From Equity Greenium to Carbon Return: Discovering Social Signal of Climate Conscience*

by

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Abstract

This study innovatively quantifies the process of belief updates concerning climate change, charting the progression toward the "carbon-aware" equilibrium where a carbon risk premium is priced, thereby providing a nuanced understanding of how market perceptions evolve in response to climate-related risks. In contrast to previous studies identifying climate change concerns in news media that lead to stock-pricing deviations away from the equilibrium, this research discovers the social signal of climate conscience to assess the effects of aggregate belief updates on the transition from the realized positive equity greenium toward the expected positive carbon return in equilibrium with both unscaled and scaled carbon emission metrics. Through situating social media as a critical information system that amplifies collective climate conscience, this research also illuminates how digital platforms catalyze societal shifts and advance behavioral insights in climate finance.

Keywords: Climate Change, Asset Pricing, Carbon Emission, Stock Return, Social Media

JEL Classification: G02, G10, G11, G12, Q54, Q58

1 Introduction

Climate change has been considered as one of the biggest risks for financial system in our time, which makes the pricing and hedging of climate risk in financial market a salient research topic known as climate finance (Stroebel & Wurgler, 2021; Giglio et al., 2021). Previous studies have tried to understand the climate risk by looking into its implications in asset pricing (Sautner et al., 2023; Barnett, 2023; Ginglinger & Moreau, 2023). Furthermore, works contributed to the signal of climate risk on the stock market have been limited to indirect paths including news media, extreme temperature, or natural disasters without a direct standpoint from the words of public audience (Engle et al.,2020; Addoum et al., 2023; Pankratz et al., 2023). On the other hand, while prior literature in information system (IS) have explored the role of social media in financial markets with textual analysis and found significant predictive power in asset pricing (Nguyen et al., 2020; Bartov et al., 2023; Bianchi et al., 2024; Cookson et al., 2024), none have isolated the climate-specific social signal and examine its aggregate influence on the asset pricing of climate risk.

In the context of climate-aware investing, "equity greenium" is defined as the differential in expected returns between environmentally sustainable (green) and non-sustainable (brown) stocks (Pástor et al., 2022). However, unlike green bond being a separately issued debt security verified by specific green criteria, the greenness of stock is hard to explicitly and precisely measured. Past works have found significant return spread between green and brown stocks that cannot be explained by the existing factors, but disagree on the direction and magnitude of the return spread while variously adopting environmental score, total GHG (greenhouse gas) emissions level or GHG emissions intensity in the greenness measurement (Bolton and Kacperczyk, 2021; Choi et el., 2022; Ardia et al., 2023). Therefore, this research aims to examine the equity greenium performance across unscaled and scaled emissions while innovatively investigating into the social signal of climate conscience from the words of social media, addressing on the question: how would equity return perform across different

greenness screening criteria considering the social signal of climate conscience based upon past realizations?

This research is primarily guided by the equilibrium model of Pástor, Stambaugh and Taylor (2021, henceforth PST), pollution premium assertion of Hsu et al. (2023), and carbon return evidence of Zhang (2024), which predict that green assets have lower expected returns than brown assets ex ante in the "carbon-aware equilibrium" with carbon-aware investments due to green assets' hedging feature against climate risk and brown assets' premium of carbon transition risk, but could exhibit outperformance over brown assets ex post during transition to the equilibrium. To research on the performance of equity greenium, the research measures stock greenness by GHG metrics to demonstrate the climate investing strategy in support of the carbon-neutral initiative.

To investigate into the dynamics of the equity greenium along the transition toward the carbon-aware equilibrium, our study constructs a novel index to quantify the social signal of climate conscience with a dataset of 620k posts about climate change from social media. The analysis on the social media text is conducted through aggregate visions of attention, positivity and popularity in discovering social signal of climate conscience to check the impact of its updates on the stocks measured by greenness, providing empirical evidence for the PST model in climate finance and contributing to the development of behavioral finance in the background of global market transition to low-carbon economy.

Our novelty lies in (i) developing the Social Media Climate Conscience (SMCC) index to quantify climate-related public awareness measuring the belief updates along the awakening to the issue of climate change from skepticism (ii) empirically linking the belief updates to the equity greenium under the transition toward the carbon-aware equilibrium, a novel approach that bridges climate finance and information system. This dual emphasis represents a significant departure from earlier work focused primarily on either social signal in financial markets or asset pricing in climate finance in isolation.

2 Hypotheses Development

As illustrated by the research model in **Figure 1**, this research strives to examine the equity return performance across different greenness screening conditions and innovatively investigating into the social signal of climate conscience from the words of public for its effect on equity greenium, addressing on the question: how would equity return perform considering social signal of climate conscience based upon past realizations and across different greenness screening criteria?

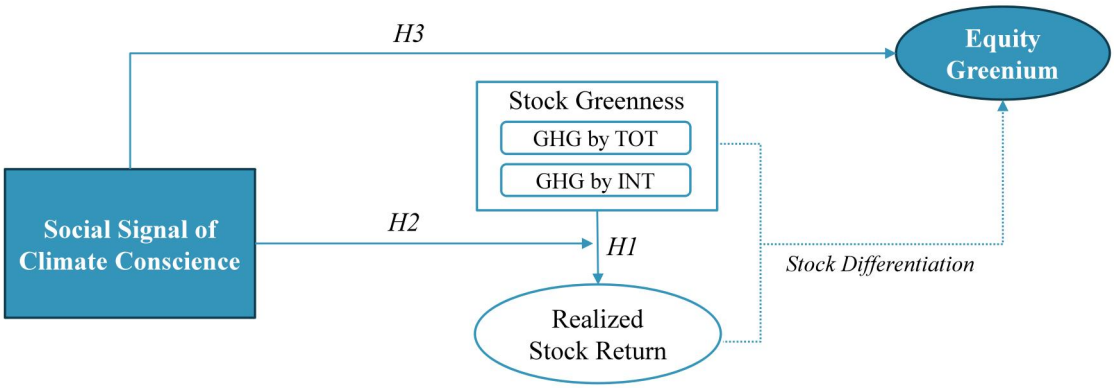


Figure 1. Research Model

2.1 Greenness and Stock Return

Bolton and Kacperczyk (2021) propose carbon risk premium hypothesis that firms with higher carbon dioxide emissions should provide higher stock returns to compensate the higher climate transition risk investors withstand by holding the browner assets. Moreover, PST equilibrium model anticipates a positive carbon premium in equilibrium where green assets have lower expected returns than brown due to green tastes of investors, and risk-hedging feature of greener assets against climate change (Pástor et al., 2021). However, past studies have provided empirical evidence for the extension of the model which posits that deviations from the equilibrium can occur while green assets have higher realized returns as demands for green assets increase unexpectedly (Ardia et al., 2023). Furthermore, the research of Zhang (2024) on the global carbon returns clarifies that green assets outperform brown assets in the developed markets with an ongoing transition to the carbon-aware equilibrium while countries with tighter climate policies (e.g., China) exhibit positive carbon returns,

compensating for climate transition risk as in equilibrium. Therefore, the hypothesis of firm greenness and stock returns is proposed as ***H1:*** *Stock Returns are affected by Stock Greenness in the cross section of stock market.*

H1a*: Greener stocks with better carbon performance have higher realized return.*

H1b: *Browner stocks with worse carbon performance have higher realized return.*

2.2 Social Signal of Climate Conscience

Choi et al. (2020) suggest that investors may update their beliefs about firms' valuation as they become more aware of climate risk upon recognizing the effect of climate change, bringing the aggregate beliefs closer to the scientific consensus. Bolton and Kacperczyk (2021) also expect that periods with greater climate change awareness (e.g., after Paris Agreement) would have a higher carbon premium. Cookson et al. (2024) provide empirical evidence supporting the impact of social signals from social media on stock returns and delves into the sentiment and attention characteristics. Zhang (2024) addresses that the outperformance of greens assets over brown assets in financial markets is consistent with the pattern during the transition to the carbon-aware equilibrium. In conjunction with insights into aggregate belief updates and social signals in relation to stock returns, the aggregate belief updates about climate change, assessed by climate conscience updates from social media, are expected to have dynamic impacts on stock return for financial markets under different stages of the transition toward the equilibrium. The hypothesis for the moderating effect of climate conscience updates thus refers to ***H2:*** *The positive (negative) relationship between the stock greenness and realized returns is associated with climate conscience updates from social media.*

H2a*: Greater climate conscience updates strengthen the negative relationship between the stock greenness and realized returns.*

H2b*: Greater climate conscience updates diminish the positive relationship between the stock greenness and realized returns.*

2.3 Climate Conscience and Equity Greenium

Pástor et al. (2022) operationalize the equity greenium through the expected return on the green-minus-brown (GMB) portfolio. Their empirical analysis estimates a negative equity greenium by removing unanticipated shocks and earnings effects from realized GMB returns, consistent with the prediction of their PST model that green assets have lower expected returns than brown assets in equilibrium. The study of carbon return across the globe also reveals that developed markets experience positive equity greenium in consistent with transition to the carbon-aware equilibrium while countries getting closer to the full carbon awareness exhibit negative equity greenium (Zhang, 2024), implying a possible reduction of equity greenium as the carbon awareness grows along the transition, while bringing aggregate beliefs closer to the equilibrium with carbon premium. Accordingly, the study formulates the hypothesis for climate conscience updates and equity greenium as **H3:** *Realized equity gereenium is affected by climate conscience updates from social media.*

H3a: *Realized equity greenium is higher when climate conscience updates get more substantial.*

H3b: *Realized equity greenium is lower when climate conscience updates get more substantial.*

3 Data and Methodology

3.1 Measuring Greenness by GHG metrics

The greenness of a company is measured by its GHG emission metrics as in the screening of climate investing strategy. GHG Protocol Corporate Standard has separated the GHG emission into three scopes with scope 1 being direct emissions of the owned/controlled sources, scope 2 being indirect emission from purchased energy and scope 3 as indirect emissions from not-owned/controlled sources along the value chain. With reference to the works of Bolton and Kacperczyk (2023) and Aswani et al. (2024), this research considers 2 metrics of GHG emissions in firm level: 1) TOT as the total emission level summing the three scopes of GHG emission in tonnes of CO2 equivalents; 2) INT as emission intensity that scales total emission by the firm's annual revenue for measuring tonness of CO2 equivalents necessary to generate $1 million in revenue. The two metrics are thus calculated as:

$$GHG_{i,t} = \begin{cases} GHG_{i,t}^{TOT} = \sum_{j=1}^{3} Scope_{j,i,t} \\ GHG_{i,t}^{INT} = \dfrac{\sum_{j=1}^{3} Scope_{j,i,t}}{\mathrm{Re}venue_{i,t}} \end{cases} \tag{1}$$

Therefore, the greenness of stocks $G_{i,t}$ can be measured by taking the negative values of log-transformed GHG emission metrics of the firm i at time t with $N^t(\cdot)$ being a normalization function that scaled the GHG value by date:

$$G_{i,t} = N^t(-\log[GHG_{i,t} + 1]) \tag{2}$$

The analysis of all stock in the U.S. stock market with GHG emission disclosure till 2021 are shown in the **Table 1.** The industry of Tobacco Products has the highest GHG disclosure rate reached 71% where the Petroluem industry generated the most total emissions of 41 million tonness with 24% disclosure rate over the last decade despite Coal industry having the highest emission intensity of 8,426 tonness for every $1 million revenue with higher disclosure rate of 29%. At the bottom of the table, summary statistics of the industry emission conditions are provided. Whereas the average GHG total emission and intensity across all industries is about 8 million and 687 tonnes of CO_2 equivalent emissions per $1 million in revenue, with the 25th and 75th percentiles listed below.

Table 1. Industry GHG Statistics

Industry	Firms	D (%)	Av.IBT (m)	Av.TOT (Kt)	Av.INT (T/m)
Tobacco Products	6	71.05	4,154	2,845	114
Shipping Containers	13	63.16	277	9,343	1,277
Utilities	96	55.66	447	31,586	3,636
Business Supplies	43	42.01	403	4,803	371
Beer & Liquor	11	35.87	1,103	11,914	373
Non-Metallic and Industrial Metal Mining	24	35.5	144	3,435	637
Aircraft	23	32.99	848	5,929	170
Food Products	75	32.58	402	5,266	383
Chemicals	91	32.23	269	8,324	1,259
Coal	19	29.27	-80	34,350	8,426
Consumer Goods	54	28.68	498	11,144	615
Automobiles and Trucks	79	28.46	410	26,131	249
Rubber and Plastic Products	22	25.28	55	1,266	183
Precious Metals	16	25	42	3,299	561
Petroleum and Natural Gas	205	24.05	309	41,822	1,973
Machinery	107	23.84	253	22,441	1,793
Transportation	86	22.11	439	14,229	641
Apparel	46	21.66	257	1,043	127
Computers	141	20.74	286	4,343	266
Other	54	20.14	1,242	23,440	2,387

Measuring and Control Equipment	85	20.07	290	521	47
Insurance	130	19.66	687	111	4
Steel Works Etc.	48	19.16	81	13,626	1,326
Retail	228	19.08	496	3,711	229
Electronic Equipment	252	17.69	611	4,642	443
Meals Restaurants, Hotels, Motels	83	15.71	264	6,805	536
Textiles	10	15.66	111	2,924	458
Defense	11	15.29	579	33,489	711
Candy & Soda	14	15.05	1,057	18,898	509
Electrical Equipment	109	13.03	116	662	203
Wholesale	134	12.73	131	3,905	202
Construction Materials	72	12.69	105	1,292	253
Real Estate	53	12.23	85	12,899	621
Recreation	30	11.98	49	206	42
Trading	153	11.61	458	144	11
Agriculture	12	10.67	218	3,181	288
Business Services	690	10.67	272	880	114
Entertainment	69	10.07	58	768	109
Printing and Publishing	24	9.66	19	224	84
Communication	125	9.17	838	5,034	87
Shipbuilding, Railroad Equipment	10	8.89	151	205	62
Construction	65	8.23	150	518	259
Medical Equipment	204	7.54	90	661	69
Personal Services	52	6.32	91	4,808	653
Healthcare	88	5.19	137	320	39
Banking	656	4.42	386	661	19
Pharmaceutical Products	752	4	151	2,637	104
Fabricated Products	11	3.28	12	52	42
Across-industry mean	112	20.83	405	8,140	687
Across-industry 25th percentile	23	10.67	110	742	108
Across-industry 75th percentile	113	26.08	450	11,336	625

Note: The above GHG data is for the recent decade till 2021 (2011 January to 2021 December). The table reports the average and standard deviation of GHG total emissions and intensities from the dataset of Refinitive (formerly Thomson Reuters), along with firms in the industry, industry GHG Disclosure rate, average IO% for Institutional Ownership and average IB% for Income before extraordinary items. The industries in the table are defined by the 48-industries classification in Fama and French (1997).

As revealed by the statistics of **Table 2**, emission data is typically reported with a one-year delay. The GHG emission reported till 2021 December only has 3.92% disclosed for 2021. Therefore, similar to Ardia et al. (2021) and Ilhan et al. (2021), emission data are shifted by 12 months in measuring the greenness of stocks to account for the delay in the reality of conducting investing strategy and avoid forward-looking bias. (e.g., Zhang, 2024)

Table 2. Annual GHG Disclosure Rate in the US Stock Market

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2011-2020 Mean	2021
D (%)	11.91	12.49	12.93	13.12	14.34	15.88	17.53	19.41	22.7	22.26	16.26	3.92

The **Figure 2** presents the annual GHG Disclosure rate (D %) in the whole US stock market and especially for S&P500. Over the last two decade since 2000, the mean of annual GHG disclosure rate has increased from 4.1% to 16.26% in the U.S. market and from 29.64%

to 75.78% for S&P500, align with the increasing addressment on climate change risk in financial market by regulators and investors. Hence, the empirical analysis will be conducted on the S&P500 sample due to its comprehensive greenhouse gas disclosure coverage and its representation of the overarching trends in the financial market.

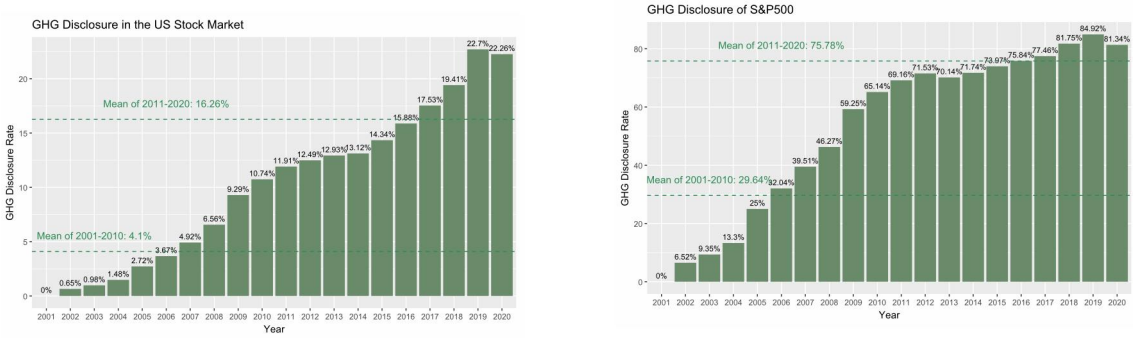


Figure 2. Annual GHG Disclosure on US Stock Market

3.2 Stock Portfolios by Greenness

Based on stock greenness measured by GHG metrics of TOT (total emission) and INT (emission intensity), equal-weighted stock portfolios are constructed for each month by evenly categorizing stocks into 3 groups of green, brown and neutral assets, where the green (brown) assets would be the equities with green scores in the top (bottom) third while neutral assets have greenness in the middle (e.g., Pástor et al., 2022).

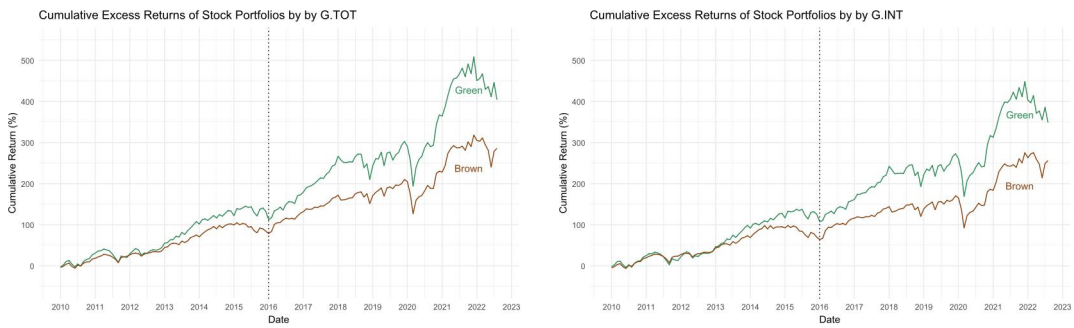


Figure 3. Cumulative Excess Returns of Stock Portfolios

As shown in **Figure 3**, green portfolios have higher cumulative return than brown portfolios when stock greenness is either measured by GHG TOT (total emissions) or INT (emission intensity), which means green stocks overall outperform the brown in recent years. The underperformance of brown assets measured by unscaled and scaled emission metrics

indicates a lack of investor confidence in companies that are high emitters or inefficient in their emissions management. For further analysis, a Green-Minus-Brown (GMB) portfolio is constructed on the S&P500 of U.S. stock market by longing green stocks while shorting brown ones (e.g., Ardia et al., 2023). The **Table 3** provides GMB 12-year realized performance since 2010 with FF3, FF5, market and economic factors where the GMB return averaged 21.6 bps and 17.9 bps per month for stock greenness measured by unscaled and scaled GHG emissions respectively. Obviously, The strong performance of GMB portfolio cannot be explained by exposures to the typical factors from previous asset pricing literature.

Table 3. GMB Performance

Greenness:	G^{TOT}					G^{INT}				
Greenium: GMB Return	G	Ctrl. FF3	Ctrl. FF5	Ctrl. MKT	Ctrl. ECON	G	Ctrl. FF3	Ctrl. FF5	Ctrl. MKT	Ctrl. ECON
Intercept	0.216	0.014	0.124	0.166	0.309	0.179	-0.01	0.101	0.747*	0.909**
	(0.154)	(0.152)	(0.147)	(0.401)	(0.411)	(0.194)	(0.175)	(0.176)	(0.424)	(0.456)
Mkt-RF		0.175***	0.155***	0.153***	0.16***		0.165***	0.15***	0.126***	0.127***
		(0.052)	(0.051)	(0.044)	(0.048)		(0.058)	(0.052)	(0.044)	(0.047)
HML		-0.11**	0.022	0.017	-0.083		-0.114**	0.006	-0.014	-0.114
		(0.051)	(0.073)	(0.076)	(0.076)		(0.048)	(0.069)	(0.075)	(0.08)
SMB		0.233***	0.158**	0.159*	0.14*		0.083	-0.006	0.017	-0.004
		(0.064)	(0.077)	(0.084)	(0.082)		(0.073)	(0.077)	(0.086)	(0.085)
CMA			-0.288***	-0.283***	-0.277***			-0.245**	-0.219*	-0.229**
			(0.104)	(0.102)	(0.101)			(0.107)	(0.118)	(0.11)
RMW			-0.178	-0.179	-0.115			-0.228**	-0.213	-0.145
			(0.115)	(0.118)	(0.133)			(0.114)	(0.141)	(0.131)
MOM				-0.007	-0.048				0.004	-0.043
				(0.058)	(0.055)				(0.064)	(0.054)
VIX				-0.002	0.002				-0.033*	-0.042
				(0.022)	(0.023)				(0.02)	(0.028)
EPU					-0.126					0.018
					(0.234)					(0.189)
TERM					4.361***					5.132***
					(1.36)					(1.244)
DFLT					2.66***					3.557***
					(0.903)					(1.034)
adj.R.squared	0	0.201	0.237	0.227	0.285	0	0.103	0.137	0.133	0.211

*Note. We estimate monthly time-series regressions for 12-year period since 2010. Factor description can be found in Appendix A. Returns are in percent per month. Robust t-statistics are in parentheses. Normalized green scores are winsorized at the 1st and 99th percentiles to address outliers. Significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.*

3.3 Climate Change Social Media Corpus

The social media corpus adopted in this research are the comments containing "climate change" from Reddit. VADER (Valence Aware Dictionary and sEntiment Reasoner) natural language model is employed to analyze the positivity of social media texts. The degree of positivity is then integrated with the Reddit user-voted score of each post and weighted by attention, for generating index to observe their effects on equity greenium.

To refine the social media text data, UDPipe (Universal Dependency Pipe) is utilized for tokenization, part-of-speech tagging, and syntactic parsing. UDPipe, is a transition-based dependency parsing model trained on a corpus of annotated text data with neural networks. After processing the climate change-related social media texts with UDPipe, the CTM (Correlated Topic Model) model is applied. The CTM model is a neural network-based machine learning algorithm that extends from the LDA (Latent Dirichlet Allocation) model, which is preferred here due to its ability to model correlations between topics using a Gaussian distribution, unlike the LDA model which relies on the Dirichlet distribution and assumes topic independence. The CTM is thus employed to mine underlying themes within the social media texts that all related to climate change. This choice is informed by Hansen et al. (2018), Faccini et al. (2021), Larsen and Thorsrud (2022) who note that the CTM model generates more coherent topics by allowing for non-zero correlations.

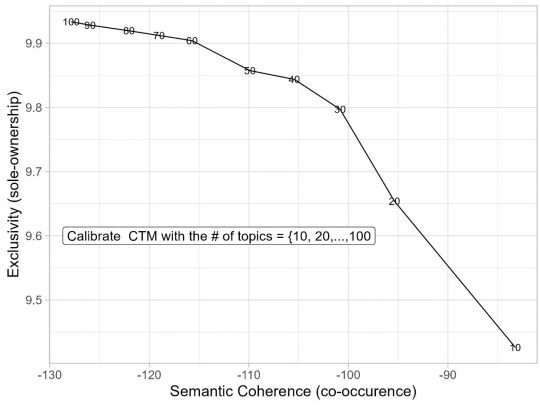


Figure 4. Simulation for the Number of Topic

As the **Figure 4** displayed, iterative simulations are conducted to determine the optimal number of topics to be 30, as this number provides the best balance of semantic coherence

and exclusivity, with a reduction in the number of topics significantly decreasing exclusivity. The resulted 30 climate-related topics with top 10 keywords are shown in **Table 4.**

Table 4. Topic with Top 10 keywords

30 Topics	*Top 10 Keywords in term of Probability*
Carbon Footprint	carbon, plant, tree, soil, food, forest, animal, forests, land, atmosphere
Urban Sewage	water, city, place, home, building, area, town, rain, property, air
Wildfire Risk	fire, area, region, wildfire, summer, year, location, risk, climate, air
Temperature	unit, range, activity, weight, temperature, auction, result, test, condition, method
Biodiversity	species, ice, climate change, change, extinction, animal, glacier, ocean, ecosystem, concept
Disaster	climate change, food, people, flood, drought, disease, world, crop, disaster, risk
Weather Event	year, climate, temperature, weather, climate change, event, time, change, century, warming
Global Warming	atmosphere, global warming, earth, temperature, carbon dioxide, warming, effect, model, planet, human
Sea Level	storm, sea level, sea, land, island, sea level rise, site, hurricane, reef, coast
Climate Research	study, research, data, climate change, paper, researcher, survey, author, finding, researchers
Government Action	climate change, change, government, state, action, concept, threat, issue, group, climate
Public Health	percent, cost, health, impact, damage, climate change, concept, year, scenario, effect
International Agreement	climate, climate change, agreement, concept, worldnews, plan, world, target, emission, nation
Cryptocurrency	project, website, community, fee, token, platform, contract, foundation, climate change, charity
Country Emission	country, emission, region, population, discussion, level, climate change, source, capita, other country
Emission Regulation	section, year, act, target, purpose, climate change, emission, scheme, gas, regulation
Company/Investment	company, business, investment, risk, market, industry, fund, investor, oil, bank
Energy Source	energy, fossil fuel, power, coal, oil, technology, electricity, gas, fuel, renewable energy
Carbon Tax	government, tax, economy, world, policy, nation, carbon tax, system, dollar, power
Legislation/Policy	party, game, election, law, member, candidate, vote, bill, legislation, policy
Adaptation Program	report, adaptation, farmer, management, program, impact, area, climate, development, land
Education/Climate Activism	movement, climate, action, school, protest, climate crisis, activist, group, student, event
Waste/Plastic	day, waste, plastic, hand, week, tree, room, man, head, time
Resource/Population	world, resource, humanity, society, population, collapse, war, year, system, crisis
Pollution/Transportation	people, problem, climate change, way, environment, solution, issue, car, change, pollution
Career/Job	idea, work, topic, information, job, people, student, field, school, subject
Multimedia	time, video, book, story, day, truth, month, people, life, internet
News/Controversy	climate change, article, climate, global warming, fact, issue, opinion, argument, media, news
Future Generation	life, world, planet, child, earth, people, human, year, kid, family
Rule/Question	question, concern, answer, thanks, rule, climate change, look, page, engineering, bit

The **Figure 5** provides visualization of the Spearman correlation network not only facilitates the interpretation of complex inter-relationships among climate change topics but also highlights the inter-connectedness within the 3 clustered themes for three broad climate-change scenarios of environment and nature, governance and economy, and society and

communication. By focusing on correlations above the 0.35 threshold, the network diagram effectively filters out weaker associations, allowing for a clearer representation of the most significant and densely connected themes within the climate change discourse.

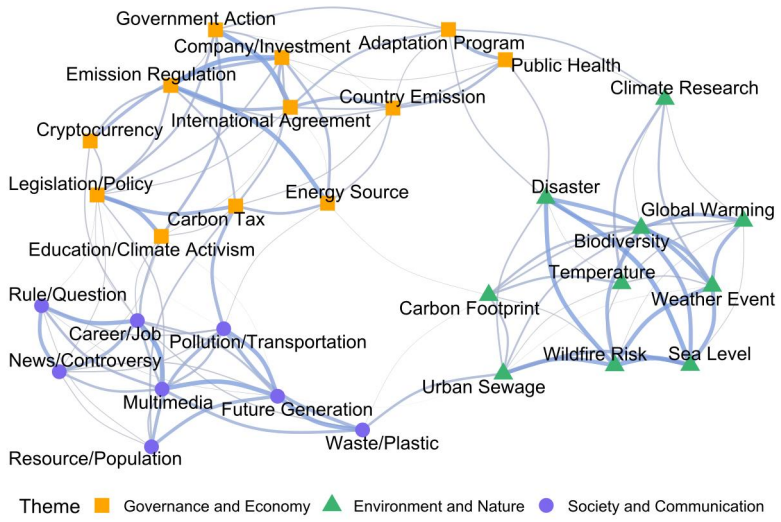


Figure 5. Topic Analysis with CTM - Neural Network

3.4 Social Media Climate Conscience Index

In light of the article selection method of climate change risk index by Engle et al (2020), the posts are filtered for the text containing "climate change". Through the analysis of social media texts related to climate change over the past decade using the VADER model, this study innovatively defines the **Social Media Climate Conscience (SMCC)** as "a thematic index to quantify the positive awareness and engagement surrounding climate change on social media", measuring the combined impact of how positive and popular "climate change" is perceived by the public with attention weight. As illustrated by **Table 5**, the social signal of climate conscience, proxied by SMCC, incorporates the attention, positivity and popularity features from Reddit posts, thereby aggregating the recognition of content generators and viewers regrading climate change across the social media attention. The index highlights the progression of the societal shift as individuals evolve their perspectives on climate change from skepticism toward acceptance, reflecting a growing

awareness and proactive stance along the course towards carbon-aware equilibrium, marking a novel contribution to the field.

Table 5. Social Signal of Climate Conscience

Social Signal	*Climate Conscience*	*Prior Literature*
Attention P:	Attention to "climate change" as volume of posts containing "climate change"	Attention and asset pricing (Da et al., 2011; Li et al., 2023); attention and climate change (Choi et el., 2022; Sautner et al., 2023); Social media attention (Shangguan et al., 2021; Cookson et al., 2024)
Positivity ψ:	Degree of positivity in each post content by compound sentiment analysis ranged in [0,1]	Sentiment and asset pricing (Han, 2008; Deng et al., 2018); sentiment and climate change (Engle et al.,2020; Ardia et al., 2023); social media sentiment and positivity (Renault, 2017; Cookson et al., 2020);
Popularity κ:	Popularity for each post as log net upvote score scaled in [1,10] from user interaction	Social media popularity (Dewan et al., 2017; Kitchens et al., 2020; Burtch et al., 2022; Agarwal et al., 2024)

Notably, the Reddit platform is designed with a voting system for user interactions to measure the post popularity and increase the visibility of post with high netupvotes, which amplifies the affordances of posts about climate change. Specifically, the Reddit popularity score is determined as the number of upvotes net of downvotes by users with initial score being 1 for new submissions, therefore the popularity score of a post is the result of user interactions supporting or against the post content. The SMCC index thus not only represents the positivity of the post itself, but as well the interest and attitude of the users who viewed the post and engaged.

Table 6. Media-based Climate Change index in Financial Markets

	Yan et al. (2024) (this research)	Ardia et al. (2022)	Engle et al. (2020)
Index	Social Media Climate Conscience (SMCC)	Media Climate Change Concerns (MCCC)	Intensity of negative climate news
Corpus Source	Social media: posts from Reddit	News media: articles from 10 newspapers & 2 newswires	News media: articles from Crimson Hexagon data vendor
Text Selection	Posts containing "climate change"	Articles tagged "climate change"	Articles containing "climate change"
Feature Extraction	1) Positivity degree by Vader sentiment intensity with structural features; 2) Attention (post volume); 3) Popularity (net upvotes)	1) Polarity by LIWC negative sentiment and uncertainty dictionaries; 2)Attention (article volume)	"Negative sentiment" category assigned by CH data vendor

Table 6 provides comparison of the SMCC index with other 2 climate change indexes adopting textual analysis in the prior literature of climate finance. Building upon the previous

works, this research analyzes the corpus from a different source that stands for the words of public audience instead of the new press, addresses the positive climate awareness to measure the growing recognition of climate change issue away from skepticism, and incorporates the user interaction feature of social digital platforms.

The conscience values of post p = 1,…,$P_{t,s}$ from subreddit s = 1,…,S at time t is calculated via having the Positivity degree ratio measured by Vader score for each post p multiplied by the log Reddit user-voted score (upvotes net of downvotes initialized from 1) scaled within [1,10], which aggregates the attitude of both post writers and viewers. As shown in equation (3), the conscience value at time t for subreddit s aggregates the post-level conscience across $P_{t,s}$ posts by having the product of attention volume and average conscience value, capturing both engagement and conscience level in the community:

$$Conscience_{t,s} = P_{t,s} \times \overline{(\underbrace{\psi_{p,t,s}}_{Positivity} \bullet \underbrace{\kappa_{p,t,s}}_{Popularity})} \tag{3}$$

The SMCC index is computed by taking the square root (increasing concave function) to the average of subreddit-specific climate conscience value at time t to account for the nonlinear relationship of decreasing effect with increasing attention while considering each subreddit independently and equally important:

$$SMCC_t = 100 \times \sqrt{\frac{1}{S}\sum_{s}^{S} Conscience_{t,s}} \tag{4}$$

In alignment with the conceptual delineations from previous literature regarding social media, this research conceptualizes the index pertaining to climate change that aggregates the corpus' features of positivity, popularity and attention as Climate Conscience, which represents the collective and individual recognition and awakening to the issue of climate change, underscoring an affirmative route to acknowledge the challenges posed by climate change along the course of becoming carbon-aware.

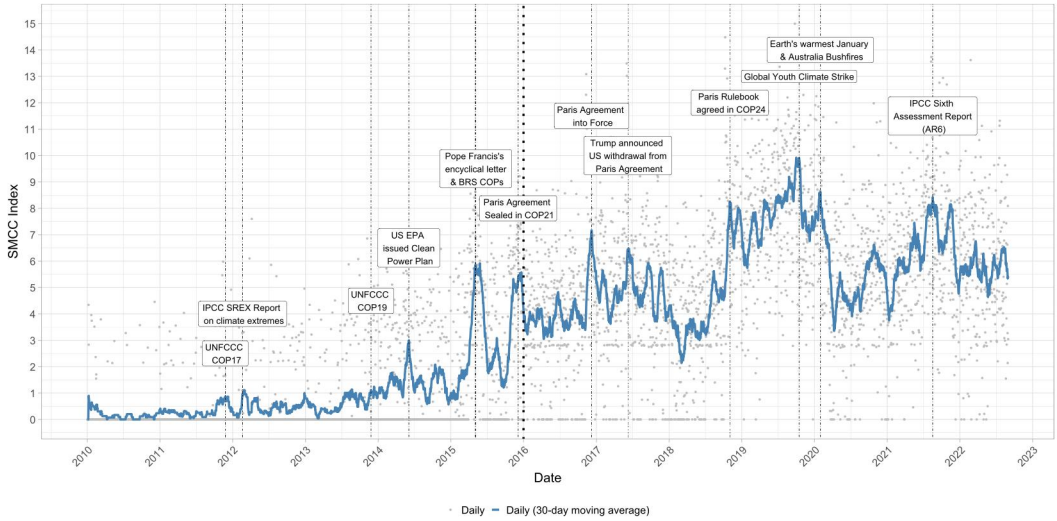


Figure 6. SMCC Daily Index with 30-day Moving Average

The evolution of the SMCC index from 2010 to 2022 is displayed in the **Figure 6** that visualizes scatter plots (gray points) of the daily index together with 30-day moving average of climate conscience (blue line). Several key events related to climate change, highlighted in boxes, are documented to help interpret the trend in conjunction with these occurrences. It is evident that the level of climate consciousness has exhibited a consistent upward trajectory over the past decade, marked by several notable spikes corresponding to significant conscience updates and milestones.

3.5 Belief Updates in Social Media Climate Conscience

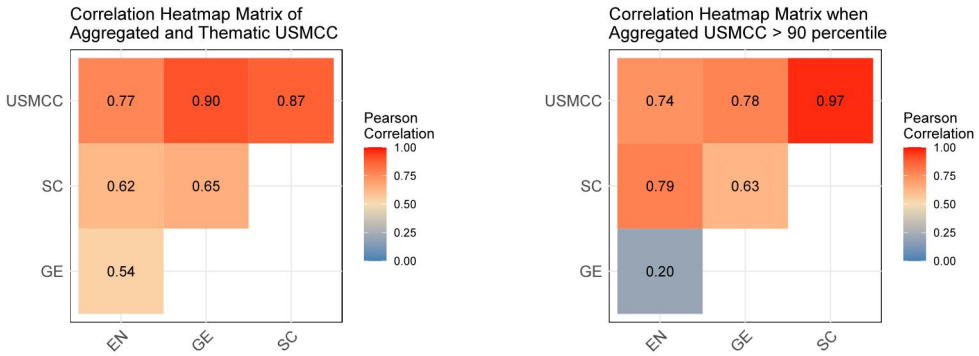
This research takes the approach to infer equity greenium from past realizations while taking considerations of unexpected changes in SMCC as belief updates along the course towards "carbon-aware" equilibrium, which is also served as empirical evidence for the PST model of Pástor et al. (2021). The Social Media Climate Conscience Updates (SMCCU) is proxied by the prediction error derived from an autoregressive model with exogenous inputs (ARX) applied to the Social Media Climate Conscience (SMCC) index.

Specifically, SMCCU at time *t* (denoted as $SMCCU_t$) is calculated as the difference between the actual SMCC value and its predicted value from the ARX model. To ensure robustness, a 72-month rolling window is employed, utilizing pre-Paris Agreement climate

conscience data (prior to 2015) to estimate the SMCC index for the post-2015 period. This approach captures social media climate conscience updates that are not explained by historical trends or exogenous factors, providing a measure of climate conscience updates from social media:

$$SMCC_t = c + \varphi SMCC_{t-1} + \gamma' X_{t-1} + \varepsilon_t \tag{5}$$

Where the vector of exogeneous inputs X_t is included to mitigate the problem of endogeneity by capturing potential confounders that may affect the $SMCC_t$ index with its variables listed in the table of variables in Appendix. The correlation between themes of SMCCU is presented in **Figure 7.**



Note. 3 themes of SMCCU include 1) GE: Governance and Economy; 2) EN: Environment and Nature; 3) SC: Society and Communication.

Figure 7. Theme-correlation Heatmap of SMCCU

4 Empirical Results

4.1 Green-scored Stock Performance

The **Figure 8** of average stock performance conditional on stock greenness indicates an overall positive relation between the average excess stock returns (net of risk-free rate) and the firm greenness measured by carbon performance since 2010. The average excess stock returns are always higher when the greenness is above the threshold than when it is below, suggesting that market has been rewarded market companies that have a higher commitment to environmental sustainability. Particularly, after greenness score threshold gets above one third, there are strong increases in the average stock excess return as the threshold becomes

larger although the confidence intervals partially converge at 0.9 percentiles for firm greenness measured by scaled carbon emissions (e.g., intensity). These preliminary findings imply that while higher greenness generally leads to better stock performance, the relationship is not straight-forward and becomes more complex at the extreme levels of greenness. This highlights the need for further research to better understand the dynamics between greenness and stock market performance along the transition to a "carbon-aware" equilibrium.

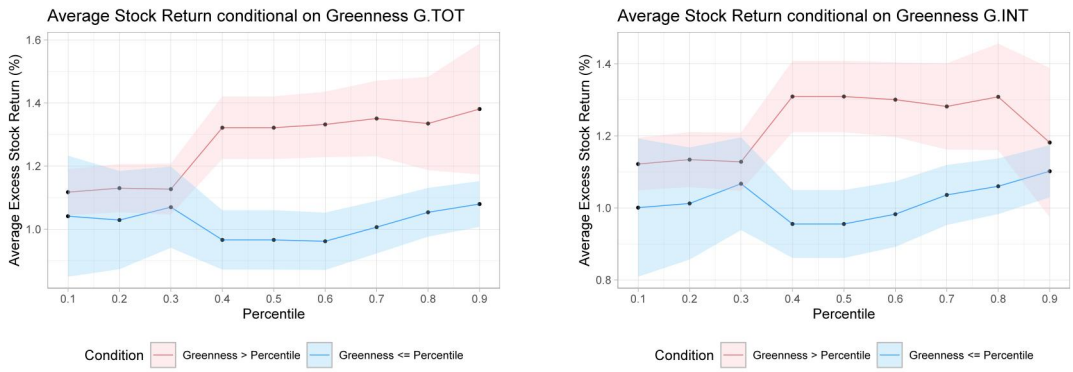


Figure 8. Average Stock Return conditional on Greenness

The empirical results of firm fixed-effect baseline panel regression model in **Table 7** supported **H1a** that greener stocks with better carbon performance have higher realized returns:

$$R_{i,t} - R_{Ft} = \alpha_i + \beta^G G_{i,t} + \gamma_i' \mathrm{Ctrl}_t + \varepsilon_{i,t} \tag{6}$$

Table 7. Firm-fixed Panel Regression of Green-scored Stock Performance

	12 year since 2010		Till 2015		Post 2015	
Ctrls	G^{TOT}	G^{INT}	G^{TOT}	G^{INT}	G^{TOT}	G^{INT}
Ctrl.FF3	0.206***	0.099	0.164	0.183	0.372***	0.313***
	(0.073)	(0.073)	(0.14)	(0.138)	(0.105)	(0.106)
Ctrl.FF5	0.2***	0.1	0.19	0.227	0.363***	0.305***
	(0.073)	(0.073)	(0.145)	(0.143)	(0.104)	(0.106)
Ctrl.MKT	0.222***	0.116	0.205	0.233	0.458***	0.358***
	(0.077)	(0.077)	(0.161)	(0.158)	(0.116)	(0.118)
Ctrl.ECON	0.286***	0.2**	0.115	0.157	0.472***	0.422***
	(0.082)	(0.082)	(0.172)	(0.169)	(0.122)	(0.123)
Observations	55400	55400	22690	22690	28544	28544

*Notes. The results reflect S&P500 post-2015 regressions with various control sets including FF3, FF5, market and economic factors increasingly as illustrated in Appendix A. To mitigate the impact of outliers, the normalized green scores are winsorized at 1st and 99th percentiles. The observations of sub-periods do not add up to the whole period due to the typical filtering criteria that removes firms with observations <50 for each timeframe. Significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.*

4.2 Stock Reaction to Climate Conscience

The empirical results of firm fixed-effect interactive panel regression model supported **H2b** that greater climate conscience updates diminish the positive relationship between the stock greenness and realized returns, while bringing aggregate belief closer to the equilibrium with carbon premium:

$$\begin{aligned} R_{i,t} - R_{Ft} = \alpha_i + \beta^G G_{i,t} + (\beta_{SMCCUt} + \beta^G_{SMCCUt} G_{i,t}) SMCCU_t \\ + (\beta_{SMCCUt-1} + \beta^G_{SMCCUt-1} G_{i,t}) SMCCU_{t-1} + \gamma_i' Ctrl_t + \varepsilon_{i,t} \end{aligned} \tag{7}$$

The **Table 8** of empirical results suggest that lagged effect of climate conscience updates on stock prices is more pronounced with the previous month's climate information exhibiting a higher degree of influence; climate conscience updates also have significant and negative delayed negative effect on stocks with average greenness score; while stock greenness tends to positively impact stock returns along the transition to equilibrium, this effect may diminish or even turn negative when climate updates get substantial.

Table 8. Firm-fixed Panel Regression of Stock Reaction to Climate Conscience Updates

Post 2015	Ctrl.FF3	Ctrl.FF5	Ctrl.MKT	Ctrl.ECON
Panel A: Greenness measured by G^{TOT}				
G	0.466***	0.504***	0.614***	0.621***
	(0.108)	(0.108)	(0.12)	(0.125)
$SMCCU_t$	-0.006	-0.007	-0.009	-0.011
	(0.007)	(0.007)	(0.007)	(0.008)
G * $SMCCU_t$	-0.012	-0.025***	-0.026***	-0.027***
	(0.008)	(0.008)	(0.008)	(0.008)
$SMCCU_{t-1}$	-0.02***	-0.021***	-0.023***	-0.023***
	(0.007)	(0.007)	(0.007)	(0.007)
G * $SMCCU_{t-1}$	-0.032***	-0.041***	-0.044***	-0.042***
	(0.008)	(0.008)	(0.008)	(0.008)
Panel B: Greenness measured by G^{INT}				
G	0.407***	0.442***	0.514***	0.562***
	(0.11)	(0.109)	(0.121)	(0.127)
$SMCCU_t$	-0.006	-0.007	-0.009	-0.011
	(0.007)	(0.007)	(0.007)	(0.008)
G * $SMCCU_t$	-0.02**	-0.031***	-0.034***	-0.034***
	(0.008)	(0.008)	(0.008)	(0.008)
$SMCCU_{t-1}$	-0.02***	-0.021***	-0.023***	-0.023***
	(0.007)	(0.007)	(0.007)	(0.007)
G * $SMCCU_{t-1}$	-0.025***	-0.032***	-0.038***	-0.034***
	(0.008)	(0.008)	(0.008)	(0.008)

*Notes. The results reflect S&P500 post-2015 regressions with various control sets including FF3, FF5, market and economic factors increasingly as illustrated in Appendix A. To mitigate the impact of outliers, the normalized green scores are winsorized at 1st and 99th percentiles. Significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.*

4.3 Equity Greenium Conditional on Climate Conscience Updates

The stock portfolio is equal-weighted built to measure the performance of equity greenium. Because of the one-year delay in emissions reporting, we rely on former-year emissions when building the portfolios. As such, our portfolio formation strategy does not suffer from look-ahead bias. Align with the **Figure 9** of cumulative GMB returns and SMCCU, the empirical results of the Time-series multivariate regression support **H3b** that realized equity greenium is lower when climate conscience updates get more substantial, driving stock returns towards the equilibrium with carbon premium:

$$R_{p,t} - R_{Ft} = \alpha_p + \beta_p^{SMCCUt} SMCCU_t + \beta_p^{SMCCUt-1} SMCCU_{t-1} + \gamma_p^{'} Ctrl_t + \varepsilon_{p,t} \quad (8)$$

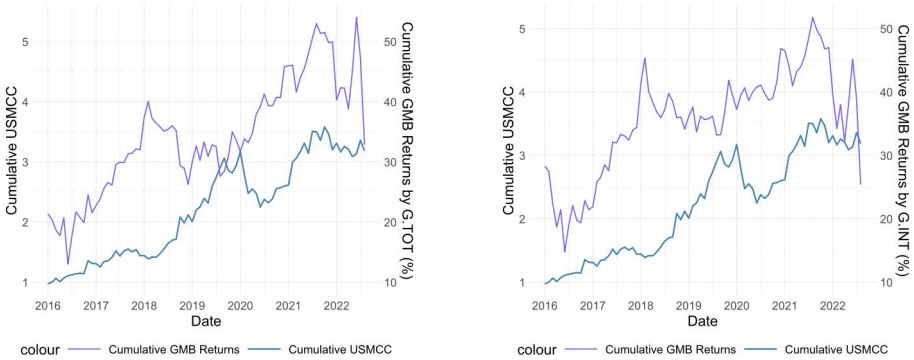


Figure 9. Cumulative GMB Returns and SMCCU

The empirical results in **Table 9** provide further empirical evidence that lagged SMCCU is more pronounced than the simultaneous SMCCU, suggesting a delayed reaction of equity regreenium to the updates of investors' belief about climate change

Table 9. Time-series Analysis of Portfolio Return and Climate Conscience Updates

Panel A: Greenness measured by G_{TOT}			
	GMB	Green	Brown
$SMCCU_t$	-0.085**	-0.032*	0.051
	-0.038	-0.019	-0.032
$SMCCU_{t-1}$	-0.147***	-0.084**	0.059*
	-0.053	-0.038	-0.033
Panel B: Greenness measured by G_{INT}			
	GMB	Green	Brown
$SMCCU_t$	-0.077**	-0.016	0.058*
	-0.036	-0.019	-0.033
$SMCCU_{t-1}$	-0.113**	-0.054*	0.056*
	-0.052	-0.032	-0.032

*Notes. The results reflect S&P500 post-2015 time-series analysis with the control set Ctrl.ECON including FF3, FF5, market and economic factors. To mitigate the impact of outliers, the normalized green scores are winsorized at 1st and 99th percentiles. Significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.*

4.4 Robustness Check

4.4.1 Greenness measurement excluding scope 3. Research of Aswani et al. (2024) has placed doubts on the scope 3 of GHG emission data for its possible substantial estimation due to potential difficulties in obtaining emission figures along the supply chain, this study validates the aforementioned findings by measuring firm greenness based on its carbon performance of scope 1 and scope 2 emissions only. As displayed in **Table 10**, the results align closely with our major findings.

Table 10. Regression Results with Scope 1 and 2 only

Scope 1&2	Greenness measured by G^{TOT}			Greenness measured by G^{INT}		
Panel A: Firm-fixed Panel Regression for Stock Return and Greenness						
G	0.679***			0.638***		
	(0.132)			(0.138)		
Observations	28472			28472		
Panel B: Firm-fixed Panel Regression with Moderator SMCCU						
G	0.817***			0.758***		
	(0.135)			(0.14)		
$SMCCU_t$	-0.011			-0.011		
	(0.008)			(0.008)		
$G \times SMCCU_t$	-0.027***			-0.033***		
	(0.008)			(0.008)		
$SMCCU_{t-1}$	-0.023***			-0.023***		
	(0.007)			(0.007)		
$G \times SMCCU_{t-1}$	-0.04***			-0.03***		
	(0.008)			(0.008)		
Panel C: Portfolio Return and SMCCU Time-series Analysis						
	GMB	Green	Brown	GMB	Green	Brown
SMCCU	-0.064**	-0.032	0.03	-0.067*	-0.026	0.039
	(0.03)	(0.022)	(0.028)	(0.038)	(0.02)	(0.03)
$SMCCU_{t-1}$	-0.095**	-0.054	0.038	-0.099**	-0.051*	0.046
	(0.047)	(0.036)	(0.025)	(0.05)	(0.029)	(0.029)

*Notes. The results reflect S&P500 post-2015 regressions using scope 1 and 2 GHG emissions with the control set Ctrl.ECON including FF3, FF5, market and economic factors. Normalized green scores are winsorized at the 1st and 99th percentiles to address outliers. Significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.*

4.4.2 Exposure to energy price fluctuations. The research extends the classic economic controls in stock pricing regressions by including energy factors in terms of crude oil, natural gas and propane price movements to account for the possible exposure of equity greenium to energy price fluctuations. The results in **Table 11** are broadly consistent with what we have obtained in main analysis.

Table 11. Regression Results with ENRG Controls

Ctrl. ENRG	Greenness measured by G^{TOT}			Greenness measured by G^{INT}		
Panel A: Firm-fixed Panel Regression for Stock Return and Greenness						
G	0.459***			0.411***		
	(0.122)			(0.124)		
Observations	28544			28544		
Panel B: Firm-fixed Panel Regression with Moderator SMCCU						
G	0.612***			0.561***		
	(0.126)			(0.127)		
$SMCCU_t$	-0.016**			-0.016**		
	(0.008)			(0.008)		
$G \times SMCCU_t$	-0.026***			-0.034***		
	(0.008)			(0.008)		
$SMCCU_{t-1}$	-0.027***			-0.026***		
	(0.007)			(0.007)		
$G \times SMCCU_{t-1}$	-0.041***			-0.035***		
	(0.008)			(0.008)		
Panel C: Portfolio Return and SMCCU Time-series Analysis						
	GMB	Green	Brown	GMB	Green	Brown
SMCCU	-0.08**	-0.028	0.05	-0.073*	-0.016	0.055*
	(0.038)	(0.02)	(0.033)	(0.037)	(0.019)	(0.033)
$SMCCU_{t-1}$	-0.145***	-0.082***	0.06*	-0.111**	-0.055*	0.053
	(0.05)	(0.031)	(0.033)	(0.052)	(0.029)	(0.033)

*Notes. The results reflect S&P500 post-2015 regressions with the control set Ctrl.ENRG including FF3, FF5, market, economic and energy factors. Normalized green scores are winsorized at the 1st and 99th percentiles to address outliers. Significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.*

4.4.3 Potential Un-disclosure Heterogeneity Regression results for the counterargument of disclosure effects across alternative control specifications are reported in **Table 12**. The null hypothesis of equivalent exposure coefficients between GHG-disclosing firms and Un-disclosing counterparts (assigned industry-average emissions) cannot be rejected at conventional significance levels. This finding validates the PST model's applicability to all firms irrespective of disclosure status, countering assertions that disclosure reduces carbon premium through investor uncertainty mitigation (Bolton and Kacperczyk, 2021).

Table 12. Firm-fixed Panel Regression considering Disclosure Status

Un-Disclosing	Ctrl.FF3	Ctrl.FF5	Ctrl.MKT	Ctrl.ECON	Ctrl.ENRG
Panel A: Greenness measured by G^{TOT}					
G	0.456***	0.473***	0.564***	0.561***	0.557***
	(0.109)	(0.109)	(0.121)	(0.126)	(0.127)
$G \times UD$	-0.299*	-0.263	-0.401**	-0.479**	-0.447**
	(0.179)	(0.179)	(0.2)	(0.209)	(0.211)
$SMCCU_{t-1}$	-0.017**	-0.016**	-0.017***	-0.017**	-0.019***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$G \times SMCCU_{t-1}$	-0.029***	-0.034***	-0.036***	-0.034***	-0.033***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
$G \times UD \times SMCCU_{t-1}$	0.023	0.023	0.015	0.01	0.015
	(0.02)	(0.02)	(0.02)	(0.02)	(0.021)

Panel B: Greenness measured by G^{INT}					
G	0.369***	0.379***	0.424***	0.472***	0.476***
	(0.112)	(0.111)	(0.123)	(0.129)	(0.129)
G × UD	-0.283	-0.275	-0.392**	-0.476**	-0.445**
	(0.173)	(0.172)	(0.192)	(0.202)	(0.203)
$SMCCU_{t-1}$	-0.017***	-0.017**	-0.018***	-0.017**	-0.019***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
G × $SMCCU_{t-1}$	-0.02***	-0.024***	-0.027***	-0.023***	-0.024***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
G × UD × $SMCCU_{t-1}$	0.019	0.021	0.016	0.01	0.015
	(0.019)	(0.019)	(0.019)	(0.019)	(0.02)

*Notes. The results reflect S&P500 post-2015 regressions with various control sets including FF3, FF5, market and economic factors increasingly as illustrated in Appendix A. UD represents the un-disclosure dummy variable. Normalized green scores are winsorized at the 1st and 99th percentiles to address outliers. Significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.*

5 Decomposing Social Signal of Climate Conscience

5.1 Dimensional Analysis with Societal Decomposition

Based on the methodology of constructing SMCC, the social signal of climate conscience is decomposed by 3 dimensions in terms of positivity, popularity and attention. The study further examines the independent effect of the dimensional USMCC on the green-scored stocks.

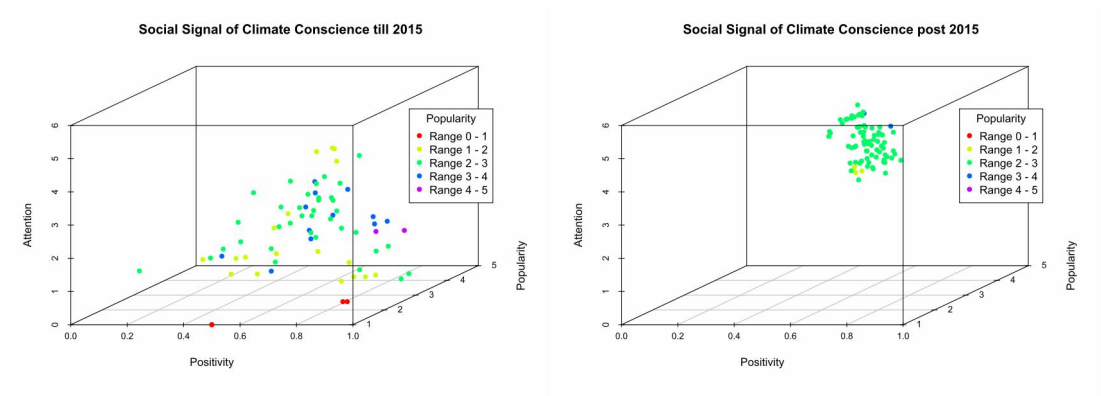


Figure 10. SMCC Decomposed by Social Signal

As shown in **Figure 10,** compared with till-2015 period, post-2015 period after Paris Agreement tends to stabilize with greater attention higher positivity, and above-average popularity. In **Table 13**, the empirical results of examining the dimensional USMCC effect on the positive relationship between stock greenness and excess stock returns suggest the significant negative effects by attention and positivity dimensions, while the popularity

dimension that amplifies the positivity degree of posts, by itself, does not have significant impact.

Table 13. Firm-fixed Societal Dimensional Panel Regression

Dimensional SMCCU	Greenness measured by G^{TOT}	Greenness measured by G^{INT}
G	0.56***	0.495***
	(0.124)	(0.125)
P_{t-1}	-0.311***	-0.31***
	(0.107)	(0.107)
$G \times P_{t-1}$	-0.509***	-0.39***
	(0.123)	(0.123)
Ψ_{t-1}	-2.593***	-2.595***
	(0.533)	(0.533)
$G \times \Psi_{t-1}$	-1.244**	-1.396**
	(0.599)	(0.6)
κ_{t-1}	-0.266	-0.265
	0.146	0.146
$G \times \kappa_{t-1}$	0.074	0.003
	0.161	0.162

*Notes. The results reflect S&P500 post-2015 regressions with the control set Ctrl.ECON including FF3, FF5, market and economic factors. To mitigate the impact of outliers, the normalized green scores are winsorized at 1st and 99th percentiles. *, **, and ***Significant coefficients at the 10%, 5%, and 1% levels, respectively.*

5.2 Thematic and Topical Decomposition

For the social signal detected from climate conscience updates, regression on further decomposition of SMCCU by thematic and topical channels are implemented to understand the mechanism of the effect. **Figure 11** presented the SMCC aggregated monthly index with thematic index values.

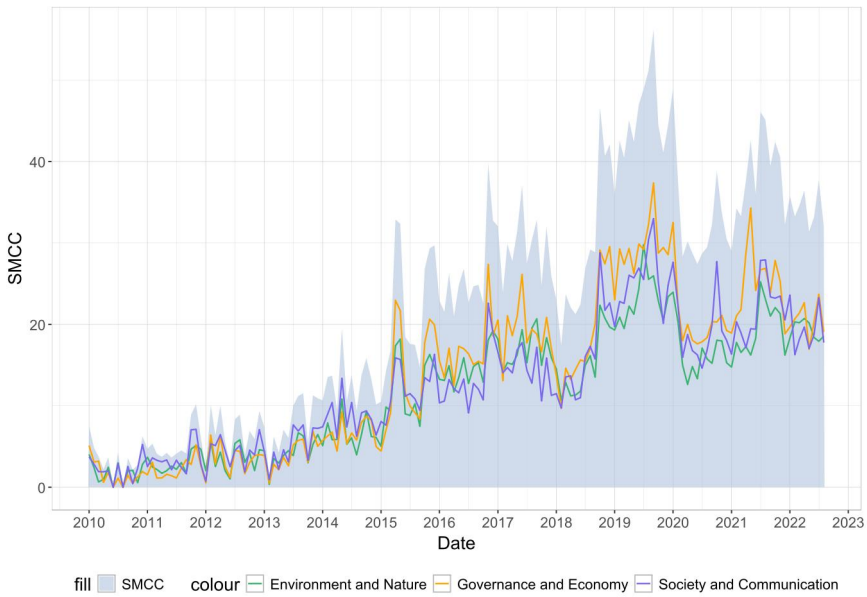


Figure 11. SMCC with Themes

Table 14 presents the empirical results of influential topics that drive the stock pricing of green and brown stocks toward the carbon-aware equilibrium. Particularly, the theme Environment and Nature has significant negative effect as a whole and by the topics of Wildfire Risk and Disaster.

Table 14. Firm-fixed Thematic and Topical Panel Regression

Risk Type	*Influential Topics*	$G^{TOT} \times SMCCUt\text{-}1$	$G^{INT} \times SMCCUt\text{-}1$
Physical	Theme: Environment and Nature	-0.062**	-0.082***
Physical	Carbon Footprint	-0.095**	-0.111**
Physical	Urban Sewage	-0.139**	-0.176***
Physical	Wildfire Risk	-0.281***	-0.391***
Physical	Biodiversity	-0.081*	-0.118***
Physical	Disaster	-0.202***	-0.216***
Physical	Weather Event	-0.046	-0.087**
Physical	Global Warming	-0.09*	-0.121**
Transition	Theme: Governance and Economy	-0.015	-0.023
Transition	Country Emission	-0.064	-0.086*
Transition	Company/Investment	-0.064	-0.115**
Transition	Energy Source	-0.065*	-0.099***
Transition	Carbon Tax	-0.081*	-0.102**
Transition	Adaptation Program	-0.151**	-0.167***
Physical/Transition	Theme: Society and Communication	-0.023	-0.027
Physical	Waste/Plastic	-0.102*	-0.079
Physical	Resource/Population	-0.039	-0.074**
Physical	Pollution/Transportation	-0.055	-0.082*
Transition	Future Generation	-0.052	-0.078*

*Notes. The results reflect S&P500 post-2015 regressions with the control set Ctrl.ECON including FF3, FF5, market and economic factors. To mitigate the impact of outliers, the normalized green scores are winsorized at 1st and 99th percentiles. *, **, and ***Significant coefficients at the 10%, 5%, and 1% levels, respectively.*

6 Conclusion

Overall, the research contributes to the literature of climate finance, asset pricing and social media by introducing a novel framework to quantify the evolving process of investor belief updates about climate change from social media along the course of transition toward the carbon-aware equilibrium, where there would be negative realized equity greenium and positive carbon return, which differentiates from the previous studies primarily measuring climate change concerns that cause deviations from the equilibrium. Moreover, the study

captures a negative effect of climate conscience updates on the realized equity greenium in the post-2015 period after Paris Agreement adopting both unscaled and scaled GHG emissions. Our work unveils the social signal of climate conscience that keeps updating the aggregate beliefs of investors to become more aware of carbon risk and provides empirical evidence to the trajectory of the transition toward carbon-aware equilibrium: as the investor climate conscience grows, the realized equity greenium diminishes along the course, while the carbon risk premium expected by the PST model in equilibrium becomes more pronounced.

By bridging social media analytics with asset pricing in climate finance, this work provides valuable insights for understanding how collective beliefs about climate change evolve and reshape markets as economies navigate the complexities of low-carbon transition, and practically support the decision making of the climate investing strategy in support of the carbon-neutral initiative. Particularly, our findings help investors to manage their climate-hedging portfolios accordingly with the dynamic transition of equity greenium under climate conscience updates, and implement stock selection with the theory prediction that stocks providing better climate hedging have lower expected returns.

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Appendix A: Control Sets and Exogeneous Inputs

Factors	Description	X_t	Ctrl. FF5	Ctrl. MKT	Ctrl. ECON	Ctrl. ENRG
Mkt-RF	Market factor of Fama and French (1992) measuring net of risk free rate	√	√	√	√	√
HML	High-minus-low value factor of Fama and French (1992)	√	√	√	√	√
SMB	Small-minus-big size factor of Fama and French (1992)	√	√	√	√	√
CMA	Conservative-minus-aggressive investment factor of Fama and French (2015)	√	√	√	√	√
RMW	Robust-minus-weak profitability factor of Fama and French (2015)	√	√	√	√	√
MOM	Momentum factor of Carhart (1997)	√		√	√	√
VIX	CBEO volatility index	√		√	√	√
EPU	U.S. economic policy uncertainty index of Baker et al. (2016)	√			√	√
TERM	Term factor of Fung and Hsieh (2004)	√			√	√
DFLT	Default spread factors of Fung and Hsieh (2004)	√			√	√
WTI	Crude oil return by West Texas Intermediate crude oil price					√
NG	Natural gas return by Henry hub natural gas spot price					√
PROP	Propane return by Mont Belvieu Texas price					√

Appendix B: Data Description

Dataset	Source	Related variables
GHG Emissions	Refinitive (formerly Thomson Reuters)	G
Post	Reddit	SMCC(U)
Firm Financials	Compustat via WRDS	R
Stock Information	CRSP via WRDS	R