Climate uncertainty and carbon emissions prices: The relative roles of transition and physical climate risks[#]

Serda Selin Ozturk [*], Riza Demirer[**] and Rangan Gupta[***]

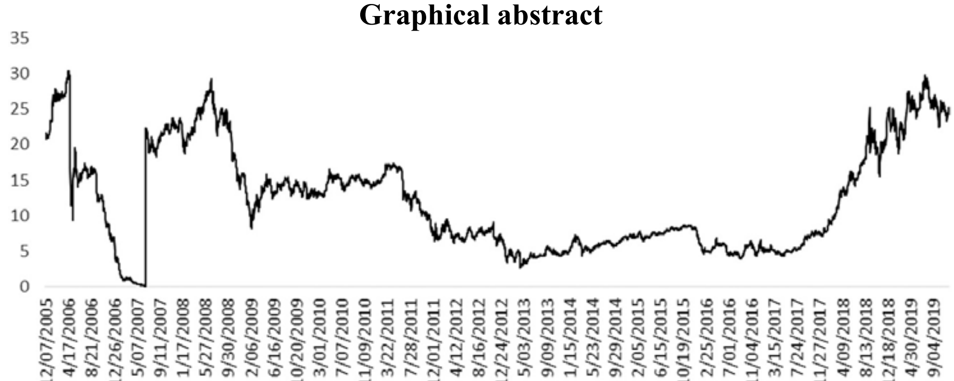
Highlights

- Analyzes the relationship between carbon allowance returns and climate risk variables.
- The effects of climate risk variables are different in the pre-Paris Agreement and post-Paris Agreement periods.
- Climate uncertainty indeed serves as a significant driver of price fluctuations in emissions prices.
- Measures of climate uncertainty can be used to improve forecasting models for emissions prices in terms of hedging strategies.

Abstract

This study examines the role of climate uncertainty over price volatility in the carbon emissions market using novel measures of uncertainty that capture transitional and physical climate risks. Applying a multivariate stochastic volatility model to daily European Union Allowance prices, we show that climate uncertainty indeed serves as a significant driver of price fluctuations in emissions prices with physical climate risks associated with uncertainty surrounding natural hazards playing a more dominant role over policy uncertainty in recent years. While our findings highlight the growing role of public concern over global warming and climate hazards than policy aspects as a driver of pricing dynamics in the emissions market, our findings present an interesting opening for hedging strategies towards attaining decarbonization goals in investment positions.

Graphical abstract



Keywords: Climate Risk, Carbon Prices, Stochastic Volatility
JEL Codes: C15; O13; Q54

[#] We would like to thank two anonymous referees, and the Editor, Professor Graham Elliott, for many helpful comments. However, any remaining errors are solely ours.

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1. Introduction

The emergence of environmental policies to control and reduce greenhouse gas emissions has exposed firms in energy intensive industries to significant transitional climate risks due to the potential costs involved in adjusting business operations to a heavily regulated, low carbon economy (Cepni et al., 2022). To that end, carbon emissions trading schemes offer a relatively cost-effective alternative for such firms as these contracts allow to trade emissions allowances, thus offering a tool to manage emissions related costs internally. Accordingly, a better understanding of price dynamics in the carbon emissions market is an important concern for corporate decision makers for the management of transitional climate risks in their business operations, particularly given the evidence that investors consider climate exposures in their firm valuation models (e.g. Bolton and Kacperczyk, 2021). The pricing of these assets is also of concern from a policy making perspective as carbon trading schemes serve as a policy tool for market regulators to control emissions in a regulated and effective way (Batten et al., 2021). Despite the growing literature on the drivers of carbon prices, however, the role of climate uncertainty in emissions price dynamics is relatively understudied. This paper provides novel insight to the role of climate uncertainty, both from a policy and natural hazard perspective, over price dynamics in the carbon emissions market. Indeed, using novel measures of climate uncertainty associated with climate policy and natural hazard risks, we show that uncertainty surrounding natural hazards have taken on a more dominant role over policy uncertainty over the recent years as a driver of price fluctuations in the emissions market. Our findings thus highlight the growing role of public concern over global warming and the occurrence of climate hazards than policy aspects as a driver of pricing dynamics in the emissions market.

The literature on carbon pricing has examined a variety of topics related to emissions trading from market microstructure and arbitrage to price drivers. Regarding price drivers, as carbon emissions are primarily driven by the burning of fossil fuels, a large literature has focused on the effect of energy and electricity prices on carbon price fluctuations (e.g. Zhu et al., 2019). While weather variables, except unanticipated temperature changes, are not found to be significant drivers of carbon prices (Batten et al., 2021), interestingly, a growing number of studies have highlighted the role of policy related factors as a factor in the pricing mechanism of carbon trades, arguing that policy effects could even overcome the effect of economic factors (Wang and Guo, 2018; Zhu et al., 2019). Indeed, Benz and Trück (2009) show that changes in regulation or policy can lead to sudden jumps in carbon prices, confirming the theoretical arguments in Christiansen et al. (2005) that relate policy regulation measures to carbon prices. Against this background, we examine the price dynamics in the carbon market from a novel perspective by exploring the role of climate uncertainty as a driver of return and volatility patterns within a multivariate stochastic volatility modelling framework. To that end, the climate uncertainty proxies recently developed in Faccini et al. (2021) present an interesting opening in that they allow us to distinguish between the transition climate risks that are associated with climate policy and international agreements and physical climate risks that are associated with natural hazards and global warming. By doing so, our analysis provides an interesting extension to the recent evidence regarding the effect of physical and transition climate risks on the price and volatility patterns in financial assets (Cepni, et al., 2022). The remainder of the paper is organized as follows. In Section 2, we describe the data and methodology. In Section 3, we present the empirical results and in Section 4, we conclude with possible directions for future research.

2. Data & Methodology

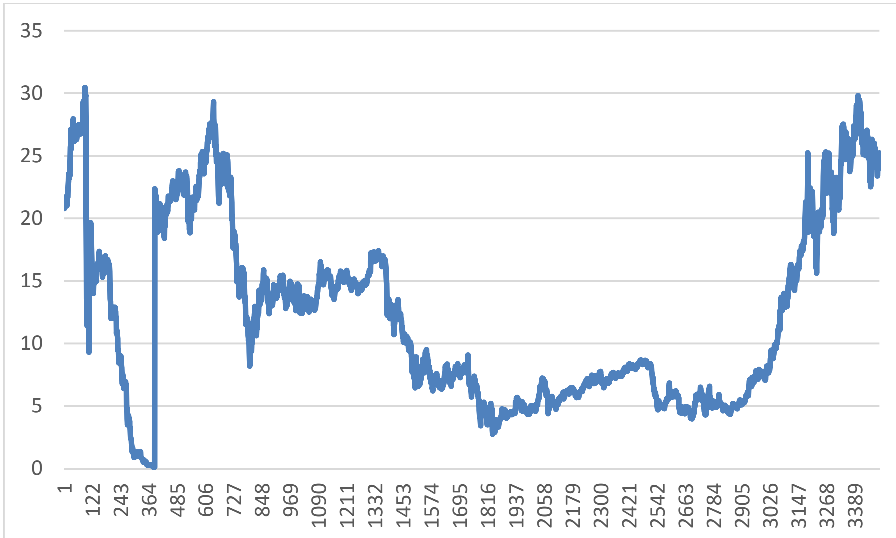
2.1 Data

We examine daily price data (euro per ton) for the European Union Allowance (EUA) futures contracts traded on the Intercontinental Exchange, sourced from Commodity Systems Inc. We focus on the nearby futures contract prices as the futures market serves as the venue for price discovery and a large percentage of the trading volume of carbon contracts occurs in the futures market. Close to the expiration of a contract, the position is rolled over to the next available contract, provided that the activity has increased and daily returns are computed as the end of day price difference (close to close). The climate risk data is based on Faccini et al. (2021) who conduct textual and narrative analysis of Reuters climate change news to compute daily proxies of climate uncertainty associated with physical and transition risks. Tracking the type and frequency of specific key words in the news articles via the Latent Dirichlet Allocation method of Blei et al. (2013), the authors use the share of an article's text associated with any given topic to derive daily measures of climate uncertainty associated with the occurrence of natural disasters, global warming, U.S. climate policy (actions and debate), and international summits on climate-change. In addition to these four climate risk proxies, the authors also derive a narrative U.S. climate policy factor by performing a narrative analysis on the content of news that is associated with the textual climate policy factor, thus capturing transition risks. Based on the common availability of the climate risk and carbon price data, the sample period is from December 6, 2015 to November 29, 2019.[1] Figure 1 presents the data for daily carbon allowance price, and its corresponding returns (without the outlier of June 28, 2007), as well as the climate risk variables utilized in our tests.

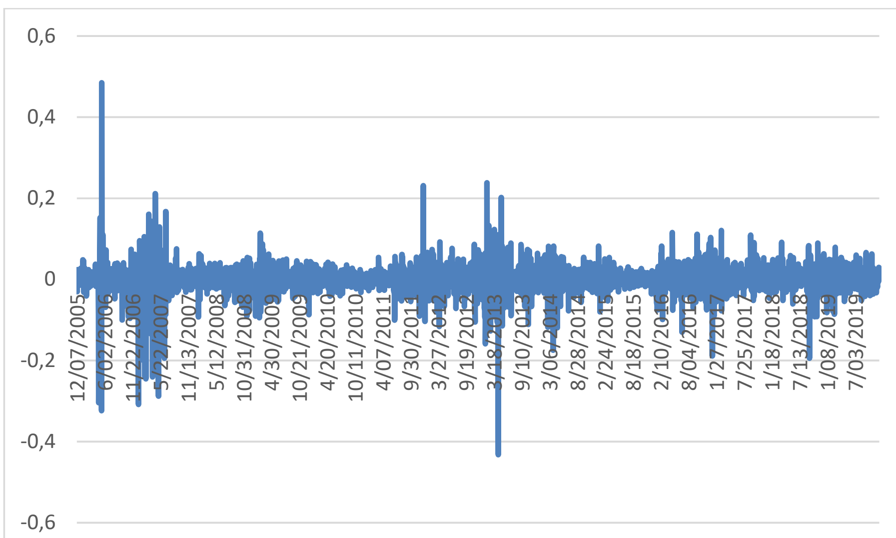
[1] Climate risks data is publicly available at: https://sites.google.com/site/econrenatofaccini/home/research.

Figure 1. Daily carbon allowance returns and climate risk variables.

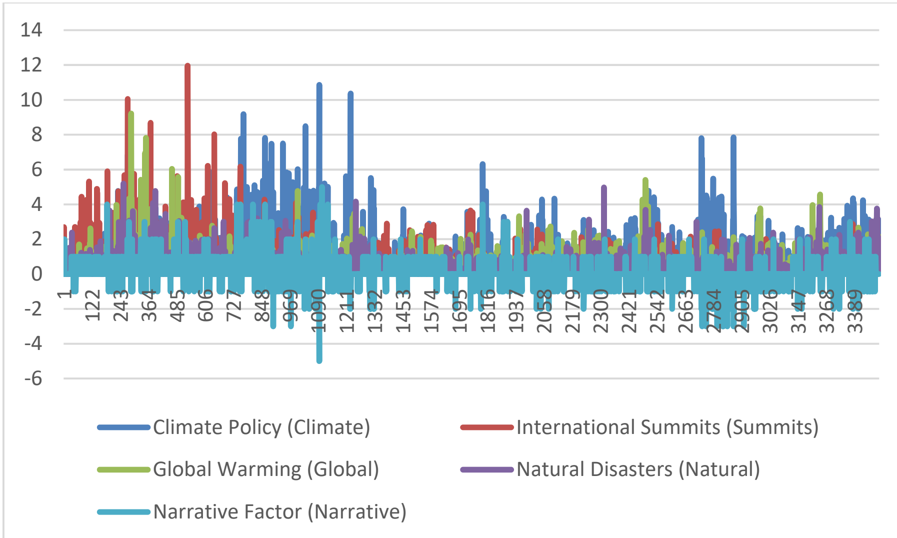
(a). Carbon allowance prices



(b). Carbon allowance returns



(c). Climate risk measures



2.2 Methodology

We estimate three different versions of the stochastic volatility (SV) model based on the standard SV model proposed by Taylor (1986). The benchmark specification is the standard SV model formulated as:

$$r_t = exp\left(\frac{\lambda_t}{2}\right)\epsilon_t \tag{1}$$

$$\lambda_t = \gamma + \delta\lambda_{t-1} + \nu\eta_t \tag{2}$$

where r_t denotes the observed carbon price return and λ_t unobserved volatility. The error terms (ϵ_t, η_t) are independent $N(0,\ 1)$ random variables. In order to examine the explanatory power of climate risk over carbon price dynamics, we augment the volatility equation with the climate uncertainty series which yields the volatility equation formulated as:

$$\lambda_t = \gamma + \delta\lambda_{t-1} + \sum_{i=1}^{n}\beta_i x_{it-1} + \nu\eta_t \tag{3}$$

where x_{it} (i=1,…,5) denotes each climate uncertainty variable described earlier. A similar approach is followed for the return equation by augmenting the standard return model with the climate risk series as:

$$r_t = \sum_{i=1}^{n}\beta_i x_{it-1} + exp\left(\frac{\lambda_t}{2}\right)\epsilon_t \tag{4}$$

In each model, a significant β parameter suggests that the corresponding risk variable has a significant effect either on the return or volatility process, while δ captures the persistence of the log volatility process such that $|\delta| < 1$ implies that returns are strictly stationary. In order to examine the explanatory power of various climate uncertainty proxies, we estimate various model combinations in $\{x_{it}\}$ for Equations 3 and 4 by including each climate risk variable one at a time and up to all five in the most comprehensive specification.

Regarding the estimation procedure, the SV model in Equations 1 and 2, and the augmented return/volatility equations characterize a Gaussian nonlinear dynamic state-space model. However, the nonlinear dependence of r_t on λ_t in the return equation prevents the application of the Kalman Filter. Therefore, we instead apply sequential Efficient Importance Sampling (EIS) to evaluate the likelihood function of our models. Originally proposed by Richard and Zhang (2007), EIS has been shown to produce highly accurate Monte Carlo (MC) estimates of likelihood functions for a wide range of SV models (see, e.g. Liesenfeld and Richard (2003, 2006). Finally, we examine the predictive accuracy of the competing forecasting models in terms of the returns, based on the Diebold and Mariano (1995) (DM) test.

3. Empirical Results

Following the EU's ratification of the Kyoto protocol in 2002, the development of the EU ETS (emissions trading scheme) has progressed in three stages including Phase 1 as a trial period (2005-2007), Phase 2 (2008-2012) wherein the scope of the scheme was extended to more countries and sectors, and Phase 3 (2013-2020) wherein a central registry system was established while EU-wide harmonized rules were instituted to manage carbon allowances. However, as Parry (2020) notes, the 2015 Paris agreement initiative has played a central role in the pricing mechanism of emissions allowances as the energy and climate policy initiatives were designed to converge towards meeting Paris emissions goals set by the EU. Accordingly, we report in Table 1, the results for the benchmark and multivariate SV models for the best fitting model specifications during the pre- and post-Paris agreement periods separately in addition to the whole sample results.[2]

Examining the results for the whole sample period reported in Panel A, we observe that international summits are the primary driver of price volatility in the carbon emissions market as the best fitting volatility model includes this variable at the highest level of statistical significance. Uncertainty surrounding international climate summits positively affect price market fluctuations, suggesting that the outcome of climate summits, i.e. whether or not these summits will yield a mutual agreement across the global economies regarding emissions regulations, constitutes the primary uncertainty factor in the volatility of emissions prices. In the case of the return model, however, we find that U.S. climate policy actions (and debates) as well as natural disaster risks play a primary role as return drivers, both with a positive effect on emissions prices in the whole sample. These findings suggest that transitional climate risk proxies associated with climate policy actions and international summits serve as

[2] The results for the SV model variations that include all climate risk proxies are presented in Table A1 in the Appendix. We also represent the results of the best fitting model for the combined model of Equation 3 and 4 in Table A2. Results indicate that although the significant variables are similar to those we found when we used climate risk variables only in return or volatility equation, the model does not improve in terms of the log-likelihood values. Furthermore, in pre-agreement period summit variable in the volatility equation becomes insignificant and in post-agreement period and whole sample period natural variable in return equation becomes insignificant.

Table 1. Multivariate stochastic volatility model results for best fitting models.

	Panel A: Whole Sample			**Panel B:** Pre-Paris Agreement			**Panel C:** Post-Paris Agreement		
Variables	**Basic SV**	**Volatility Model**	**Return Model**	**Basic SV**	**Volatility Model**	**Return Model**	**Basic SV**	**Volatility Model**	**Return Model**
γ	-0.017*** (0.0053)	-0.0029*** (0.0084)	-0.017*** (0.0052)	-0.0258*** (0.0077)	-0.0474*** (0.0125)	-0.0259*** (0.0078)	-0.0290*** (0.0284)	-0.1408*** (0.0541)	-0.0367*** (0.0315)
δ	0.975*** (0.0056)	0.970*** (0.0064)	0.975*** (0.0056)	0.9701*** (0.0066)	0.9639*** (0.0074)	0.9701*** (0.0065)	0.8903*** (0.0559)	0.8186*** (0.645)	0.8758*** (0.0606)
ν	0.233*** (0.0213)	0.241*** (0.0233)	0.233*** (0.0223)	0.2861*** (0.0253)	0.2982*** (0.0252)	0.2890*** (0.0249)	0.3439*** (0.0913)	0.4383*** (0.0841)	0.3755*** (0.0983)
Climate Policy	-	-	0.016** (0.0080)	-	-	0.0214*** (0.0076)	-	0.0887** (0.0412)	-
International Summits	-	0.019** (0.0085)	-	-	0.0267*** (0.0107)	-	-	-	-
Global Warming	-	-	-	-	-	-	-	-	
Natural Disasters	-	-	0.028* (0.0162)	-	-	0.0488*** (0.0170)	-	-	-0.1556** (0.0687)
Narrative	-	-	-	-	-	-	-	-	-
Log-likelihood	-3625.32	-3620.14	-3622.25	-2963.09	-2960.25	-2959.54	-659.71	-656.07	-657.11

Note: The table presents the estimation results for the best fitting models for return and volatility. Panels B and C present the findings for the pre- (2005-2016) and post- (2017-2019) Paris Agreement periods, respectively. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

a primary factor in the return and volatility dynamics in the carbon emissions market, both contributing positively to price and volatility in this market.

Further examining the pre- and post-Paris agreement periods in Panels B and C, we confirm in Panel B that transitional climate risk proxies associated with climate policy and international summits serve as the main driver of price volatility in emissions prices with a positive effect on volatility. In the case of return dynamics however, we observe that physical climate risk captured by the occurrence of natural disasters serve as the more dominant return drivers during both sub-periods. This is in contrast with the evidence in Fraccini et al. (2021 that only climate policy uncertainty is priced in the cross section of U.S. stocks, while uncertainty associated with the occurrence of natural disasters, the rise in temperatures, and the debate in international summits are not significant drivers of pricing patterns in the stock market. Interestingly, however, while natural disasters have a positive effect on emissions returns during the pre-Paris agreement period, we find that this relationship is reversed after the Paris agreement, possibly as carbon pricing initiatives gained widespread momentum among public and private sectors following the Paris commitment. This is good news from policy making perspective as it shows that the new opportunities and initiatives that emerged from the Paris commitment has helped eased carbon emissions prices despite the occurrence of natural hazard risks during the post-Paris agreement period.

Further extending our analysis to a forecasting context, we next examine in Table 2 the predictive power of the climate risk proxies over future emission prices. To this end, we perform a rolling-window forecasting procedure for the pre- and post-Paris agreement subsamples. For the first period, we set 2005-2015 as the estimation period and generate a forecast for the first day of 2016. We then repeat this procedure by rolling the forecast window one observation ahead until the end of 2016. Similarly, for the post-Paris agreement subperiod, we use 2017-2018 period to generate a forecast the first day of 2019 and continue the process until the end of the sample period in 2019. Note that the forecasting models are estimated using the best fitting models that include only the risk variables that are significant in each case. Finally, the forecast results are evaluated based on the Diebold and Mariano (1995) (DM) test wherein the forecasts from the SV model augmented with climate uncertainty predictors are compared against those from the benchmark SV model.

Table 2. Predictive power of climate uncertainty.

	2016	**2019**
Volatility model	3.5310***	2.1005**
Return model	-2.5960***	-3.5634***

Note: The table presents the Diebold-Mariano (DM) test results to compare the predictive accuracy of the SV model augmented with climate uncertainty predictors against the benchmark SV model. A negative (positive) test result suggests improved predictive performance for the benchmark SV (augmented) model. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

We observe in Table 2 that the predictive power of the climate uncertainty proxies is primarily focused on the model where we include the risk variables in the volatility equation, implied by the positive and significant DM test statistics for both sub-samples. This is consistent with the findings in Table 1 that higher climate uncertainty is associated with greater volatility in emissions prices. In the case of the model where the risk variables are included in the return equation, however, the results in Table 2 show that the augmented model is significantly worse than the benchmark model, suggesting that climate uncertainty is not necessarily a reliable predictor of short-term price patterns. Further examining the relative predictive power of the transitional and physical climate risks, we find in the first row of Table 3 that transitional climate risks capture greater predictive information during the earlier part of the sample. However, physical climate risks play a more dominant role as a return predictor during the latter period when variables are included in the volatility equation. This result shows that the Paris agreement has largely mitigated the effect of climate uncertainty regarding policy changes and international agreements over price volatility in the emissions market. However, following the Paris agreement, uncertainty associated with the occurrence of natural disasters and global warming has played a more dominant role as a driver of future price fluctuations in the carbon emissions market.

Table 3. Predictive power of transitional versus physical climate risks.

	2016	**2019**
Volatility model	-2.3680**	2.1680**
Return model	0.1415	0.0248

Note: The table presents the Diebold-Mariano (DM) test results to compare the predictive accuracy of the SV model augmented with carbon policy related predictors against that augmented with disaster related predictors. A negative (positive) test result suggests improved predictive performance for the policy-based (natiral disaster based) SV model. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Finally, when the risk variables are included in the return equation, we find no significant difference in terms of the predictions based on the physical climate risks and the transitional climate risks in both sub-periods. This finding coincides with the finding in Table 2 which shows that the benchmark model is superior to the model where the risk variables are included in the return equation. In sum, the results suggest that the improvement in the volatility forecasts due to the inclusion of the climate risk variables in the volatility equation, also help improve the return forecasts, thus resulting in significant DM test results in favor of the augmented model. When the risk variables are included in the return equation, however, we do not observe significant improvement in the volatility predictions, and therefore we do not get any significant improvement in the return predictions. Accordingly, we argue that the predictive power of climate risk variables over carbon market returns is primarily driven by the predictive information these variables contain regarding volatility in the carbon market.

Table A1. Multivariate stochastic volatility model results with all climate variables.

Variables	Volatility Model			Return Model		
	Pre-Paris Agreement	Post-Paris Agreement	Whole Sample	Pre-Paris Agreement	Post-Paris Agreement	Whole Sample
γ	-0.037*** (0.0121)	-0.079* (0.0422)	-0.033*** (0.0105)	-0.018*** (0.0060)	-0.052 (0.0319)	-0.017*** (0.0050)
δ	0.972*** (0.0067)	0.795*** (0.0672)	0.971*** (0.0066)	0.977*** (0.0059)	0.815*** (0.0694)	0.976*** (0.0054)
ν	0.246*** (0.0247)	0.411*** (0.0758)	0.240*** (0.0228)	0.242*** (0.0252)	0.428*** (0.868)	0.232*** (0.0209)
Climate Policy	-0.001 (0.0081)	0.069* (0.0370)	-0.001 (0.0073)	0.027*** (0.0097)	0.000 (0.0319)	0.022*** (0.0096)
International Summits	0.023* (0.0128)	0.029 (0.1037)	0.023*** (0.0115)	-0.007 (0.0153)	0.036 (0.0774)	-0.009 (0.0143)
Global Warming	0.019 (0.0182)	-0.081 (0.0734)	0.013 (0.0158)	-0.012 (0.0169)	-0.088 (0.0622)	-0.018 (0.0159)
Natural Disasters	-0.009 (0.0216)	-0.097* (0.0534)	0.009 (0.0174)	0.056*** (0.0208)	-0.055 (0.0479)	0.040*** (0.0192)
Narrative	-0.029 (0.0212)	-0.042 (0.0525)	-0.029 (0.0173)	0.021 (0.0181)	0.053 (0.0456)	-0.012 (0.0164)
Log-likelihood	-2960.10	-652.29	-3618.96	-2959.19	-655.36	-3617.59

Note: The table presents the estimation results for the return and volatility models that include all climate variables. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table A2. Multivariate stochastic volatility model results for best fitting models when Equation 3 and Equation 4 are combined

Variables	Pre-Paris Agreement	Post-Paris Agreement	Whole Sample
Climate Policy in return	0.0209*** (0.0085)	-	0.0164** (0.0082)
International Summits in return	-	-	-
Global Warming in return	-	-	-
Natural Disasters in return	0.0558*** (0.0189)	-0.0875 (0.0542)	0.0289 (0.0183)
Narrative in return	-	-	-
γ	-0.0404*** (0.0121)	-0.1514*** (0.0583)	-0.0292*** (0.0083)
δ	0.9703*** (0.0069)	0.8101*** (0.0643)	0.9709*** (0.0062)
ν	0.2861*** (0.0263)	0.4689*** (0.0779)	0.2816*** (0.0273)
Climate Policy in volatility	-	-	-
International Summits in volatility	0.0170 (0.0139)	0.0907** (0.0451)	0.0138** (0.0068)
Global Warming in volatility	-	-	-
Natural Disasters in volatility	-	-	-
Narrative in volatility	-	-	-
Log-likelihood	-2962.48	-657.49	-3623.50

Note: The table presents the estimation results for the best-fitting combined model of return and volatility models. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Conclusion

This paper contributes to the emerging literature on the role of climate uncertainty as a driver of return and volatility patterns in financial markets by extending the evidence to the carbon emissions market. Utilizing novel measures of climate uncertainty that capture transitional and physical climate risks and price data on EUA carbon futures, we find that climate uncertainty indeed serves as a significant driver of price fluctuations in emissions prices. Interestingly, however, physical climate risks associated with uncertainty surrounding natural hazards have taken on a more dominant role over policy uncertainty over the recent years as a driver of price fluctuations in the emissions market. This suggests that the 2015 Paris agreement has led to a structural shift in the pricing patterns in the emissions market wherein the market focus has shifted towards natural hazard risks rather than policy uncertainty in the pricing mechanism of carbon emissions. While our findings highlight the growing role of public concern over global warming and the occurrence of climate hazards than policy aspects as a driver of pricing dynamics in the emissions market, important implications emerge regarding the management and hedging of climate risk exposures. Considering that optimal hedge positions to mitigate carbon risk in investment positions depend on the accuracy of volatility forecasts, our findings suggest that measures of climate uncertainty can be used to improve the effectiveness of hedging strategies to manage physical and transition climate risks. For future research, it will be interesting to examine whether incorporating climate risk proxies in forecasting models can help achieve utility gains for investors who set decarbonization levels for their investment positions.

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Appendix