund with at least 24 return observations, we estimate GMB beta by regressing the fund excess returns on the six-factor benchmark factors. We then estimate cross-sectional regressions of a fund's performance over the next month on GMB beta and controls for a fund's characteristics. We define monthly fund alpha as the difference between fund excess return and the six-factor benchmark loadings multiplied by the factor realizations, where factor loadings are estimated over the last 24 months. We control for the role of the logarithm of lagged fund AUM (Berk and Green (2004); Ramadorai (2013)), lagged fund age in years (Aggarwal and Jorion (2010)), share restrictions such as the redemption and notice periods, and the lockup dummy (Aragon (2007)), compensation structure variables (Agarwal, Daniel, and Naik (2009)), such as management fee, performance fee, and indicator variables for whether the fund uses a high-water mark and leverage. All specifications contain style dummies, and standard errors are estimated using Newey and West (1987) with two lags.

The multivariate regression estimates reported in Table 4 corroborate our findings from the univariate sorts for GMB beta and its t-statistic. The coefficients for both GMB beta and its t-statistic are significant and positive across model specifications. The role of GMB beta remains important after controlling for fund characteristics. Collectively, our fund return-level results provide robust evidence that GMB beta is a positive and significant predictor of fund performance.

4. Evidence from hedge fund holdings

4.1. Stock selection skill

Having established in the previous section that hedge funds with high GMB betas outperform, we focus on the underlying stock and option holdings of hedge funds in this section. Suppose hedge fund managers are skilled in picking green stocks and timing the climate concerns on an individual stock level. In that case, we should detect such ability in portfolios replicating hedge fund managers' holdings. To examine that possibility, we form "copycat" portfolios that invest in aggregate hedge fund shareholdings obtained from 13F filings. At the end of each quarter from December 2012 to December 2022, we will form two copycat portfolios, one for the green stocks and one for the brown stocks. Within both copycat portfolios, we weigh returns for each stock in portion to the green or brown of hedge fund holdings. Then, we compare the performance of both copycat portfolios against the market "benchmark" portfolio of green or brown stocks. We use the Pástor et al. (2022) environmental score to build both these copycat portfolios.

Panel A of Table 5 shows that hedge funds' green copycat portfolio outperforms the brown copycat portfolio by 5.11% per year in terms of the six-factor alpha based on the five Fama and French (2015) and Pástor and Stambaugh (2003) factors. Moreover, hedge funds' green copycat portfolio delivers economically significantly higher abnormal returns than the market portfolio of green stocks. Although the 1.05% per year difference is only marginally statistically significant, the six-factor alpha for the copycat portfolio is around one-third higher than those of the green market portfolio. We further document that hedge funds cannot pick brown stocks since the brown copycat's performance is indistinguishable from the brown market-based benchmark's performance. Overall, our findings are consistent with our return-based evidence reported in Tables 1 that green funds outperform brown funds.

Panel B of Table 5 shows the results from a subsample analysis of different types of hedge funds. For both UNPRI and non-UNPRI funds, the green copycat portfolio outperforms the brown copycat portfolio. In addition, we observe a 1.67% per year higher alpha for green UNPRI-members' copycat portfolio than the market holdings-based benchmark; however, this difference is not significant. In contrast, the results for non-signers are similar to the ones reported for all hedge funds; their green copycat portfolios deliver an alpha that is 1.00% and marginally significant higher than the market benchmark.

Finally, Table 5 shows that the risk-adjusted return difference between the green and brown copycat portfolios is more pronounced during times of high climate concerns, consistent with Pástor et al. (2022) and Zhang (2023). In addition, the outperformance of hedge funds green copycat portfolios is more pronounced during times of low climate concerns. Although the green copycat portfolio delivers a high six-factor alpha during times of high climate concerns, it does not beat the market benchmark. During periods of low climate concern, the green copycat portfolio delivers a significant six-factor alpha of 2.25% per year.

4.2. What explains the outperformance of green copycat portfolios?

To uncover the underlying mechanisms of why the green copycat portfolio outperforms, we explain the stock-level copycat portfolio weights using a set of variables related to greenhouse carbon emissions, green innovation, and climate change exposures. In doing so, we run a set of regressions in which the stock-level portfolio weights of copycat portfolios are explained by (i) greenhouse gas emissions, (ii) green patent measures, and (iii) Sautner, van Lent, Vilkov, and Zhang (2023) Climate Change Exposure measures. All regression specifications include a quarterly lagged firm market capitalization, book-to-market ratio, and 12-month past return as controls. The regression specifications also contain time and firm-level fixed effects. The sample period is from December 2012 to December 2022.

One potential reason why hedge funds' green copycat portfolios outperform is the overweighting of stocks with certain greenhouse gas emission profiles that are documented to be associated with higher stock returns. For instance, Bolton and Kacperczyk (2021) and

Bolton and Kacperczyk (2023) document a positive market-based premium that is associated with carbon-transition risk for stocks with higher total carbon emissions. However, a recent paper by Zhang (2023) shows that the positive carbon return found in earlier studies arises from the forward-looking emission information rather than the risk premium. She further documents that after accounting for the emission data release lag in a realistic way, carbon returns turn negative when emissions are scaled by sales, i.e., measured using the emission intensity.

Table 6 shows that all coefficients for total emissions and emission intensity are negative. Hence, hedge funds underweight high-emissions stocks, both in the green (Panel A) and brown (Panel B) sectors. For example, Panel A shows that hedge funds overweight green stocks with a significantly lower 12-month lagged emission intensiy. These findings suggest that hedge fund managers utilize real-time information on firms' carbon emission intensity when selecting stocks.

Table 6 also shows that both green and brown copycat portfolios underweight stocks with the measures of green innovation. Although this may be surprising at first glance, this finding is consistent with evidence that green patent announcements (Andriosopoulos et al. (2022)) and sophisticated textual measures of green innovations (Leippold and Yu (2023)) are associated with lower risk-adjusted stock returns.

4.3. Option selection skill

In this section, we examine the predictive power of hedge funds' option positions for future stock returns. For each stock i held each quarter end q, we first compute quarterly excess returns $R_{i,q+1} - R_{ib,q+1}$, where $R_{i,q+1}$ is the realized return on stock i in quarter q+1, and $R_{ib,q+1}$ is the corresponding return on a size, book-to-market, and momentum characteristics-based benchmark portfolio. The benchmarks are from Daniel et al. (1997). We then estimate the following model over the period from December 2012 to December

2022:

$$R_{i,q+1} - R_{ib,q+1} = \alpha_{q+1} + \gamma_{1,q+1} BULL_{i,q} + \gamma_{2,q+1} BEAR_{i,q} +$$

$$\gamma_{3,q+1} PPUT_{i,q} + \gamma_{4,q+1} STRAD_{i,q} + \beta_{q+1} COM_{i,q} + \epsilon_{i,q+1},$$

$BULL_{i,q}$ is the proportion of advisors disclosing a directional call option position on underlying security i at the end of quarter q, among all advisors that hold at least one stock or option positions in security i during the quarter. $BEAR_{i,q}$, $PPUT_{i,q}$, and $STRAD_{i,q}$ are defined similarly for directional puts, protective puts, and straddles, respectively. In addition to the option variables, we also include a measure of hedge fund stock ownership ($COM_{i,q}$), defined as the proportion of advisors disclosing a long equity position in security i at the end of quarter q, among all advisors filing Form 13F during the quarter. Finally, we include interactions with a dummy variable that equals one if the stock is a green stock. This enables us to test whether hedge funds' option demand is particularly informative about green stock returns.

Table 7 reports averages of the monthly estimated coefficients for the full sample period from December 2012 to December 2022. We find that hedge funds' directional put option positions ($BEAR$) have significant predictive power for excess returns on green stocks. The coefficient on $Green \times BEAR$ is negative and significant, indicating that hedge funds are skillful at anticipating the poor performance of green stocks. In addition, our subsample analysis shows that this finding is driven by funds that are not signatories to the UNPRI. For the smaller sample of funds that are signatories, we find no evidence that hedge funds can skillfully select green stocks.

To better understand whether hedge funds can exploit green stock price movements associated with climate concerns, we divide our sample into low- and high-concerns states and re-run the above Fama-MacBeth regressions within subsamples. We find that during a low climate concerns state, the average coefficients for $Green \times BEAR$ are now even lower and more significant, but, in contrast, insignificant during the high climate concerns state, when there is no need to hedge and green stock returns are high. Table 7 also shows positive and highly significant average coefficients for $Green \times BULL$ during the high climate concerns state, while that average coefficient is insignificant during the low climate concerns state. This indicates that hedge funds' bullish bets are profitable exactly when green stocks tend to generate the highest returns. Overall, our evidence indicates that hedge funds skillfully exploit green stock price fluctuation related to climate concerns in the options market.

5. Capital raising and economic rents

In this section, we examine whether "green" hedge funds are able to attract capital flows from investors. We also build investment strategies to test whether investors could exploit in practice the superior performance of green hedge funds.

5.1. Fund flows and GMB beta

We next examine hedge fund investors' preference for green exposure revealed in fund returns. Literature has documented that hedge funds that are UNPRI signatories (Liang et al. (2022)) receive more flows than non-signatories. However, whether investors place more flows with higher loadings to green is not yet known. To explore that question, we run a set of quarterly panel regressions in which fund capital flows are explained by the GMB beta, UNPRI signatory indicator variable, and ESG fund dummy. The regression contains various controls, including past performance, fund size and age, share restriction variables, and compensation structure variables. All regressions include fixed effects for fund style and quarter. We cluster standard errors by fund and quarter.

Panel A of Table 8 reveals that both GMB beta and its t-statistic positively predict fund flows even after controlling for UNPRI membership and self-reported intention to follow ESG strategy. Using a subset of 13F filers, Panel B of Table 8 shows that during the later period, the GMB beta and GMB beta t-statistics are positively and strongly related to flows.

To better understand investors' preferences for green hedge funds, we divide our sample into early (t = 2012 Q4 through 2017 Q1) and later periods (t = 2017 Q2 through 2022 Q4). For the later period, we find that both GMB beta and its t-statistic are strongly related to flows; in contrast, UNPRI and ESG dummies are not significant drivers of flows during the later period. Overall, our findings suggest that investors reward fund managers for their greater exposure to climate concerns.

5.2. Economic rents

So far, our analysis of GMB beta relationship to fund performance has used gross-of-fee returns. It has been based on a monthly rebalancing of portfolios and ignored a time lag required for due diligence and data availability (Joenväärä, Kosowski, and Tolonen (2019). Hence, it does not tell us what investors could have earned by investing in green funds. To address this question, we build practical investment strategies and evaluate performance using the net-of-fee returns. This also allows us to examine who captures economic rents, hedge fund managers or investors.

Panel A of Table 9 reports the results for the baseline sorts when the performance is evaluated using the net-of-fee returns instead of gross-of-fee returns used in Panel A of Table 1. Compared to the baseline, the magnitudes of mean returns and alphas are lower, but the spreads between top green and brown funds remain large and significant.

Following standard practice in hedge fund literature (e.g., Avramov, Kosowski, Naik, and Teo (2011), and Avramov, Barras, and Kosowski (2013)), we next form an investment strategy based on the GMB beta so that the portfolio is rebalanced annually each December. The results are reported in Panel B of Table 9. We find marginally significant spreads between the top green and bottom brown funds (t-statistic=2.01). The investable top decile of green funds delivers a high mean return of 7.18%, which is marginally significant.

Panel C of Table 9 shows the results from imposing a one-month formation lag required for due diligence and data availability (Joenväärä et al. (2019)). The Green−Brown spread is positive and significant, consistent with our baseline results. Finally, Panel D shows the results from imposing both the one-year holding period and one-month formation lag into portfolio formation. Similar to the Panel B results, we find marginally significant spreads between the top green and bottom brown funds (t-statistic=2.10).

Overall, our evidence confirms our baseline results that a fund's climate concerns is a positive and significant predictor of its performance, and shows that the size of the economic benefits from such predictability depends on the specific portfolio constraints faced by real-world fund investors.

6. Conclusions

We measure hedge funds' exposures to the returns on green-minus-brown (GMB) portfolios that track the performance of green stocks compared to brown stocks. We find significant dispersion in hedge funds' GMB portfolio tilts that predict their future performance. Funds with top-decile GMB betas ("green funds") subsequently outperform funds with GMB betas in the bottom decile. The difference in performance is economically meaningful and about 6% per year.

Hedge fund portfolio holdings show that the superior performance of green funds can be attributed to stock selectivity skills. A copycat portfolio of green stocks held by hedge funds outperforms a benchmark portfolio of green stocks, and the holdings of put options tend to precede large drawdowns in the valuations of green stocks.

Hedge funds exploit green stock price fluctuations related to climate concerns. Although green hedge funds generate high returns, when climate concerns are high, their outperformance in risk-adjusted returns is the highest during low climate concerns. In addition, using option trades, hedge funds can time both their bearish and bullish bets consistently related to climate concerns associated with stock price movements.

Hedge funds overweight low carbon emission intensity stocks relative to green market portfolio. This finding is consistent with Zhang (2023) and suggests that the source of hedge fund outperformance is not the high exposure to carbon-transition risk (e.g., Bolton and Kacperczyk (2021)). Despite their ability to anticipate the returns on green stocks, hedge funds cannot anticipate green innovation. Indeed, their green (or brown) portfolio tilts relative to the market portfolio, and they apply for fewer green patents.

While existing studies show that UNPRI-signatory hedge funds (Liang et al. (2022)) receive more flows than non-signatories, we find that GMB beta positively predicts flows, especially in the more recent sample period. In contrast, the UNPRI signatories or ESG-compliant hedge funds no longer receive significantly more flows than during the early period. Our results support the view that during the most recent period, truly green hedge funds received more flows than those who are saying or self-reporting to be green.

References

Abreu, D. and M. K. Brunnermeier (2002). Synchronization risk and delayed arbitrage. *Journal of Financial Economics 66*(2-3), 341–360.

Abreu, D. and M. K. Brunnermeier (2003). Bubbles and crashes. *Econometrica 71*(1), 173–204.

Agarwal, V., N. D. Daniel, and N. Y. Naik (2009). Role of managerial incentives and discretion in hedge fund performance. *The Journal of Finance 64*(5), 2221–2256.

Agarwal, V., S. Ruenzi, and F. Weigert (2017). Tail risk in hedge funds: A unique view from portfolio holdings. *Journal of Financial Economics 125*(3), 610–636.

Aggarwal, R. K. and P. Jorion (2010). The performance of emerging hedge fund managers. *Journal of Financial Economics 96*(2), 238–256.

Alekseev, G., S. Giglio, Q. Maingi, J. Selgrad, and J. Stroebel (2022, December). A quantity-based approach to constructing climate risk hedge portfolios. Working Paper 30703, National Bureau of Economic Research.

Andrikogiannopoulou, A., P. Krueger, S. Mitali, and F. Papakonstantinou (2022, 01). Discretionary information in esg investing: A text analysis of mutual fund prospectuses. *SSRN Electronic Journal*.

Andriosopoulos, D., P. Czarnowski, and A. P. Marshall (2022). Does green innovation increase shareholder wealth? Technical report, SSRN 4012633.

Aragon, G. and J. S. Martin (2012). A unique view of hedge fund derivatives usage: Safeguard or speculation? *Journal of Financial Economics 105*, 436–456.

Aragon, G. O. (2007). Share restrictions and asset pricing: Evidence from the hedge fund industry. *Journal of Financial Economics 83*(1), 33–58.

Aragon, G. O. and V. Nanda (2017). Strategic delays and clustering in hedge fund reported returns. *Journal of Financial and Quantitative Analysis 52*(1), 1–35.

Ardia, D., K. Bluteau, K. Boudt, and K. Inghelbrecht (2023). Climate change concerns and the performance of green versus brown stocks. *Management Science, Forthcoming*.

Aswani, J., A. Raghunandan, and S. Rajgopal (2023, 04). Are Carbon Emissions Associated with Stock Returns?*. *Review of Finance*, rfad013.

Avramov, D., L. Barras, and R. Kosowski (2013). Hedge fund return predictability under the magnifying glass. *Journal of Financial and Quantitative Analysis 48*, 1057–1083.

Avramov, D., R. Kosowski, N. Y. Naik, and M. Teo (2011). Hedge funds, managerial skill, and macroeconomic variables. *Journal of Financial Economics 99*(3), 672–692.

Bali, T. G., S. Brown, and M. O. Caglayan (2014). Macroeconomic risk and hedge fund returns. *Journal of Financial Economics 114*(1), 1–19.

Bali, T. G., S. J. Brown, and M. O. Caglayan (2011). Do hedge funds' exposures to risk factors predict their future returns? *Journal of Financial Economics 101*(1), 36–68.

Bali, T. G., S. J. Brown, and M. O. Caglayan (2012). Systematic risk and the cross section of hedge fund returns. *Journal of Financial Economics 106*(1), 114–131.

Bali, T. G., S. Gokcan, and B. Liang (2007). Value at risk and the cross-section of hedge fund returns. *Journal of Banking Finance 31*(4), 1135–1166. Bricks versus Clicks: The Changing Nature of Banking in the 21st Century.

Barber, B. M., X. Huang, and T. Odean (2016). Which factors matter to investors? evidence from mutual fund flows. *The Review of Financial Studies 29*(10), 2600–2642.

Berk, J. and J. H. Van Binsbergen (2021). The impact of impact investing.

Berk, J. B. and R. Green (2004). Mutual fund flows and performance in rational markets. *Journal of Political Economy 112*(6), 1269–1295.

Berk, J. B. and J. H. van Binsbergen (2016). Assessing asset pricing models using revealed preference. *Journal of Financial Economics 119*(1), 1–23.

Bolton, P. and M. Kacperczyk (2021). Do investors care about carbon risk? *Journal of financial economics 142*(2), 517–549.

Bolton, P. and M. Kacperczyk (2023). Global pricing of carbon-transition risk. *Journal of Finance, Forthcoming*.

Brown, G. W., P. Howard, and C. T. Lundblad (2022). Crowded Trades and Tail Risk. *Review of Financial Studies 35*(7), 3231–3271.

Brunnermeier, M. and S. Nagel (2004). Hedge funds and the technology bubble. *The Journal of Finance 59*(5), 2013–2040.

Chen, Y., B. Han, and J. Pan (2021). Sentiment trading and hedge fund returns. *The Journal of Finance 76*(4), 2001–2033.

Cohen, L., U. G. Gurun, and Q. H. Nguyen (2020). The esg-innovation disconnect: Evidence from green patenting. Technical report, National Bureau of Economic Research.

Engle, R. F., S. Giglio, B. Kelly, H. Lee, and J. Stroebel (2020). Hedging Climate Change News. *The Review of Financial Studies 33*(3), 1184–1216.

Fama, E. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy 81*(3), 607–36.

Fama, E. F. and K. R. French (2015). A five-factor asset pricing model. *Journal of Financial Economics 116*(1), 1–22.

Fung, W. and D. A. Hsieh (2000). Performance charasteristics of hedge funds and commodity funds: Natural vs. spurious biases. *Journal of Financial and Quantitative Analysis 35*(3), 291–307.

Gao, G. P., P. Gao, and Z. Song (2018, 03). Do Hedge Funds Exploit Rare Disaster Concerns? *The Review of Financial Studies 31*(7), 2650–2692.

Gibson Brandon, R., S. Glossner, P. Krueger, P. Matos, and T. Steffen (2022, 09). Do Responsible Investors Invest Responsibly?*. *Review of Finance 26*(6), 1389–1432.

Goldstein, I., A. Kopytov, L. Shen, and H. Xiang (2022, April). On esg investing: Heterogeneous preferences, information, and asset prices. Working Paper 29839, National Bureau of Economic Research.

Hartzmark, S. M. and A. B. Sussman (2019). Do investors value sustainability? a natural experiment examining ranking and fund flows. *The Journal of Finance 74*(6), 2789–2837.

Huij, J., D. Laurs, P. A. Stork, and R. C. J. Zwinkels (2021). Carbon beta: A market-based measure of climate risk. *SSRN Electronic Journal*.

Ilhan, E., Z. Sautner, and G. Vilkov (2020, 06). Carbon Tail Risk. *The Review of Financial Studies 34*(3), 1540–1571.

Joenväärä, J., M. Kauppila, R. Kosowski, and P. Tolonen (2021). Hedge fund performance: are stylized facts sensitive to which database one uses? *Critial Finance Review*.

Joenväärä, J., R. Kosowski, and P. Tolonen (2019). The effect of investment constraints on hedge fund investor returns. *Journal of Financial and Quantitative Analysis 54*(4), 1539–1571.

Jorion, P. and C. Schwarz (2019, 02). The fix is in: Properly backing out backfill bias. *The Review of Financial Studies 32*(12), 5048–5099.

Klingler, S. (2022). High funding risk and low hedge fund returns. *Critical Finance Review 11*(3-4), 505–539.

Krueger, P., Z. Sautner, and L. T. Starks (2020, 02). The Importance of Climate Risks for Institutional Investors. *The Review of Financial Studies 33*(3), 1067–1111.

Leippold, M. and T. Yu (2023). The Green Innovation Premium: Evidence from U.S. Patents and the Stock Market. Swiss finance institute research paper series, Swiss Finance Institute.

Liang, B. (2000). Hedge funds: The living and the dead. *Journal of Financial and Quantitative Analysis 35*(03), 309–326.

Liang, H., L. Sun, and M. Teo (2022). Responsible Hedge Funds*. *Review of Finance 26*(6), 1585–1633.

Newey, W. K. and K. D. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 703–08.

Pástor, L., R. Stambaugh, and L. A. Taylor (2021). Sustainable investing in equilibrium. *Journal of Financial Economics 142*(2), 550–571.

Pástor, L. and R. F. Stambaugh (2003). Liquidity risk and expected stock returns. *Journal of Political Economy 111*(3), 642–685.

Pástor, L., R. F. Stambaugh, and L. A. Taylor (2022). Dissecting green returns. *Journal of Financial Economics 146*(2), 403–424.

Pedersen, L. H., S. Fitzgibbons, and L. Pomorski (2021). Responsible investing: The esg-efficient frontier. *Journal of Financial Economics 142*(2), 572–597.

Ramadorai, T. (2013). Capacity constraints, investor information, and hedge fund returns. *Journal of Financial Economics 107*(2), 401–416.

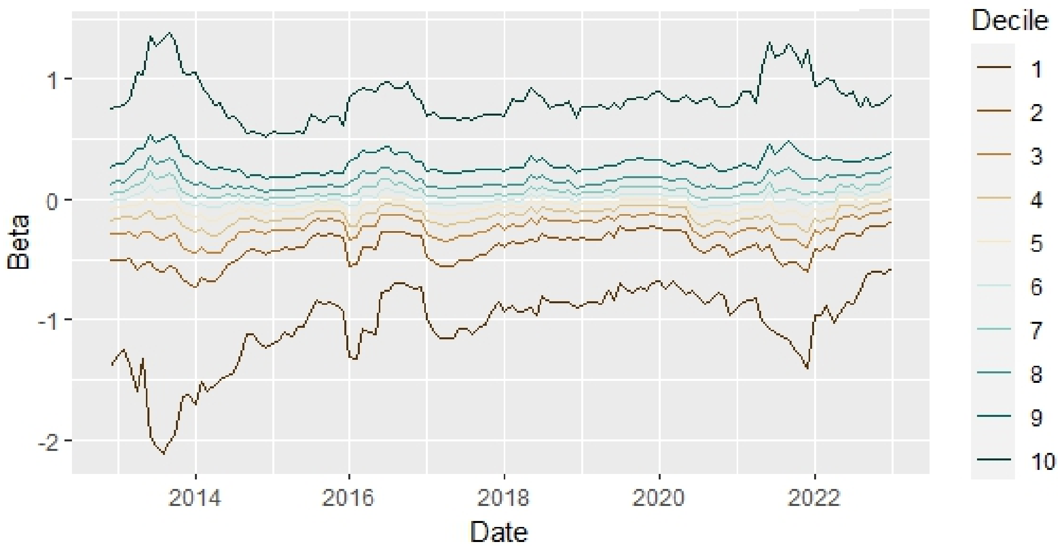
Riedl, A. and P. Smeets (2017). Why do investors hold socially responsible mutual funds? *The Journal of Finance 72*(6), 2505–2550.

Sadka, R. (2010). Liquidity risk and the cross-section of hedge-fund returns. *Journal of Financial Economics 98*(1), 54–71.

Sautner, Z., L. van Lent, G. Vilkov, and R. Zhang (2023). Firm-level climate change exposure. *The Journal of Finance 78*(3), 1449–1498.

Zhang, S. (2023). Carbon returns across the globe. *Journal of Finance, Forthcoming*.

Panel A: Average GMB betas



Panel B: Average GMB beta t-statistics

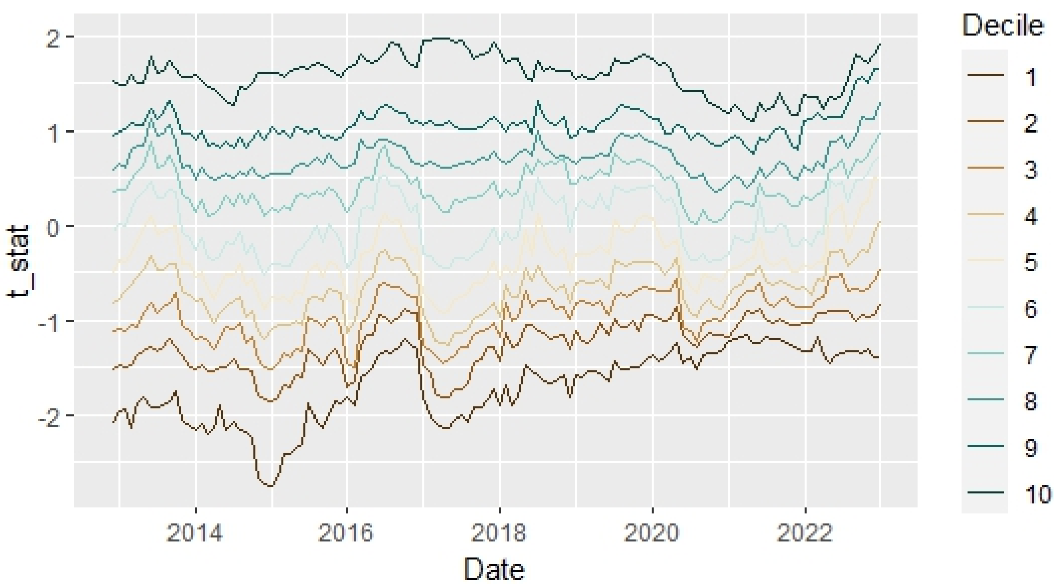


Figure 1 – This figure plots for each decile portfolio average GMB betas and their t-statistics from November 2012 through December 2022. The GMB beta estimated using a seven-factor model containing the Pastor, Stambaugh, and Taylor (2022) Green-minus-Brown (GMB) portfolio, Fama and French (2015), and Pastor and Stambaugh (2001) factors and 24 most recent return observations. Cumulate abnormal returns estimated using the Fama and French (2015) five-factor model and the Pastor and Stambaugh (2001) liquidity risk factor. Decile 1 (Decile 10) refers to the highest (lowest) GMB beta.

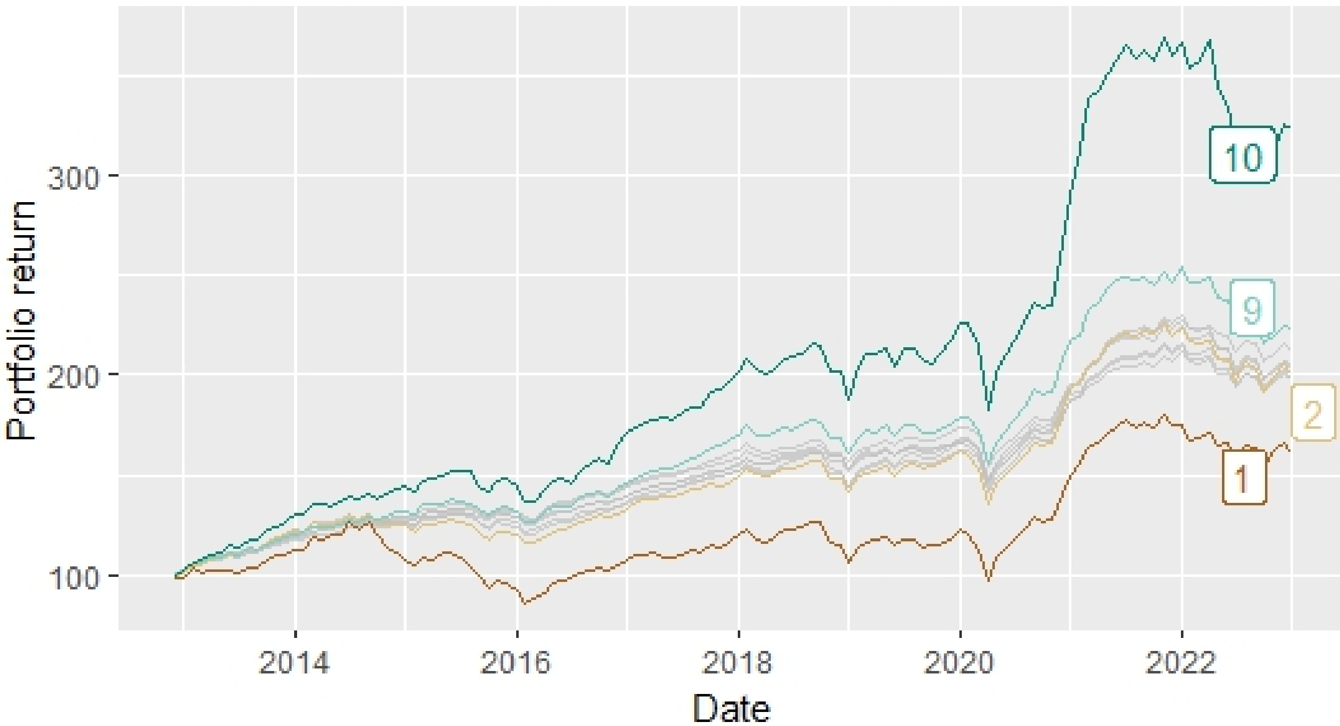


Figure 2 – This figure plots for each decile cumulative returns from November 2012 through December 2022. The GMB beta estimated using a seven-factor model containing the Pastor, Stambaugh, and Taylor (2022) Green-minus-Brown (GMB) portfolio, Fama and French (2015), and Pastor and Stambaugh (2001) factors. The GMB beta (Panel A) or the t-statistic of GMB beta (Panel B) is estimated using the 24 most recent return observations. Cumulative returns are estimated using the two-year rolling window. Decile 10 (Decile 1) refers to the highest (lowest) GMB beta.

Table 1 – GMB-beta sorted portfolios

This table sorts hedge funds into decile portfolios based on the GMB beta (Panel A) or the t-statistic of GMB beta (Panel B) estimated using a seven-factor model containing the Pastor, Stambaugh, and Taylor (2022) Green-minus-Brown (GMB) Portfolio, Fama and French (2015), and Pastor and Stambaugh (2001) factors. The GMB beta (Panel A) or the t-statistic of GMB beta (Panel B) is estimated using the 24 most recent return observations. The out-of-sample portfolio returns range from November 2012 through December 2022. Panels A and B estimate the post-ranking decile portfolio six-factor alphas and betas using the six-factor Fama and French (2015) and Pastor and Stambaugh (2001) model. To correct for backfill bias, funds must be actively reporting to databases by the end of month t-1. The t-statistics (in parentheses) are based on standard errors by Newey and West (1997). ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A. Sorted by GMB betas

Portfolio	GMB Beta	Return	Alpha	MKTRF	SMB	HML	RMW	CMA	PS LIQ
1 (Brown)	-1.05	4.98	-3.28	0.72	0.21	0.13	-0.14	0.14	0.08
2	-0.41	6.77	0.61	0.54	0.12	0.11	-0.10	0.02	0.04
3	-0.24	6.99	1.67	0.47	0.09	0.10	-0.08	-0.03	0.03
4	-0.14	6.63	1.79	0.43	0.05	0.11	-0.09	-0.04	0.05
5	-0.06	6.51	2.22	0.38	0.05	0.12	-0.04	-0.06	0.07
6	0.00	7.28	3.38	0.34	0.04	0.12	-0.01	-0.06	0.07
7	0.07	6.93	2.62	0.37	0.06	0.08	-0.03	0.00	0.05
8	0.16	6.87	1.62	0.45	0.05	0.12	-0.01	-0.04	0.09
9	0.30	7.76	1.96	0.50	0.11	0.11	-0.04	0.02	0.08
10 (Green)	0.84	12.09	4.90	0.66	0.29	0.14	-0.21	0.12	0.13
Spread	1.89***	7.11***	8.18***	-0.06	0.08	0.01	-0.07	-0.02	0.05
t-statistic		2.81	3.28	-1.53	0.90	0.10	-0.86	-0.18	0.68

Panel B. Sorted by *t*-statistics of GMB betas

Portfolio	GMB Beta *t*-stat.	Return	Alpha	MKTRF	SMB	HML	RMW	CMA	PS LIQ
1 (Brown)	-2.10	4.98	-1.58	0.57	0.10	0.13	-0.09	0.04	0.02
2	-1.26	6.17	0.21	0.51	0.10	0.11	-0.05	0.00	0.04
3	-0.85	6.67	1.34	0.48	0.10	0.10	-0.11	0.00	0.04
4	-0.54	6.02	0.81	0.47	0.09	0.13	-0.10	-0.03	0.05
5	-0.26	6.79	1.24	0.49	0.10	0.11	-0.08	-0.02	0.09
6	0.01	7.74	2.61	0.45	0.09	0.12	-0.05	-0.02	0.07
7	0.29	7.37	2.27	0.45	0.07	0.11	-0.06	-0.01	0.08
8	0.61	8.19	2.93	0.45	0.15	0.06	-0.08	0.11	0.08
9	1.02	9.02	3.52	0.48	0.17	0.11	-0.07	0.04	0.08
10 (Green)	1.93	9.89	4.22	0.50	0.11	0.17	-0.06	-0.02	0.14
Spread	4.03***	4.92***	5.79***	-0.06**	0.02	0.04	0.02	-0.06	0.12**
t-statistic		2.61	3.57	-2.27	0.24	0.78	0.39	-0.57	2.19

Table 2 – Robustness: PMC-beta sorted portfolios

The table shows portfolio alphas when hedge fund are sorted into decile portfolios based on the PMC beta (Panel A) or t-statistic of PMC beta (Panel B) estimated using a seven-factor model containing the Pollute-minus-Clean (PMC) of Huij, Dries, Stork, and Zwinkels (2023), Fama and French (2015), and Pastor and Stambaugh (2001) factors. Huij et al.'s (2023) PMC factor is constructed using firm-level emission intensity. The PMC beta (t-statistic) is estimated using the 24 most recent return observations. The out-of-sample portfolio returns range from November 2012 through December 2022. The post-ranking decile portfolio alphas are estimated using the six-factor Fama and French (2015) and Pastor and Stambaugh (2001) model. To correct for backfill bias, funds must be actively reporting to databases by the end of month t-1. The t-statistics (in parentheses) are based on standard errors by Newey and West (1997). ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Panel A: PMC betas			Panel B: t-stat. of PMC beta		
Portfolio	PMC Beta	Return	Alpha	PMC Beta t-stat.	Return	Alpha
1 (Clean)	-0.85	10.99	3.52	-1.96	8.66	2.8
2	-0.33	8.44	2.41	-1.1	7.34	2.33
3	-0.18	8.13	2.98	-0.7	7.85	2.44
4	-0.09	7.21	2.52	-0.36	7.84	2.6
5	-0.01	6.63	2.3	-0.06	8.07	2.43
6	0.05	6.93	2.51	0.22	7.43	1.7
7	0.13	6.5	1.84	0.52	7.1	1.45
8	0.24	6.68	1.39	0.85	6.95	1.45
9	0.41	6.93	0.96	1.25	6.02	0.47
10 (Pollute)	1.07	4.36	-2.94	2.09	5.57	-0.16
Spread	1.92***	-6.63***	-6.46***	4.05***	-3.09**	-2.96**
t-statistic		-3.11	-3.23		-2.33	-2.25

Table 3 – UNPRI and ESG funds

This table presents GMB beta sorts for subsamples of UNPRI versus non-UNPRI funds, and ESG versus non-ESG funds. UNPRI refers to hedge funds that are signatories of the United Nations Principles for Responsible Investment. Non-UNPRI funds are not signed with the United Nations Principles for Responsible Investment. ESG hedge funds self-report to have an ESG-compliant strategy or fund name containing ESG terms. Non-ESG funds are conventional hedge funds that follow standard strategies without ESG considerations. The sorting procedure is as in Table 1. The out-of-sample portfolio returns range from November 2012 through December 2022. The post-ranking decile portfolio alphas and betas are estimated using the Fama and French (2015) and Pastor and Stambaugh (2001) six-factor model augmented with the Pastor, Stambaugh, and Taylor (2022) Green-minus-Brown (GMB) Portfolio. To correct for backfill bias, funds must be actively reporting to databases by the end of month t-1. The t -statistics (in parentheses) are based on Newey and West (1997) standard errors. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	UNPRI	Non-UNPRI	ESG	Non-ESG
1 (Brown)	-3.91	-3.36	1.17	-3.42
2	-0.28	1.05	3.14	0.80
3	0.75	1.56	3.15	1.48
4	1.90	1.63	2.79	1.85
5	-1.26	2.55	3.77	2.10
6	0.00	3.75	4.75	3.23
7	0.64	2.65	3.40	2.66
8	1.26	1.82	2.96	1.66
9	0.21	2.27	2.34	1.97
10 (Green)	-1.07	5.23	15.48	4.46
Spread	2.85	8.59	14.31	7.88
t-statistic	1.03	3.76	5.17	3.08

Table 4 – Fama-MacBeth regressions

This table reports results from Fama–MacBeth (1973) cross-sectional regressions of hedge fund excess return and alpha on GMB beta, controlling for fund characteristics and style dummies. In each month and for each hedge fund with at least 24 return observations, GMB Beta (t-statistic) is estimated by regressing the fund excess returns on the Pastor, Stambaugh, and Taylor (2022) Green-minus-Brown (GMB) Portfolio, Fama and French (2015), and Pastor and Stambaugh (2001) factors. Then, cross-sectional regressions of fund excess return, or alpha, are performed over the next month on GMB beta with controls for fund characteristics and style dummies. The fund characteristics include fund size, fund age, management fee, incentive fee, a high-water mark dummy equal to one if a high-water mark provision is used and zero otherwise, lockup period, redemption period, and notice period. Both monthly excess return and alpha are reported in percentages. To correct for backfill bias, funds must be actively reporting to databases by the end of month t-1. The t-statistics are based on Newey–West (1987) standard errors with two lags. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A. GMB Beta

	Excess Return				Alpha			
	Coef.	*t*-stat.	Coef.	*t*-stat.	Estimate	*t*-stat.	Coef.	*t*-stat.
GMB Beta	0.34***	3.02	0.32***	2.94	0.30**	2.49	0.29**	2.42
log(AUM)			0.00	0.01			0.02**	2.10
Age (years)			0.00	-0.44			-0.01***	-3.41
High-Water Mark			0.01	0.13			-0.04	-0.87
Management Fee (%)			0.06	1.26			0.15***	3.82
Incentive Fee (%)			0.01***	3.14			0.02***	7.42
Lockup Dummy			0.11	1.53			0.12***	2.70
Notice period			0.00**	1.96			0.00**	2.41
Redemption period			0.17	1.56			0.18*	1.82
Leverage Dummy			-0.02	-0.37			-0.03	-1.17
Fund Style Dummies	No		Yes		No		Yes	
R2	1.66%		6.21%		1.73%		3.25%	

Panel B. GMB Beta *t*-statistics

	Excess Return				Alpha			
	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.
GMB Beta t-statistic	0.10***	2.86	0.08**	2.32	0.09**	2.34	0.08**	2.18
log(AUM)			-0.01	-0.41			0.02	1.56
Age (years)			0.00	-0.24			-0.01***	-3.15
High-Water Mark			-0.03	-0.36			-0.07	-1.28
Management Fee (%)			0.03	0.54			0.11**	2.50
Incentive Fee (%)			0.01**	2.20			0.01***	5.76
Lockup Dummy			0.07	1.09			0.08*	1.85
Notice period			1.17***	5.34			1.30***	6.59
Redemption period			0.06	0.61			0.05	0.58
Leverage Dummy			0.00	0.10			-0.01	-0.47
Fund Style Dummies	No		Yes		No		Yes	
R2	1.19%		5.73%		1.05%		2.74%	

Table 5 – Selection skill from stock holdings

This table shows Fama-French 5-factor plus liquidity factor regression results for different portfolios constructed using 13F stock holdings. Green (Brown) Copycat Portfolio that replicates hedge fund holdings of green (brown) stocks. Column (1) is the difference between the Green Copycat Portfolio and the Brown Copycat Portfolio. Column (2) is the Green Copycat Portfolio. Column (3) is the Green Benchmark Portfolio of all green stocks. Column (4) is the difference between the Green Copycat Portfolio and the Green Benchmark Portfolio. Column (5) is the Brown Copycat Portfolio. Column (6) is the Brown Benchmark Portfolio of all brown stocks. Column (7) is the difference between the Brown Copycat Portfolio and the Brown Benchmark Portfolio. Tests are run separately to subgroups of UNPRI, non-UNPR firms, during the low climate concern states and high climate concern states. MCCC refers to Ardia, Bluteau, Boudt and Inghelbrecht (2023) Climate Concern Index. WSJ refers to Engle, Giglio, Kelly, Lee and Stroebel (2000) Climate Change News Index. The sample period is from December 2012 to December 2022. The t-statistics are reported in parentheses. *, **, and *** denote significance at the by 10%, 5%, and 1% levels, respectively.

Panel A: Green versus brown selection skill

	Copycat		Benchmark		Differences		
	Green	Brown	Green	Brown			
	(1)	(2)	(3)	(4)	(1)-(2)	(1)-(4)	(2)-(5)
Alpha	3.056***	-2.058	2.007*	-2.678*	5.114**	1.050*	0.620
	(2.78)	(-1.31)	(1.90)	(-1.81)	(2.41)	(1.77)	(0.87)
Mkt	1.027***	1.058***	1.005***	0.983***	-0.031	0.021*	0.075***
	(45.50)	(34.01)	(46.60)	(32.52)	(-0.73)	(1.73)	(4.76)
SMB	-0.008	0.295***	-0.098**	0.177***	-0.302***	0.090***	0.117***
	(-0.18)	(4.87)	(-2.34)	(3.02)	(-3.61)	(3.77)	(3.85)
HML	-0.017	0.189***	0.046	0.180***	-0.206***	-0.063***	0.009
	(-0.46)	(3.80)	(1.33)	(3.72)	(-2.99)	(-3.18)	(0.38)
RMW	-0.233***	0.115	-0.171***	0.132*	-0.348***	-0.062**	-0.017
	(-4.54)	(1.63)	(-3.49)	(1.93)	(-3.56)	(-2.20)	(-0.48)
CMA	-0.067	0.159*	-0.013	0.228***	-0.226**	-0.054*	-0.068
	(-1.12)	(1.93)	(-0.22)	(2.84)	(-1.98)	(-1.66)	(-1.65)
PS LIQ	0.080**	0.016	0.034	-0.031	0.065	0.047***	0.047**
	(2.48)	(0.35)	(1.09)	(-0.71)	(1.04)	(2.63)	(2.07)
R2	95.89%	93.76%	95.88%	92.93%	46.44%	53.50%	49.46%

Panel B: Subsample analysis

	Green Copycat	Green Copycat −Brown Copycat	Green Copycat −Green Benchmark
UNPRI	3.683**	6.364**	1.676
	(2.45)	(2.10)	(1.32)
Non-UNPRI	2.999***	5.061**	0.992*
	(2.73)	(2.40)	(1.69)
Low Climate Concerns	1.168	0.003	2.252***
	(0.74)	(0.99)	(3.12)
High Climate Concerns	0.003**	0.005*	0.000
	(2.41)	(1.86)	(-0.18)

Table 6 – Carbon emissions and green innovation

This table reports the results of quarterly regressions, in which the stock-level components of copycat portfolios is explained by emissions and green patent measures. Panel A (Panel B) reports the results for green (brown) copycat portfolios. All regression specifications include as controls a quarterly lagged firm market capitalization, book-to-market ratio, and 12-month past return as well as time and firm level fixed effects. The sample period is from December 2012 to December 2022. The t-statistics are reported in parentheses. *, **, and *** denote significance at the by 10%, 5%, and 1% levels, respectively.

Panel A: Green Portfolio Weight$_q$ − Green Market Weight$_q$					
	(1)	(2)	(3)	(4)	(5)
Emissions Scope 1+2$_{q-1}$	-0.007***				
	(0.002)				
Emissions Scope 1+2/Sales$_{q-1}$		-0.003			
		(0.002)			
Lagged Emissions Scope 1+2/Sales$_{q-4}$			-0.014***		
			(0.001)		
Log (Granted Green Patents)$_{q-1}$				-0.022**	
				(0.009)	
Ratio of Granted Green Patents$_{q-1}$					-0.003
					(0.009)
Controls?	Yes	Yes	Yes	Yes	Yes
Obs.	15,214	15,185	15,134	11,364	11,364
R2	0.033	0.033	0.031	0.017	0.016

Panel B: Brown Portfolio Weight$_q$ − Brown Market Weight$_q$					
	(1)	(2)	(3)	(4)	(5)
Emissions Scope 1+2$_{q-1}$	-0.017***				
	(0.002)				
Emissions Scope 1+2/Sales$_{q-1}$		-0.005**			
		(0.002)			
Lagged Emissions Scope 1+2/Sales$_{q-4}$			-0.003		
			(0.003)		
Log (Granted Green Patents)$_{q-1}$				-0.002	
				(0.005)	
Ratio of Granted Green Patents$_{q-1}$					-0.004
					(0.011)
Controls?	Yes	Yes	Yes	Yes	Yes
Obs.	15,214	15,185	15,134	11,364	11,364
R2	0.033	0.033	0.031	0.017	0.016

Table 7 – Selection skill from option holdings

This table reports the results from Fama-MacBeth regressions of future stock returns against various aggregate hedge fund demands of options and common shares on a particular stock. The sample period is from December 2012 to December 2022. Newey and West (1986) t -statistics (in parenthesis) are computed based on the time-series variability of coefficients estimated from cross-sectional regressions. *, **, and *** denote significance at the by 10%, 5%, and 1% levels, respectively.

	HF	UNPRI	Non-UNPRI	Low Climate Concern	High Climate Concern
Green x BEAR	-0.982***	-0.004	-0.909**	-1.661***	0.184
	(-2.83)	(-0.06)	(-2.64)	(-2.81)	(0.46)
Green x BULL	0.357	0.010	0.468*	0.146	0.588***
	(1.27)	(0.13)	(1.76)	(0.28)	(3.02)
Green x STRA	-0.629	-0.014	-0.746	-0.297	-0.140
	(-0.43)	(-0.17)	(-0.51)	(-0.25)	(-0.14)
Green x PPUT	1.452	0.092*	1.347	0.864	0.280
	(1.15)	(1.96)	(1.13)	(0.31)	(0.76)
Green x COM	-0.002	-0.001	-0.003	0.004	0.000
	(-0.54)	(-0.32)	(-0.59)	(0.58)	(-0.09)
BEAR	-0.066	-0.005	-0.200	-0.259	-0.660
	(-0.13)	(-0.11)	(-0.46)	(-0.45)	(-1.78)
BULL	0.171	-0.075	0.109	-0.197	0.046
	(1.17)	(-1.29)	(0.88)	(-1.48)	(0.29)
STRA	-0.172	-0.006	-0.152	-0.235	-0.553
	(-0.53)	(-0.16)	(-0.50)	(-0.54)	(-1.52)
PPUT	-0.210	-0.109**	-0.187	0.147	-0.441
	(-0.72)	(-2.28)	(-0.67)	(0.83)	(-0.87)
COM	-0.373	-0.057	-0.429	-0.855	-0.473
	(-0.61)	(-0.94)	(-0.77)	(-4.29)	(-0.81)
Intercept	0.374	0.057	0.430	0.853	0.473
	(0.61)	(0.94)	(0.77)	(4.26)	(0.82)

Table 8 – Fund flows

This presents results for the quarterly flow regressions. Panel A shows results for all funds. Panel B shows results for the 13F universe of hedge funds. Full period (t = 2012 Q4 through 2022 Q4), Early period (t = 2012 Q4 through 2017 Q1) and Late period (t = 2017 Q2 through 2022 Q4). Both GMB Beta and GMB Beta t-statistic are estimated using a six-factor model (i.e., FF5 plus Pastor-Stambaugh liquidity factor). Dependent variables are measured at the end of quarter t. Control variables are measured at the end of quarter t-1. As controls are used UNPRI and ESG indicators as well as standard controls (six-factor alpha, fund size, fund age, management fee, incentive fee, high-water mark, lockup dummy, notice period, redemption period and leverage dummy). All regressions include fixed effects for fund style, and quarter. Standard errors are clustered by fund and quarter. Quarterly flow and six-factor alphas are winsorized at 1% and 99% levels. The t-statistics are reported in parentheses. *, **, and *** denote significance at the by 10%, 5%, and 1% levels, respectively.

Panel A. All hedge funds

	Quarterly flow (%)					
	Full Period		Early period		Late period	
GMB Beta	0.99***		0.90**		1.03*	
	(2.82)		(2.20)		(1.82)	
GMB Beta t-statistic		0.40***		0.30*		0.60***
		(2.76)		(1.67)		(2.52)
UNPRI-complain fund	1.48**	1.45**	3.15*	3.16*	1.07	1.07
	(2.05)	(2.01)	(1.75)	(1.76)	(1.39)	(1.38)
ESG- compliant fund	1.72*	1.73*	3.92**	3.92**	0.11	0.10
	(1.86)	(1.87)	(2.15)	(2.15)	(0.15)	(0.13)
Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	1.70 %	1.67 %	1.74 %	1.70 %	1.75 %	1.76 %
N	50,567	50,567	26,883	26,883	23,684	23,684

Panel B. 13F hedge funds only

	Quarterly flow (%)					
	Full Period		Early period		Late period	
GMB Beta	1.87***		1.56**		1.97**	
	(2.78)		(2.09)		(2.08)	
GMB Beta t-statistic		0.41**		0.21		0.78**
		(2.05)		(0.92)		(2.22)
UNPRI-complain fund	2.29**	2.29**	5.51***	5.51***	1.45	1.45
	(2.40)	(2.39)	(2.61)	(2.60)	(1.31)	(1.32)
ESG- compliant fund	0.18	0.19	1.24	1.34	-0.65	-0.68
	(0.19)	(0.19)	(0.68)	(0.74)	-(0.44)	-(0.47)
Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	1.62 %	1.49 %	1.48 %	1.34 %	2.23 %	2.21 %
N	19,025	19,025	9,496	9,496	9,529	9,529

Table 9 – Hedge fund investor returns

This table presents GMB beta sorts for several practical investment strategies. Mean returns and alphas are reported or the bottom (Brown) and top (Green) deciles, and the spread between them. Instead of gross-of-fee returns, the results in this table are generated using the net-of-fee returns earned by investors. Baseline refers to the baseline case presented in Panel A of Table 1. 1-year holding period indicates that portfolios are rebalanced every December instead of every month. 1-month formation lag indicates that we account for a one-month formation lag when portfolios are built. 1-year holding period and 1-month formation lag indicate that both December rebalancing and a one-month formation lag is imposed when portfolios are formed. The sorting procedure is as in Table 1. The out-of-sample portfolio returns range from November 2012 through December 2022. The post-ranking decile portfolio alphas and betas are estimated using the Fama and French (2015) and Pastor and Stambaugh (2001) six-factor model augmented with the Pastor, Stambaugh, and Taylor (2022) Green-minus-Brown (GMB) Portfolio. The t-statistics are in parentheses and based on Newey and West (1997) standard errors.

	Panel A: Baseline		Panel B: 1-year holding period	
Portfolio	Mean return	Alpha	Mean return	Alpha
1 (Brown)	2.22	-5.79	2.25	-5.35
	(0.54)	(-2.49)	(0.51)	(-2.07)
10 (Green)	8.31	1.45	7.18	0.23
	(2.10)	(0.88)	(1.80)	(0.14)
Spread	6.10	7.24	4.93	5.58
	(2.50)	(3.14)	(1.97)	(2.01)
	Panel D: 1-month formation lag		Panel D: 1-year holding period and 1-month formation lag	
Portfolio	Mean return	Alpha	Mean return	Alpha
1 (Brown)	2.45	-5.62	1.89	-5.64
	(-.60)	(-2.43)	(0.44)	(-2.08)
10 (Green)	8.40	1.48	7.30	0.41
	(2.10)	(0.91)	(1.88)	(0.26)
Spread	5.95	7.09	5.41	6.05
	(2.56)	(3.21)	(2.09)	(2.10)