Economics Bulletin

Volume 44, Issue 1

Climate policy uncertainty and US industry stock returns: A quantile regression approach

Guillaume Pijourlet
Université Clermont Auvergne

Abstract

This paper examines the impact of climate policy uncertainty (CPU) on US industry stock returns. We document heterogenous impacts of CPU on monthly returns of ten US industries. We find that CPU impacts negatively consumer staples, energy, industrials, financials, and real estate stock returns, but has a positive influence on consumer discretionary and technology stock returns. Our quantile regressions also show that the effect of CPU depends on market conditions. More precisely, higher CPU leads to lower basic materials, consumer staples, real estate and industrials returns in bullish markets, but to higher basic materials and technology returns in bearish markets.

Citation: Guillaume Pijourlet, (2024) "Climate policy uncertainty and US industry stock returns: A quantile regression approach", *Economics Bulletin*, Volume 44, Issue 1, pages 182-189
Contact: Guillaume Pijourlet - guillaume.pijourlet@uca.fr.
Submitted: October 13, 2023. **Published:** March 30, 2024.

1. Introduction

Many scientific studies now clearly underline the economic and financial consequences of climate change (Nordhaus 2006; Stern 2007; Dietz *et al.* 2016; Battiston *et al.* 2017). At the same time, investors increasingly recognize that climate risks may affect the value of their portfolios (Stroebel & Wurgler 2021). More particularly, both academics and finance professionals consider that regulatory risk is the most important climate risk facing investors in the medium run (Stroebel & Wurgler 2021). Changes in climate policy indeed entail a transition risk for companies, which may impact their stock returns (Bolton & Kacperczyk 2021; Boungou & Urom 2023). Significant attention has thus been recently paid to the effect of climate policy uncertainty (CPU) on stock market returns (Bouri *et al.* 2022; Liang *et al.* 2022; Treepongkaruna *et al.* 2023). Using a recent news-based measure of CPU developed by Gavriilidis (2021), existing literature has already shown that CPU has a significant effect on firm valuation (Azimli 2023), stock market returns (Bouri *et al.* 2022; He & Zhang 2022; Treepongkaruna *et al.* 2023) and volatility (Liang *et al.* 2022; Lv & Li 2023).

CPU can influence stock returns through supply and demand channels, for instance by changing firms' investment policies to mitigate and to adapt to climate risks (Lopez et al. 2017; Gavriilidis 2021; Bouri et al. 2022) or by influencing consumption and transportation behaviors (Gavriilidis 2021). CPU also has a negative impact on consumption and investment opportunities (Huynh & Xia 2021; Treepongkaruna *et al.* 2023) and modify firms' risk profile (Lv & Li 2023). In addition, recent papers indicate that CPU can influence stock returns at the industry level. For instance, an increase in CPU may lead investors to favor green energy stocks and to neglect brown energy ones due to growing concerns about climate change, resulting in the former outperforming the latter (Bouri *et al.* 2022). It has also been shown that CPU influences crude oil supply and demand and thus oil industry stock returns (He & Zhang 2022).

As we can see, little is yet known about the impact of CPU on industry stock returns. We aim to fill this gap for the first time in the literature by investigating the structure of dependence between CPU and ten US industry stock returns. We expect heterogeneous responses of various industry stock returns to CPU due to different sensitivities to climate issues (Lv & Li 2023). This question is of particular importance, as understanding the determinants of industry stock returns is crucial from an asset allocation and risk management perspective. Industry portfolios are indeed widely used in many asset allocation strategies (Yu *et al.* 2017). Contrary to previous works, we adopt a quantile regression approach to study the impact of CPU on the full conditional distribution of US industry stock returns for the January 1988-December 2021 period. This method seems more appropriate than OLS regressions, as it is less sensitive to outliers and skewness in data. This also allows us to evaluate the possibility that the effect of CPU on stock market returns may differ according to market conditions. We thus contribute to the emerging literature that studies the influence of CPU on stock returns (Bouri *et al.* 2022; He & Zhang 2022; Treepongkaruna *et al.* 2023) by revealing heterogeneous effects of CPU on US industry stock returns under different market circumstances (You *et al.* 2017; Peng *et al.* 2018; Qin *et al.* 2020).

The rest of this paper is organized as follows. We present our data in the second section. Our methodology is described in a third section. In the fourth section, we present and comment our empirical results. We conclude in the last section.

2. Data

In this paper, we use monthly data from January 1988 to December 2021 to examine the effect of CPU on US industry stock returns. Following the previous literature (Bouri *et al.* 2022; Guo *et al.* 2022; He & Zhang 2022; Liang *et al.* 2022; Azimli 2023; Lv & Li 2023), we use the monthly CPU index developed by Gavriilidis (2021) to evaluate uncertainty induced by climate policy change. Similar to the methodology of Baker *et al.* (2016) to measure economic policy uncertainty, a textual analysis of news on climate policy that may lead to uncertainty and published in eight major US newspapers is performed. To assess the intensity of CPU, the number of relevant articles in a month is divided by the total number of articles in that month for each of the eight newspapers. These eight series are then standardized, and a monthly and normalized average to have a mean value of 100 for the calculation period is obtained (Gavriilidis 2021).

For computing US industry-level monthly stock returns, we use sector equity indices provided by Datastream (Naeem *et al.* 2020). Based on Refinitiv Business Classification, Datastream sector indices are broken down into five levels (Economic Sector, Business Sector, Industry Group, Industry and Activity). In this study, we consider the following ten US Datastream sector indices : the US Datastream Basic Materials Index (Mnemonic: BMATRUS), the US Datastream Consumer Discretionary Index (CODISUS), the US Datastream Consumer Staples Index (COSTPUS), the US Datastream Energy Index (ENEGYUS), the US Datastream Financials Index (FINANUS), the US Datastream Healthcare Index (HLTHCUS), the US Datastream Industrials Index (INDUSUS), the US Datastream Real Estate Index (RLESTUS), the US Datastream Technology Index (TECNOUS), and the US Datastream Utility Index (UTILSUS). We also use the US Datastream Total Market Index (TOTMKUS) to control for market risk. We calculate monthly industry-level stock returns as the log difference of prices for each US Datastream sector indices, multiplied by 100. The descriptive statistics of our variables are depicted in Table 1.

Table 1: Descriptive statistics

	Obs.	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	PP
Basic Materials	408	0,60	6,01	-0,62	5,77	156,91***	-19,82***	-19,84***
Consumer Discretionary	408	0,85	4,42	-0,38	4,42	44,34***	-19,31***	-19,31***
Consumer Staples	408	0,78	3,87	-0,36	4,54	49,26***	-19,47***	-19,47***
Energy	408	0,46	6,11	-1,00	12,13	1484,78***	-21,00***	-21,03***
Financials	408	0,70	5,54	-1,00	6,78	310,37***	-18,18***	-18,21***
Healthcare	408	0,90	4,05	-0,35	3,89	21,98***	-20,57***	-20,58***
Industrials	408	0,82	5,10	-0,70	5,30	123,34***	-19,48***	-19,47***
Real Estate	408	0,51	5,78	-1,24	10,05	949,39***	-18,67***	-18,72***
Technology	408	1,03	6,91	-0,65	4,90	90,03***	-20,39***	-20,39***
Utilities	408	0,42	4,16	-0,58	3,96	38,57***	-19,72***	-19,73***
Total Market	408	0,77	4,16	-0,77	4,98	107,05***	-19,52***	-19,52***
CPU	408	98,19	52,69	2,13	9,14	949,96***	-6,00***	-11,27***

This table reports descriptive statistics for monthly returns for the ten US Datastream sector indices, the US Datastream Total Market Index and monthly CPU index between January 1988 and December 2021. We also provide the results of Jarque-Bera test of normality, and the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) stationarity tests. Test statistics are reported. *,**, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Our Jarque-Bera test results indicate that our variables are not normally distributed. We also observe that all industry stock returns are negatively skewed and leptokurtic. This shows the presence of outliers that justify the use of quantile regression (Azimli 2020). Additionally, our Augmented Dickey-Fuller and Phillips-Perron test results underline that our variables are all stationary.

3. Methodology

In this article, we run quantile regressions (Koenker & Bassett 1978) to explore the dependence structure between CPU and US industry stock returns. More precisely, we adapt the model estimated by Peng *et al.* (2018) who investigate the relationship between economic policy uncertainty and stock market returns in G7 and BRIC countries. We thus consider the following model:

$$Q_{R_{i,t}}(\tau|X) = \alpha_i(\tau) + \gamma_i(\tau)CPU_t + \beta_i(\tau)RM_t + \eta_i(\tau)R_{i,t-1}$$

$Q_{R_{i,t}}(\tau|X)$ refers to the τth conditional quantile of $R_{i,t}$, which depends linearly on a set of variables denoted X (Baur 2013). $R_{i,t}$ is the monthly return at month t of the sector i. We consider quantiles from to 0.05 to 0.95 by step of 0.025 for each of our industry stock returns series. CPU_t is the CPU index at month t. $\gamma_i(\tau)$ thus estimates the impact of CPU_t on $R_{i,t}$ at τth quantile. RM_t is the monthly return at month t of the total market proxied by US Datastream Total Market Index. $R_{i,t-1}$ is the lagged monthly return at month t of the sector i.

4. Results

Results of our quantile regressions are presented in Table 2. For the sake of brevity, we only report CPU coefficients for each quantile for the ten US industry stock returns.

In order to improve the reading and interpretation of our results, we also present them graphically in Figure 1. Quantiles are indicated in horizontal axis. The right vertical axis depicts the impact of CPU on different industry stock returns, whereas the left vertical axis represents p-values. Also, the red line shows the quantile estimates, while the blue line describes the p-values. Finally, the dashed black line indicates a p-value of 10%.

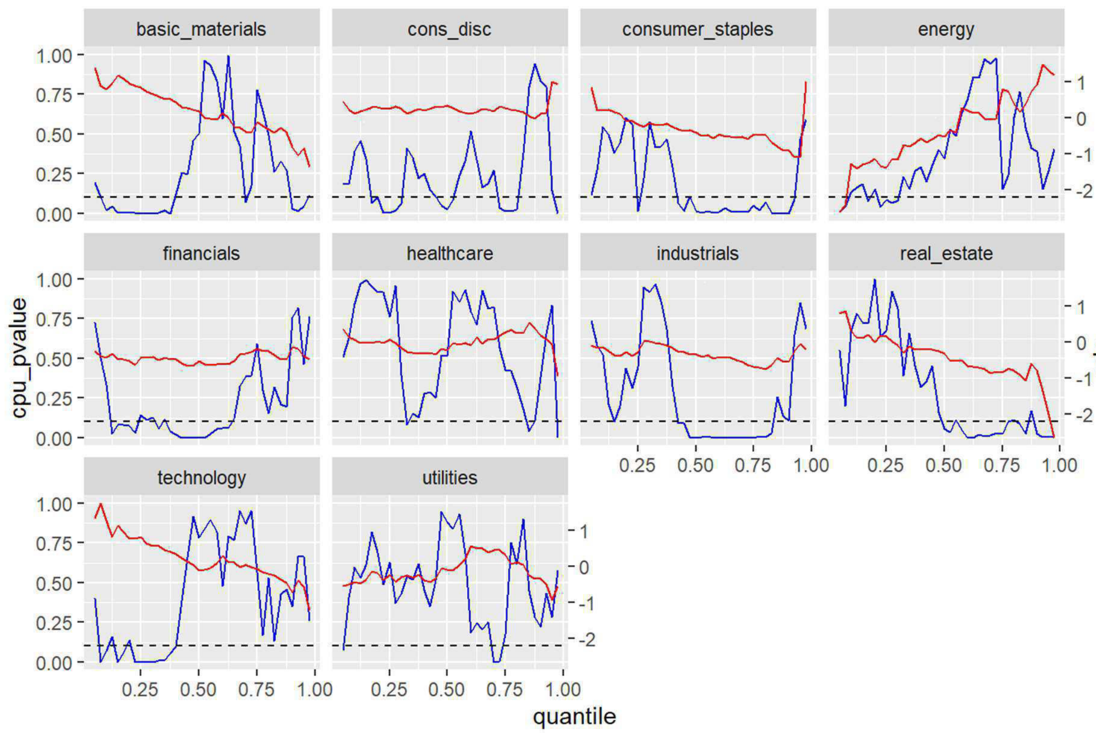
Following Zhu *et al.* (2020), we run Wald tests for equality of CPU coefficients at lower quantiles (5th) with CPU coefficients at upper quantiles (75th, 90th and 95th). The null hypothesis is that CPU coefficients are equal across quantiles. These tests allow us to identify the type of dependence structure between CPU index and US industry stock returns (Peng *et al.* 2018; Das & Dutta 2020; Zhu *et al.* 2020). The dependence structure is said to be constant when estimated coefficients remain the same across quantiles, monotonic when they increase or decrease with quantiles, and symmetric (or asymmetric) when they are similar (or dissimilar) at lower and upper quantiles (Das & Dutta 2020). Results are reported in Table 3.

Table 2 : Quantile regression results

Quantile	Basic Materials	Consumer Discretionary	Consumer Staples	Energy	Healthcare	Industrials	Financials	Technology	Utilities	Real Estate
0,050	**1,385*** **	0,447	0,841	**-2,607*** **	0,363	-0,086	-0,242	1,338	**-0,551***	0,799
	(1,30)	(1,33)	(1,57)	**(-2,68)**	(0,66)	(-0,34)	(-0,35)	(0,84)	**(-1,79)**	(0,6)
0,100	**0,808** **	0,112	0,218	-1,260	0,066	-0,140	-0,439	**1,274***	-0,424	0,311
	(2,31)	(0,86)	(0,6)	(-1,49)	(0,19)	(-0,64)	(-0,96)	**(1,82)**	(-0,53)	(0,42)
0,150	**1,173*** **	0,226	0,169	-1,281	-0,003	-0,370	**-0,472***	**1,129*** **	-0,357	0,110
	(2,96)	(0,95)	(0,88)	(-1,33)	(-0,01)	(-1,64)	**(-1,74)**	**(3,52)**	(-0,51)	(0,35)
0,200	**0,955*** **	0,288	-0,085	-1,133	0,032	-0,275	**-0,527***	0,771	-0,188	-0,001
	(3,16)	(1,63)	(-0,52)	(-1,43)	(0,1)	(-0,78)	**(-1,78)**	(1,48)	(-0,4)	(0)
0,250	**0,839*** **	**0,260*** **	**-0,190** **	**-1,374***	0,071	-0,272	-0,439	**0,811*** **	-0,232	0,168
	(3,18)	**(2,79)**	**(-2,49)**	**(-1,71)**	(0,3)	(-0,76)	(-1,46)	**(2,95)**	(-0,49)	(0,42)
0,300	**0,671*** **	**0,256***	-0,135	**-1,160***	-0,146	0,032	-0,399	**0,573*** **	-0,304	-0,092
	(4,19)	**(1,87)**	(-0,56)	**(-1,74)**	(-0,85)	(0,1)	(-1,52)	**(3,29)**	(-0,79)	(-0,24)
0,350	**0,526** **	0,177	-0,199	-0,791	-0,284	-0,053	-0,427	**0,449*** **	-0,324	-0,120
	(2,32)	(0,94)	(-0,81)	(-1,42)	(-1,43)	(-0,18)	(-1,56)	**(2,68)**	(-0,64)	(-0,44)
0,400	0,432	0,206	-0,243	-0,573	-0,310	-0,151	**-0,474** **	**0,350***	-0,375	-0,189
	(1,54)	(1,15)	(-1,05)	(-1,05)	(-1,09)	(-0,99)	**(-2,34)**	**(1,67)**	(-0,75)	(-1)
0,450	0,285	0,322	**-0,361** **	-0,588	-0,340	-0,265	**-0,645*** **	0,127	-0,345	-0,206
	(1,16)	(1,62)	**(-2,52)**	(-1,03)	(-1,14)	(-1,68)	**(-3,76)**	(0,44)	(-0,66)	(-0,75)
0,500	0,180	**0,349** **	**-0,415** **	-0,511	-0,228	**-0,344*** **	**-0,522*** **	-0,106	-0,079	**-0,307** **
	(0,67)	**(2,24)**	**(-2,39)**	(-0,95)	(-0,65)	**(-6,7)**	**(-3,36)**	(-0,28)	(-0,15)	**(-1,93)**
0,550	-0,023	0,174	**-0,484** **	-0,404	-0,057	**-0,372*** **	**-0,631** **	-0,050	0,042	-0,521
	(-0,08)	(1,17)	**(-2,41)**	(-0,69)	(-0,18)	**(-2,59)**	**(-2,27)**	(-0,13)	(0,08)	(-1,58)
0,600	0,143	0,115	**-0,451*** **	0,207	-0,092	**-0,398*** **	**-0,602***	0,299	0,564	**-0,655*** **
	(0,53)	(0,64)	**(-2,62)**	(0,36)	(-0,26)	**(-3,65)**	**(-1,89)**	(0,71)	(1,33)	**(-6,42)**
0,650	-0,240	0,244	**-0,528** **	0,141	-0,035	**-0,433*** **	-0,519	0,112	0,510	**-0,704** **
	(-0,65)	(1,4)	**(-2,47)**	(0,18)	(-0,09)	**(-3,51)**	(-1,54)	(0,29)	(1,26)	**(-2,37)**
0,700	**-0,378***	0,193	-0,509	-0,045	0,081	**-0,539*** **	-0,312	0,058	**0,461*** **	**-0,859** **
	(-1,81)	(1,09)	(-2,55)	(-0,07)	(0,22)	**(-4,71)**	(-0,87)	(0,16)	**(4,34)**	**(-2,39)**
0,750	-0,105	**0,279** **	**-0,448** **	0,792	0,266	**-0,673*** **	-0,190	-0,069	0,311	**-0,842** **
	(-0,28)	**(2,47)**	**(-1,97)**	(1,42)	(0,8)	**(-3,24)**	(-0,54)	(-0,57)	(1,36)	**(-2,25)**
0,800	-0,322	**0,209** **	**-0,472***	0,392	0,258	**-0,749*** **	-0,242	-0,199	0,111	-0,784
	(-0,68)	**(2,22)**	**(-1,8)**	(0,51)	(1,00)	**(-2,98)**	(-1,42)	(-0,63)	(0,50)	(-1,58)
0,850	-0,278	0,051	**-0,799*** **	0,391	**0,548** **	-0,439	-0,480	-0,362	-0,250	**-1,055** **
	(-0,98)	(0,25)	**(-3,32)**	(0,61)	**(2,03)**	(-1,13)	(-1,25)	(-0,79)	(-0,76)	**(-2,24)**
0,900	**-0,811** **	0,124	**-0,895*** **	0,926	0,190	-0,540	-0,131	-0,721	-0,337	**-0,794** **
	(-2,19)	(0,21)	**(-3,46)**	(0,85)	(0,87)	(-1,61)	(-0,31)	(-0,93)	(-1,22)	**(-2,24)**
0,950	**-0,836** **	0,999	-1,078	1,315	-0,071	-0,038	-0,376	-0,572	-0,933	**-1,985** **
	(-1,99)	(1,46)	(-0,72)	(1,12)	(-0,21)	(-0,19)	(-0,74)	(-0,44)	(-1,07)	**(-2,53)**

This table depicts quantile regression results. For the sake of brevity, only CPU coefficients are reported. We present estimates of the impact of CPU on monthly returns of US industry stock returns at quantiles from to 0.05 to 0.95 by step of 0.05. Coefficients are multiplied by 100 to ease readability. T-statistics are in parentheses. *,**, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. Coefficients significant at least at the 10% level are shown in bold.

Figure 1: Plot of quantile regression results



The red full line and the blue full line respectively describe CPU coefficients estimates (right vertical axis) and their p-values (left vertical axis). The dashed black line represents a p-value of 10%. Coefficients are multiplied by 100 to ease readability. Quantiles are depicted in horizontal axis.

Table 3: Wald test for equality of coefficients

Quantile	Basic Materials	Consumer Discretionary	Consumer Staples	Energy	Financials	Healthcare	Industrials	Real Estate	Technology	Utilities
50	3.39* (0.066)	0.06 (0.804)	4.14** (0.043)	2.45 (0.118)	0.13 (0.720)	1.83 (0.177)	0.76 (0.384)	1.36 (0.244)	2.59 (0.108)	0.53 (0.468)
75	4.78** (0.029)	0.16 (0.688)	5.34** (0.021)	5.53** (0.019)	0.00 (0.951)	0.03 (0.865)	3.52* (0.061)	3.23* (0.073)	3.72* (0.055)	1.88 (0.171)
90	7.11*** (0.008)	0.28 (0.599)	6.16** (0.013)	7.01*** (0.008)	0.02 (0.900)	0.24 (0.625)	0.71 (0.401)	1.24 (0.267)	5.64** (0.017)	0.09 (0.761)
95	9.86*** (0.002)	0.44 (0.505)	1.61 (0.206)	4.48** (0.035)	0.02 (0.884)	0.78 (0.377)	0.01 (0.943)	3.89** (0.049)	2.04 (0.149)	0.32 (0.575)

This table presents results of Wald tests for equality of CPU coefficients at lower quantiles (5th) with CPU coefficients at upper quantiles (75th, 90th and 95th) for the ten US industry returns. We report the test statistics. P-values are in parentheses. *,**, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

We observe that the effect of CPU on stock returns is mostly insignificant for healthcare and utilities industry, suggesting that demand for goods and services provided by these industries are largely insensitive to CPU. For the financial sector, we find that the effect of CPU is negative and significant for intermediary quantile, but not for lower and upper quantiles. However, we fail to reject the null hypothesis of equality of CPU coefficients across quantiles. In addition, CPU has a positive impact on the consumer discretionary stock returns for several quantiles. Our Wald tests indicate a constant dependence structure.

More interestingly, the effect of CPU on basic materials returns seems to be positively significant for lower quantiles and negatively significant for upper quantiles, but insignificant for intermediary quantiles. More precisely, we observe that an increase in CPU leads to higher returns in bearish markets but to lower returns in bullish markets, revealing an asymmetric dependence structure. Coefficient equality tests confirm that the effect of CPU decreases with quantiles. For the technology industry, CPU also has a positive and significant on stock returns for lower quantiles, but an insignificant effect for others quantiles. Results presented in Table 3 corroborate a decreasing dependence structure.

On the contrary, we observe that the impact of CPU on stock returns is insignificant for lower quantiles for consumer staples, real estate and industrials. However, the effect is negative and significant for intermediary and upper quantiles. This asymmetric dependence structure means that investors do not take climate policy considerations into account during bearish markets for these sectors. This result could be explained by investors' risk appetite behavior (Peng *et al.* 2018). Wald tests lead us to conclude to a decreasing dependence structure for consumer staples and real estate. Finally, for the energy sector, it would appear that the CPU effect is negative. However, this effect is only significant for lower quantiles. Also, as shown by the Wald tests we performed, the influence of CPU seems here to increase with quantiles.

5. Conclusion

In this paper, we investigate the effects of CPU on monthly returns for ten US Datastream sector indices by adopting a quantile regression approach. Our contribution to the literature is twofold. First, we document heterogeneous effects of CPU on US industry stock returns. We reveal that CPU has no significant impact on healthcare and utilities industry stock returns, which suppose that the fundamentals of these sectors are not sensitive to climate policy uncertainty. However, CPU seems to have a negative and significant influence on consumer staples, energy, industrials, financials, and real estate stock returns, but a significantly positive effect on consumer discretionary and technology stock returns. Second, we demonstrate the existence of asymmetric dependence structure between CPU and stock returns of some US industry portfolios. We thus find that the effect of CPU on US industry stock returns differs according to market conditions. It appears that an increase in CPU leads to lower basic materials, consumer staples, real estate and industrials returns in bullish markets. We also observe that CPU has a positive effect on basic materials and technology returns in bearish markets, but a negative one on energy stock returns.

By revealing different sensitivities of various industries to climate issues and transition risks, our work can help investors to better understand the impact of CPU on the value of their portfolios. Our results also indicate that investors can hedge against climate risk by investing in industry portfolios that are insensitive to or positively impacted by CPU. Finally, our results suggest that legislators should take the influence of CPU on different industries into account when setting environmental policies. Further research should be focused on understanding the determinants of the sensitivities of different industry stocks returns to CPU.

References

Azimli, A. (2020) "The impact of COVID-19 on the degree of dependence and structure of risk-return relationship: A quantile regression approach" *Finance Research Letters* **36**, 101648.

Azimli, A. (2023) "The impact of climate policy uncertainty on firm value: Does corporate social responsibility engagement matter?" *Finance Research Letters* **51**, 103456

Baker, S.R., Bloom, N., Davis, S.J. (2016) "Measuring economic policy uncertainty" *The Quarterly Journal of Economics* **131**, 1593-1636.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., Visentin, G. (2017) "A climate stress-test of the financial system" *Nature Climate Change* **7**, 283-288.

Baur, D.G. (2013) "The structure and degree of dependence: A quantile regression approach" *Journal of Banking & Finance* **37**, 786-798.

Bolton, P., Kacperczyk, M. (2021) "Do investors care about carbon risk?" *Journal of Financial Economics* **142**, 517-549.

Boungou, W., Urom, C. (2023) "Climate change-related risks and bank stock returns" *Economics Letters* **224**, 111011.

Bouri, E., Iqbal, N., Klein, T. (2022) "Climate policy uncertainty and the price dynamics of green and brown energy stocks" *Finance Research Letters* **47**, 102740.

Das, D., Dutta, A. (2020) "Bitcoin's energy consumption: Is it the Achilles heel to miner's revenue?" *Economics Letters* **186**, 108530.

Dietz, S., Bowen, A., Dixon, C., Gradwell, P. (2016) "'Climate value at risk'of global financial assets" *Nature Climate Change* **6**, 676-679.

Gavriilidis, K. (2021) "Measuring climate policy uncertainty" Available at SSRN 3847388.

Guo, J., Long, S., Luo, W. (2022) "Nonlinear effects of climate policy uncertainty and financial speculation on the global prices of oil and gas" *International Review of Financial Analysis* **83**, 102286.

He, M., Zhang, Y. (2022) "Climate policy uncertainty and the stock return predictability of the oil industry" *Journal of International Financial Markets, Institutions and Money* **81**, 101675.

Huynh, T.D., Xia, Y. (2021) "Climate change news risk and corporate bond returns" *Journal of Financial and Quantitative Analysis* **56**, 1985-2009.

Koenker, R., Bassett, G. (1978) "Regression quantiles" *Econometrica* **46**, 33-50.

Liang, C., Umar, M., Ma, F., Huynh, T.L. (2022) "Climate policy uncertainty and world renewable energy index volatility forecasting" *Technological Forecasting and Social Change* **182**, 121810.

Lopez, J.M.R., Sakhel, A., Busch, T. (2017) "Corporate investments and environmental regulation: The role of regulatory uncertainty, regulation-induced uncertainty, and investment history". *European Management Journal* **35**, 91-101.

Lv, W., Li, B. (2023) "Climate policy uncertainty and stock market volatility: Evidence from different sectors" *Finance Research Letters* **51**, 103506.

Naeem, M.A., Balli, F., Shahzad, S.J.H., de Bruin, A. (2020) "Energy commodity uncertainties and the systematic risk of US industries" *Energy Economics* **85**, 104589.

Nordhaus, W.D. (2006) "Geography and macroeconomics: New data and new findings" *Proceedings of the National Academy of Sciences* **103**, 3510-351.

Peng, G., Zhu, H., You, W. (2018) "Asymmetric dependence between economic policy uncertainty and stock market returns in G7 and BRIC: A quantile regression approach" *Finance Research Letters* **25**, 251-258.

Qin, Y., Hong, K., Chen, J., Zhang, Z. (2020) “Asymmetric effects of geopolitical risks on energy returns and volatility under different market conditions” *Energy Economics* **90**, 104851.

Stern, N. (2007) “The economics of climate change” in *the Stern review*, Cambridge University Press.

Stroebel, J., Wurgler, J. (2021), “What do you think about climate finance?” *Journal of Financial Economics* **142**, 487-498.

Treepongkaruna, S., Chan, K.F., Malik, I. (2023) “Climate policy uncertainty and the cross-section of stock returns” *Finance Research Letters* **55**, 103837.

You, W., Guo, Y., Zhu, H., Tang, Y. (2017) “Oil price shocks, economic policy uncertainty and industry stock returns in China: Asymmetric effects with quantile regression” *Energy Economics* **68**, 1-18.

Yu, H., Fang, L., Du, D., Yan, P. (2017) “How EPU drives long-term industry beta” *Finance Research Letters* **22**, 249-258.

Zhu, H., Huang, R., Wang, N., Hau, L. (2020) “Does economic policy uncertainty matter for commodity market in China? Evidence from quantile regression” *Applied Economics* **52**, 2292-2308.