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What drives green betas? Climate uncertainty or speculation☆

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ABSTRACT

Examining green equity sectors including geothermal, wind, solar, bioclean, and clean energy within a DCC-MIDAS framework, we show that green betas are predominantly driven by speculative sentiment in technology stocks rather than climate uncertainty. We argue that the lottery-like features of green assets, whose values are highly tied to the success of new technologies, result in a negative risk-mispricing relationship driven by technology speculation. Further economic analysis shows that a forward-looking investment strategy conditional on technology sentiment yields improved risk-adjusted returns for passive equity investors, particularly following the 2016 Paris Agreement. Our findings establish a new speculation-based channel for characterizing the systematic risk of green assets.

1. Introduction

According to the Capital Asset Pricing Model (CAPM), exposure to aggregate market fluctuations measured by beta is the sole asset-specific determinant of expected returns. Beta estimates are often used by fund managers in their strategic and tactical allocation models and are essential in risk management applications to hedge market exposures. However, the market forces that drive asset betas are often understudied, although beta is a critical input in financial decisions. While prior works have established a significant relationship between uncertainty and systematic risk in equity markets (e.g. Yu et al., 2017; Naeem et al., 2020), the literature has not yet extended the analysis to green equities that have attracted much attention in the burgeoning climate finance literature. The main contribution of this paper is to extend the emerging literature on climate finance in a novel direction by exploring the role of climate uncertainty as a driver of market betas using data from a wide range of green equity sectors that capture geothermal, wind, solar, bioclean, and clean energy stocks. This is an important consideration as asset betas capture market exposures, which in turn serve as determinants of expected returns. As another novelty of our analysis, building on the evidence that establishes a close link between technology stocks and renewable energy companies (e.g. Kumar et al., 2012; Inchauspe et al., 2015), we explore whether sentiment in technology stocks plays a predictive role in green betas. Indeed, our results show that green betas are predominantly driven by speculative sentiment in technology stocks rather than climate uncertainty, thereby establishing a new channel that links the clean energy market to the technology industry. Subsequently, we propose a forward-looking investment

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strategy in green industries that is conditional on technology sentiment and presents evidence of improved risk-adjusted returns for passive equity investors.

The literature on climate finance is growing rapidly, and there is now a well-established literature on the role of climate as a driver of stock returns (e.g. Bolton and Kacperczyk, 2021; Dutta et al., 2023; Faccini et al., 2023), while recent studies also show that the uncertainty associated with climate policy is a dominant determinant of return and volatility in this growing asset class (Bouri et al., 2023). In a recent study, Treepongkaruna et al. (2023) show that stocks with low exposure to climate policy uncertainty (CPU) earn 5.5%–6.3% higher returns, suggesting that uncertainty-averse investors are willing to pay a premium on low-CPU exposure stocks. The importance of climate risk on firm valuations is further highlighted by the growing attention on "double materiality" that aims to capture the bidirectional interactions between firm operations and climate-related impacts in the financial reporting regulations (Chiu, 2022; Pizzi et al., 2023; Carvajal and Nadeem, 2023; Xie et al., 2023). Separately, a burgeoning literature establishes a close link between technology stocks and renewable energy companies as the performance of alternative energy companies is highly sensitive to the success of technological innovations in their efforts to transition into a less carbon-intensive economy (Bouri et al., 2023). Thus, studies including Kumar et al. (2012) and Inchauspe et al. (2015) argue that investors' perceptions of clean energy and technology stocks are often similar. Interestingly, however, the literature has not yet explored the potential impact of these dynamics on industry betas, particularly on the clean energy industry. Our key finding is that green betas are predominantly driven by speculative sentiment in technology stocks rather than climate uncertainty, thus establishing a new investor sentiment channel that links clean energy and technology stocks. We argue that the lottery-like features of green assets, whose values are highly tied to the success of new technologies, result in a negative risk-mispricing relationship driven by speculation in technology stocks. Further economic analysis shows that a forward-looking investment strategy conditional on technology sentiment yields improved risk-adjusted returns for passive equity investors who supplement their positions with green stocks, particularly following the 2016 Paris Agreement.

It is worth noting that financial regulators encourage market actors to transition their investments from high-carbon to low-carbon assets, while also encouraging efforts to diminish the carbon footprint of existing high-carbon operations (Gunningham, 2020), fostering investments in green assets, as highlighted by D'Orazio and Popoyan (2019). Considering the evidence that investors already demand compensation for their exposure to climate-related risks, our findings are important in characterizing the systematic risk of green assets with significant investment implications. This is especially important considering that asset betas are not directly observable and the growing emphasis on double materiality in financial reporting will only make the assessment of risk exposures in green assets more challenging. In that regard, our findings offer novel insight to the assessment of systematic risks in this growing asset class by focusing on the role of speculative sentiment, rather than the dominant focus on climate risk. This reveals a novel connection between the clean energy market and the technology sector, creating a new pathway for understanding their interplay. Moreover, our findings offer a forward-looking investment strategy that relies on technology sentiment and provides substantiation of enhanced risk-adjusted returns for passive equity investors.

The remainder of the paper is organized as follows. Sections 2 and 3 describe the sample data and methodology. Section 4 presents the findings and Section 5 concludes with several remarks.

2. Data

We use daily data for five green equity indexes, namely the NASDAQ OMX Bio/Clean Fuels (GRNBIOX), Wind (GRNWIND), Solar (GRNSOLAR), and Geothermal (GRNGEO) total return indexes and the iShares Global Clean Energy ETF (ICLN), over the period October 21, 2010–March 2, 2023, obtained from Datastream. The market index is represented by the MSCI World Index, which captures large- and mid-cap representation across 23 developed markets. The Climate Policy Uncertainty (CPU) index of Gavriilidis (2021) is obtained from the Economic Policy Uncertainty database.[1] To capture investor sentiment in technology stocks, we use the speculative ratio originally proposed by Garcia et al. (1986) as a model-free measure of the speculative tendencies of investors based on trading volume and open interest information obtained from futures market transactions. For this purpose, we collect data for NASDAQ 100 futures contracts from Commodity Systems Inc. that track the performance of the NASDAQ 100 index, which incorporates non-financial firms from industries that drive global innovation and growth. Following Balcılar et al. (2017), the technology speculative ratio (TSR) on a given day t is computed as V_t/OI_t where V_t is the trading volume during period t and OI_t is the value of the open interest at the end of the same period. Considering that speculators tend to engage in short-term positions compared with hedgers, Lucia et al. (2015) argue that speculators' trading activity of taking opposite positions during a given period results in faster growth in trading volume relative to open interest, thus leading to a higher value for TSR, which indicates the relative importance of speculative activity in the market with respect to hedging.

The time series plots in Fig. A.1 in the Appendix display a notable spike in the technology speculation series following the official announcement of the COVID-19 pandemic by the World Health Organization (WHO) on March 11, 2020, which also coincides with a positive shift in the green index values during that period. Likewise, we observe a notable spike in the CPU index in mid-2016 following the initiation of the Paris Climate Agreement and later in 2021 following the presidential elections. Although not reported due to space considerations, the descriptive statistics show that Solar records the highest mean and volatility in returns among the green equity indices. With the exception of Geothermal, all green equity indexes exhibit a left-skewed distribution, indicating large negative outliers in daily returns.

[1] https://www.policyuncertainty.com/climate_uncertainty.html.

3. Methodology

3.1. Estimating green betas

We estimate the betas for green equity indexes via the Asymmetric Dynamic Conditional Correlation (ADCC) Model of Cappiello et al. (2006) which allows us to jointly estimate the time-varying covariance between the green industries and the market index. Given the $\mathrm{n} \times 1$ vector of returns, r_t, the mean equation on the information set $I_{\mathrm{t}-1}$ is specified as

$$r_t = \mu + \psi r_{t-1} + \varepsilon_t \tag{1}$$

with the residuals represented by $\varepsilon_{\mathrm{t}} = \mathrm{H}_{\mathrm{t}}^{1/2}\mathrm{z}_{\mathrm{t}}$ where H_{t} is the conditional covariance matrix of r_t and z_t is a $\mathrm{n} \times 1$ vector of i.i.d errors. Formulating H_t as $H_t = D_t^{1/2} R_t D_t^{1/2}$ where $D_t = \mathrm{diag}\left(h_{i,t}, \ldots, h_{n,t}\right)$ captures the diagonal conditional variances, the conditional correlation matrix R_t is defined as

$$\mathrm{R_t} = \mathrm{diag}\left(q_{1,t}^{-1/2}, \ldots, q_{n,t}^{-1/2}\right) \mathrm{Q_t}\, \mathrm{diag}\left(q_{1,t}^{-1/2}, \ldots, q_{n,t}^{-1/2}\right) \tag{2}$$

where Q_t is a symmetric positive definite matrix with $\mathrm{Q_t} = \left(1 - \theta_1 - \theta_2\right)\overline{\mathrm{Q}} + \theta_1 \mathrm{z}_{\mathrm{t}-1}\mathrm{z}'_{\mathrm{t}-1} + \theta_2 \mathrm{Q}_{\mathrm{t}-1}$. Here, $\overline{\mathrm{Q}}$ denotes the $\mathrm{n}\times\mathrm{n}$ unconditional matrix of the standardized residuals $\mathrm{z}_{\mathrm{i,t}}$ where θ_1 and θ_2 are non-negative satisfying the condition $\theta_1 + \theta_2 < 1$. The beta estimator for green industry i is then formulated as $\beta_{i,t} = \frac{q_{i,m,t}}{q_{m,m,t}}$ where m denotes the market index. Cappiello et al. (2006) propose an asymmetric version of the DCC model of Engle (2002) in which the conditional volatility of the GARCH(1,1) model is defined as

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \tau_i h_{i,t-1} + \gamma_i \varepsilon_{i,t-1}^2 I\left(\varepsilon_{i,t-1}\right) \tag{3}$$

where the indicator function $I_{t-1} = 1$ if $\varepsilon_{i,t-1} < 0$ otherwise $I_{t-1} = 0$. In this setting, the "asymmetric" effect is captured by a positive value for d which implies that positive residuals tend to increase variance less than negative residuals. Thus, Q_t is represented by

$$Q_t = \left(\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{Q} - G\right) + A' z_{t-1} z'_{t-1} A + B' Q_{t-1} B + G' z_t^- z_t'^- G \tag{4}$$

where A, B and G are $\mathrm{n} \times \mathrm{n}$ parameter matrices and z_t^- are zero-threshold standardized errors with an unconditional matrix $\bar{Q}^-$.

3.2. Reverse MIDAS model

Given that climate policy uncertainty is available on a monthly basis while the beta estimates are obtained from daily returns, we follow the reverse-MIDAS (R-MIDAS) model, derived from the mixed data sampling framework of Ghysels et al. (2006), to predict high-frequency beta series based on the low-frequency CPU series. Assuming a dependent variable x generated by an $AR(p)$ process and variable y as the exogenous predictor, where x is observed at high frequency every $t = \frac{1}{k}$ periods, while y can only be observed at low frequency every k periods, the R-MIDAS follows the form

$$x_t = \lambda_i(L^{k+i}) y_t + \sigma_{1i} A_i(L, \theta_i) x_{t-1/k} + \epsilon_t \tag{5}$$

$$t = 0 + \frac{i}{k}, 1 + \frac{i}{k+1}, 2 + \frac{i}{k+2} \tag{6}$$

$$i = 0, \ldots, k-1 \tag{7}$$

where L denotes the lag operator operating in high frequency and $A_i(L, \theta_i)$ can be an exponential Almon lag polynomial

$$A_i(L, \theta_i) = \sum_{j=0}^{Q} a_i(j, \theta_i) L^j, a_i(j, \theta_i) = \frac{exp(\theta_{i1} j + \theta_{i2} j^2)}{\sum_{j=0}^{K} exp(\theta_{i1} j + \theta_{i2} j^2)}. \tag{8}$$

In this setting, the daily beta series, x_t, is always related to the latest available value of the low-frequency monthly CPU series, y, and its monthly lags, and to the latest and additional daily lags of x itself. In our application, our predictors include monthly CPU series along with the daily technology speculation series.

4. Empirical results

4.1. Drivers of green betas

The ADCC model results reported in Table 1 indicate positive and statistically significant short-term persistence (α) for most green equity indexes, which are less than the long-term persistence parameters (τ), suggesting the presence of volatility clustering in green returns. The significant γ values reveal asymmetric effects, indicating that positive and negative residuals tend to impact conditional volatility in different magnitudes. The time-varying betas, reported in Fig. 1, take on values above unity for most green equities, notably Solar, highlighting the risky nature of these assets whose fluctuations are highly tied to the success of new technologies (Bouri et al., 2023). The estimated betas display notable spikes in 2020, likely triggered by the COVID-19 pandemic, as the beta

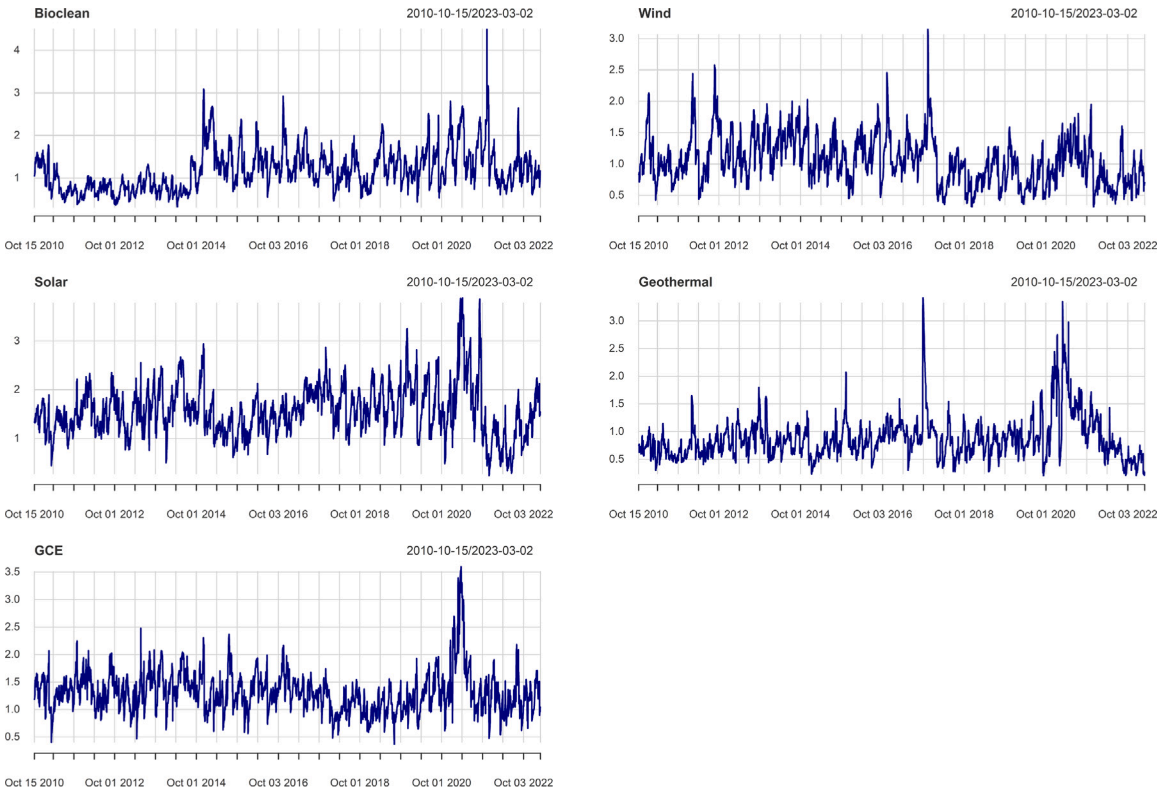

Fig. 1. Time-varying green betas. **Note:** This figure plots the time-varying betas for green equity indices obtained via the Asymmetric DCC-GARCH model.

Table 1
Asymmetric DCC-GARCH parameter estimates.

	Bio/Clean	Wind	Solar	Geothermal	GCI	
μ	0.00038*	0.000649***	0.000636***	0.000518**	0.000369	
ψ	0.047823***	0.062645***	0.084555***	0.013424	0.020862	
ω	0.000002***	0.000007	0.000006**	0.000007	0.000003	
α	0.044996*	0.049039***	0.036509***	0.045533	0.052973	
τ	0.920305***	0.900163***	0.926681***	0.890472***	0.912033	
γ	0.063691**	0.057728**	0.049886**	0.084367**	0.051225	
DCC estimation						
	θ_1	θ_2	Akaike	Bayes	Shibata	Hannan–Quinn
	0.0166***	0.9658**	−37.238	−37.123	−37.239	−37.197

Note: This table reports the ADCC model estimates for green equity sectors. *, **, *** denote significance at 10, 5, 1% levels, respectively.

values drop back to unity subsequently, with the exception of Solar and Wind displaying a rising pattern in betas during the latter part of the sample.

Although the theoretical framework that one can use to relate betas to uncertainty is rather limited, recent studies offer some theoretical insight to the role of speculation as a determinant of the risk-return tradeoffs in equities. In the first approach, Hong and Sraer (2016)argue that high beta assets are more sensitive to disagreement among investors which makes them prone to speculative overpricing due to short-sale constraints. This, in turn, obscures the risk-return relationship for high beta stocks — which green equities certainly qualify as, leading to a negative expected return-beta relationship when disagreement is high. In the second approach, Ghazi and Schneider (2022) propose a framework in which asset returns are decomposed into speculation and non-speculation components and show that the non-speculative component captures a positive risk premium that the standard models hypothesize, while the speculative component is associated with a negative speculative premium. The authors show that these two components of returns can help explain the risk and mispricing related factors that relate to CAPM anomalies including the well-known beta anomaly.

In line with the arguments stated above, examining the R-MIDAS estimates reported in Table 2, we find that technology speculation (TSR) has a robust impact on green betas consistently across all five green industries. While we obtain mixed results

Table 2
The effect of speculation and climate uncertainty on green betas.

	c	CPU	TSR	R^2
Bioclean	−0.136	0.268***		0.073
	(0.434)	(0.085)		
	1.171***		−0.299***	0.087
	(0.065)		(0.086)	
	−0.065	0.254***	−0.286***	0.152
	(0.486)	(0.093)	(0.086)	
Wind	2.507	−0.293***		0.143
	(0.285)	(0.057)		
	1.086***		−0.161***	0.041
	(0.049)		(0.061)	
	2.551***	−0.301***	−0.176***	0.194
	(0.290)	(0.058)	(0.056)	
Geothermal	0.444	0.095		0.012
	(0.364)	(0.076)		
	0.910***		−0.207***	0.054
	(0.048)		(0.073)	
	0.495	0.085	−0.203***	0.064
	(0.358)	(0.076)	(0.075)	
Solar	2.265***	−0.137		0.013
	(0.667)	(0.141)		
	1.602***		−0.275***	0.053
	(0.072)		(0.072)	
	2.336***	−0.151	−0.282***	0.069
	(0.681)	(0.144)	(0.071)	
GCI	2.099***	−0.163***		0.045
	(0.271)	(0.057)		
	1.307***		−0.234***	0.089
	(0.044)		(0.064)	
	2.160***	−0.175***	−0.243***	0.14
	(0.286)	(0.062)	(0.062)	

Note: This table reports the MIDAS regression estimates for green betas regressed against climate policy uncertainty (CPU) and technology speculative ratio (TSR). *, **, *** denote significance at 10, 5, 1% levels, respectively (standard errors reported in parentheses).

for climate uncertainty with insignificant effects observed for Wind and Geothermal, we find that technology speculation has a consistently negative effect on green betas in all industries at the highest level of statistical significance.[2] This result could be explained by the lottery-like features in these high-beta assets, which make them more subject to speculative demand. Bali et al. (2017) note that lottery investors generate demand for stocks with high upside probabilities in the stock price, which is more likely during periods of high speculative sentiment. The disproportionately high price pressure based on lottery demand then pushes the prices of these stocks up, thereby decreasing future returns. This, in turn, generates an intercept greater than the risk-free rate (positive alpha zero-beta stocks) and a slope less than the market risk premium, leading to a negative alpha on these stocks. Our results show that this manifests itself in the form of a negative relationship between speculation and betas, which is consistent with the recent evidence in Ghazi and Schneider (2022) that lottery-like stocks earn a negative speculative premium. Indeed, examining the green betas and average returns during high and low market states reported in Table 3, we observe in Panel A that green industries experience consistently lower betas during periods of high technology speculation, indicated by negative mean differences in betas (High–Low), while we also observe in Panel B that these higher green betas during high speculation are coupled with negative mean returns in all green industries, supporting a negative risk premium conditional on speculation. These findings are also in line with the evidence in Scheinkman and Xiong (2003) that stocks are overpriced when the level of speculative trading is high as lottery-seeking investors drive up the valuations of these stocks, leading to their underperformance.

4.2. Economic analysis

To explore the economic implications of our findings, given that the return-beta trade-off for green equities is driven by speculative sentiment in technology stocks, we examine a forward-looking investment strategy that is conditional on the level of speculation. To that end, we consider a passive investor currently invested in the MSCI World index and form a diversified portfolio by supplementing the passive index with each green industry index separately. Using the conditional volatility and covariance estimates obtained from the ADCC model, we estimate each month the optimal portfolio allocation for the passive market index

[2] Our findings are robust to the inclusion of the global VIX and EPU as control variables in the model as presented in Table A.1 in Appendix.

Table 3
Green betas, returns and market states.

Panel A: Green betas						
	Technology speculation			Climate uncertainty		
	High	Low	High–Low	High	Low	High–Low
Bioclean	1.1785	1.1771	0.0013 (0.053)	1.3741	1.0927	0.2814*** (2.771)
GCI	1.1893	1.3259	−0.1365*** (−4.707)	1.2643	1.2960	−0.031 (−0.407)
Geothermal	0.8554	0.8722	−0.016 (−0.637)	0.9842	0.8689	0.1152 (1.3613)
Solar	1.3995	1.5899	−0.1904*** (−5.205)	−0.00134	0.01346	−0.0148 (−0.1301)
Wind	0.7286	1.1049	−0.3762*** (−23.29)	0.00322	0.00418	−0.00096 (−0.0086)

Panel B: Green returns						
	Technology speculation			Climate uncertainty		
	High	Low	High–Low	High	Low	High–Low
Bioclean	−0.52%	0.079%	−0.60%*** (−4.363)	0.014%	0.41%	−0.39% (−0.9093)
GCI	−0.44%	0.060%	−0.50%*** (−3.936)	−0.017%	0.093%	−0.11% (−0.3302)
Geothermal	−0.32%	0.064%	−0.39%*** (−2.762)	0.071%	−0.21%	0.29% (0.7969)
Solar	−0.39%	0.10%	−0.49%*** (−3.238)	−0.49%	0.19%	−0.69%* (−1.4324)
Wind	−0.30%	0.063%	−0.36%*** (−3.017)	−0.12%	0.13%	−0.25% (−0.7685)

Note: Panel A (B) reports the average green betas (green equity returns) during high and low market states associated with each column. A High (Low) market state is characterized by the index value above (below) the 90% percentile. The column 'High–Low' reports the mean difference between the high and low market states. *, **, *** denote significance at 10, 5, 1% levels, respectively (t-statistics reported in parentheses).

Table 4
Economic implications.

Panel A: Pre-Paris agreement period (10/22/2010–12/31/2015)						
	Bioclean	Wind	Solar	Geothermal	GCI	MSCI World
Average	−0.0032%	0.0265%	−0.0238%	−0.0098%	−0.0455%	0.0209%
Std. Dev.	1.514%	0.936%	1.796%	1.265%	1.624%	0.9731%
SR	−0.319%	1.620%	−1.337%	−0.792%	−2.814%	2.381%
Beta	0.946	1.107	1.344	0.694	1.344	
TR	−0.003%	0.020%	−0.017%	−0.014%	−0.034%	0.020%

Panel B: Post-Paris agreement period (1/4/2016–3/2/2023)						
	Bioclean	Wind	Solar	Geothermal	GCI	MSCI World
Average	0.0719%	0.0142%	0.0967%	0.0394%	0.0362%	0.0255%
Std. Dev.	1.282%	1.733%	2.270%	1.927%	1.754%	1.624%
SR	5.019%	0.631%	4.117%	1.880%	1.879%	2.161%
Beta	0.999	0.732	1.399	0.810	1.220	
TR	0.022%	0.014%	0.066%	0.044%	0.027%	0.025%

Note: Panel A(B) reports the performance metrics for the dynamic investment strategy that involves the passive market index and each green equity index before (after) the 2016 Paris Climate Agreement. Beta, SR, and TR are the beta, Sharpe, and Treynor ratios for the dynamic portfolio strategy, respectively.

and each green industry via

$$w_t^{x/y} = \frac{h_t^y - h_t^{x/y}}{h_t^x - 2h_t^{x/y} + h_t^y}, \qquad w_t^{x/y} = \begin{cases} 0, & \text{if } w_t^{x/y} < 0 \\ w_t^{x/y}, & \text{if } 0 \le w_t^{x/y} \le 1 \\ 1, & \text{if } w_t^{x/y} > 1 \end{cases} \tag{9}$$

where $h_t^{x/y}$ is the conditional covariance and the weight of the passive index x in a one-dollar portfolio of the two assets is given by $w_t^{x/y}$. Next, following Cepni et al. (2022), we supplement the passive market index with a position in each green industry when speculative sentiment is low and remain passive during the high speculation state, characterized by the (TSR) values above the 90th percentile of the trailing 6-month empirical distribution. We then compare the performance metrics of the subsequent returns for

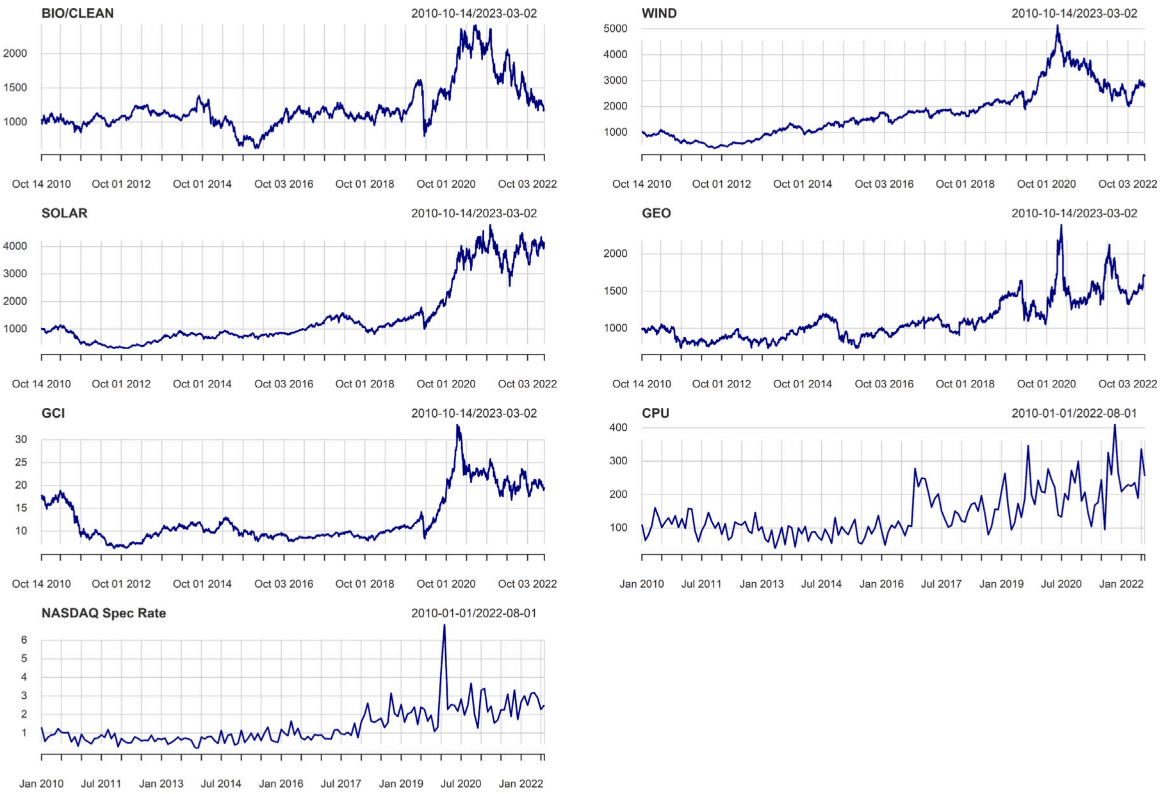

Fig. A.1. Green equity indices, CPU, and technology speculation.

the passive market index against the active portfolio strategy supplemented with each green industry one at a time. Furthermore, motivated by the finding by Monasterolo and De Angelis (2020) that the Paris Climate Agreement (PCA) has had a prominent impact on the systematic risk for green equities, we further split the sample into pre- and post-PCA to examine the efficiency of our active portfolio strategy.

The portfolio metrics reported in Table 4 indicate that supplementing the passive market index with green equity indexes conditional on speculative sentiment provides remarkable benefits, particularly during the post-Paris Agreement period. While the results for the pre-Paris period are dismal, we observe in Panel B that all portfolios supplemented with green industries, except wind yields, improved returns compared with the passive market index during the post-Paris agreement period. Bioclean and Solar stand out with the most significant improvement in portfolio returns of 0.0719% and 0.0967%, respectively. In contrast, the active portfolio supplemented with positions in Solar offers significantly improves risk-adjusted returns with Sharpe ratio and Treynor index value of 4.117 and 0.066 percent, respectively, compared to 2.161 and 0.025 percent for the passive market index. In short, our results show that the effect of technology sentiment on systematic risk and return dynamics in green equity sectors can indeed be exploited within a forward-looking investment strategy to supplement passive investments with green equities.

5. Conclusion

Beta is a key factor in assessing the market exposure of assets and beta estimates are often used by fund managers in their strategic and tactical allocation models. We extend the emerging literature on climate finance in a novel direction by exploring the drivers of betas in a variety of green equity sectors, including geothermal, wind, solar, bioclean, and clean energy stocks. Our findings show that green betas are predominantly driven by speculative sentiment in technology stocks rather than climate uncertainty. We argue that the lottery-like features of green assets whose values are highly tied to the success of new technologies result in a negative risk-mispricing relationship driven by speculation in technology stocks. Subsequently, we show that a forward-looking investment strategy conditional on technology sentiment can offer improved risk-adjusted returns for passive equity investors. Our findings establish a new speculation-based channel for characterizing the systematic risk of green assets. This is an important consideration as betas are not directly observable although beta estimates are widely used by fund managers in investment decisions. Thus, our findings offer an alternative setting to estimate betas to be utilized in tactical asset allocation models for this growing asset class. Furthermore, our findings open a new channel of interaction between green and technology stocks from a new perspective, highlighting the role of technology sentiment on green asset performance. Finally, our findings underscore the lottery-like nature of green equities, tied to the success of emerging technologies, and suggest that mispricing in these assets could be driven by investor sentiment in technology stocks, which in turn, can be used in betting against beta strategies that involve green equities.

Table A.1
The effect of speculation, climate and economic uncertainty on green betas.

	c	CPU	TSR	GEPU	VIX	R^2
Bioclean	−0.118	0.287***		0.287	−0.263	0.073
	(0.838)	(0.001)		(0.202)	(0.205)	
	1.024***		−0.293***	−0.122	0.050	0.089
	(0.451)		(0.082)	(0.207)	(0.156)	
	−0.017	0.270***	−0.277***	−0.179	−0.041	0.159
	(0.641)	(0.098)	(0.081)	(0.186)	(0.142)	
Wind	2.995***	−0.242***		−0.219	0.250***	0.207
	(0.302)	(0.053)		(0.158)	(0.069)	
	2.083***		−0.152***	−0.222	−0.339	0.152
	(0.049)		(0.061)	(0.154)	(0.078)	
	3.056***	−0.252***	−0.167***	−0.168	−0.253	0.252
	(0.309)	(0.053)	(0.055)	(0.161)	(0.070)	
Geothermal	0.505	0.130		−0.463	−0.076	0.061
	(0.648)	(0.071)		(0.211)	(0.187)	
	1.030*		−0.191***	−0.382	−0.040	0.086
	(0.561)		(0.069)	(0.207)	(0.190)	
	0.571	0.119	−0.184**	−0.408*	−0.0180	0.103
	(0.659)	(0.072)	(0.072)	(0.205)	(0.186)	
Solar	2.230***	−0.109		−0.467	−0.032	0.038
	(0.805)	(0.137)		(0.201)	(0.197)	
	1.842***		−0.257***	−0.414*	−0.080	0.076
	(0.531)		(0.068)	(0.190)	(0.186)	
	2.326***	−0.125	−0.265**	−0.387*	−0.037	0.087
	(0.797)	(0.140)	(0.069)	(0.191)	(0.194)	
GCI	1.836***	−0.163***		−0.303*	0.090	0.068
	(0.515)	(0.053)		(0.167)	(0.141)	
	1.234***		−0.223***	−0.0271	0.025	0.106
	(0.393)		(0.060)	(0.146)	(0.143)	
	1.920***	−0.178***	−0.233***	−0.233	0.086	0.155
	(0.536)	(0.055)	(0.061)	(0.159)	(0.142)	

Note: This table reports the MIDAS regression estimates for green betas regressed against climate policy uncertainty (CPU) and technology speculative ratio (TSR) along with control variables including the CBOE Volatility Index (VIX), and global economic policy uncertainty index (GEPU). *, **, *** denote significance at 10, 5, 1% levels, respectively (standard errors reported in parentheses).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

See Fig. A.1 and Table A.1.

References

Balcılar, M., Demirer, T., Ulussever, R., 2017. Does speculation in the oil market drive investor herding in emerging stock markets? Energy Econ. 65, 50–63.
Bali, T., Brown, S., Murray, S., Tang, Y., 2017. A lottery-demand-based explanation of the beta anomaly. J. Financ. Quant. Anal. 52, 2369–2397.
Bolton, P., Kacperczyk, M., 2021. Do investors care about carbon risk? J. Financ. Econ. 142, 517–549.
Bouri, E., Dudda, T.L., Rognone, L., Walther, T., 2023. Climate risk and the nexus of clean energy and technology stocks. Ann. Oper. Res. http://dx.doi.org/10.1007/s10479-023-05487-z.
Cappiello, L., Engle, R.F., Sheppard, K., 2006. Asymmetric dynamics in the correlations of global equity and bond returns. J. Financ. Econom. 4 (4), 537–572.
Carvajal, M., Nadeem, M., 2023. Financially material sustainability reporting and firm performance in New Zealand. Medit. Account. Res. 31 (4), 938–969.
Cepni, O., Demirer, R., Rognone, L., 2022. Hedging climate risks with green assets. Econom. Lett. 212, 110312.
Chiu, I.H., 2022. The EU sustainable finance agenda: developing governance for double materiality in sustainability metrics. Eur. Bus. Organ. Law Rev. 23 (1), 87–123.
D'Orazio, P., Popoyan, L., 2019. Fostering green investments and tackling climate-related financial risks: Which role for macroprudential policies? Ecol. Econom. 160, 25–37.

Dutta, A., Bouri, E., Rothovius, T., Uddin, G.S., 2023. Climate risk and green investments: New evidence. Energy 265, 126376.
Engle, R., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. J. Bus. Econom. Statist. 20 (3), 339–350.
Faccini, R., Matin, R., Skiadopoulos, G., 2023. Dissecting climate risks: Are they reflected in stock prices? J. Bank. Financ. 155, 106948.
Garcia, P., Leuthold, R.M., Zapata, H., 1986. Lead–lag relationships between trading volume and price variability: New evidence. J. Futures Mark. (1986-1998) 6 (1), 1.
Gavriilidis, K., 2021. Measuring climate policy uncertainty. Available at SSRN 3847388.
Ghazi, S., Schneider, M., 2022. Market risk and speculation factors (Sep. 2 2022). Available at SSRN: https://ssrn.com/abstract=4187398.
Ghysels, E., Santa-Clara, P., Valkanov, R., 2006. Predicting volatility: getting the most out of return data sampled at different frequencies. J. Econometrics 131 (1–2), 59–95.
Gunningham, N., 2020. A quiet revolution: Central banks, financial regulators, and climate finance. Sustainability 12 (22), 9596.
Hong, H., Sraer, D.A., 2016. Speculative betas. J. Finance 71 (5), 2095–2144.
Inchauspe, J., Ripple, R.D., Trück, S., 2015. The dynamics of returns on renewable energy companies: A state-space approach. Energy Econ. 48, 325–335.
Kumar, S., Managi, S., Matsuda, A., 2012. Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. Energy Econ. 34 (1), 215–226.
Lucia, J.J., Mansanet-Bataller, M., Pardo, Á., 2015. Speculative and hedging activities in the European carbon market. Energy Policy 82, 342–351.
Monasterolo, I., De Angelis, L., 2020. Blind to carbon risk? An analysis of stock market reaction to the Paris Agreement. Ecol. Econom. 170, 106571.
Naeem, M.A., Balli, F., Shahzad, S.J.H., de Bruin, A., 2020. Energy commodity uncertainties and the systematic risk of US industries. Energy Econ. 85, 104589.
Pizzi, S., Principale, S., De Nuccio, E., 2023. Material sustainability information and reporting standards. Exploring the differences between GRI and SASB. Medit. Account. Res. 31 (6), 1654–1674.
Scheinkman, J.A., Xiong, W., 2003. Overconfidence and speculative bubbles. J. Polit. Econ. 111, 1183–1219.
Treepongkaruna, S., Chan, K.F., Malik, I., 2023. Climate policy uncertainty and the cross-section of stock returns. Finance Res. Lett. 55, 103837.
Xie, J., Tanaka, Y., Keeley, A.R., Fujii, H., Managi, S., 2023. Do investors incorporate financial materiality? Remapping the environmental information in corporate sustainability reporting. Corp. Soc. Responsib. Environ. Manag. 30 (6), 2924–2952.
Yu, H., Fang, L., Du, D., Yan, P., 2017. How EPU drives long-term industry beta. Finance Res. Lett. 22, 249–258.