Time Series Extended Abstract

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Modeling Volatility in the US Energy Sector in Response to Global Climate Change Sentiment

Introduction

In the paper *Common Volatility Shocks Driven by the Global Carbon Transition* by Campos-Martins and Hendry (2024), the authors propose a method to measure common movements in the global oil and gas (O&G) industry. Specifically, they aim to quantify how much of that movement is driven by climate change concerns about the global climate transition, which they measure using a text-based analysis of climate change news.

In our research, we have decided to focus on the US O&G industry by looking at how the Energy Select Sector SPDR Fund (XLE) is affected by global climate change sentiment. We consider XLE to be a proxy for the U.S O&G industry as it is made up of the biggest O&G firms, such as ExxonMobil and ConocoPhillips. Due to size of American energy firms and the dominant role of the U.S in geopolitics, we think that U.S energy firms would be more resilient to climate change shocks. Our measure of the sentiment index broadly considers climate change news related to research, policy, and climate events. To study this, we derive the volatility of the XLE fund by taking the square root of the conditional variance from a GARCH (1,1) model. We then analyze the short and long run effects of the shock through a Local Projection IRF model.

Data and Variables

The data for the stocks and their weights in the XLE fund come from Alpha Vantage, and the closing prices for the stocks in the XLE fund are derived from the $yfinance$ module in Python. This module takes stock prices and dates from Yahoo Finance. These returns are then adjusted for annual inflation. We also use this module to get data for the S&P 500 returns. We get data for the WTI crude oil price, the Brent crude oil price, NASDAQ returns, and US government expenditure from FRED. The climate change sentiment data consists of the total number of global publications that mention "climate change" during the given time and identifies the number of articles that present negative evidence against climate change, with a focus on business news. This data is extracted from Nexus Uni, where they have a separate section that identifies negative news. However, the news sentiment data and the fiscal policy data are measured annually and quarterly, respectively, while the other controls are measured monthly. To correct this, the monthly news sentiment data and fiscal policy data is created by interpolating the values between each each year or quarter to create the 12 months in each year. We adopt a similar method that Campos-Martins and Hendry use in their paper to compute a concern index for climate change. The computation is as follows:

$$Index_t = \frac{Negative\ Coverage_t}{All\ Coverage_t} * \frac{Negative\ Coverage_t - Positive\ Coverage_t}{All\ Coverage_t}$$

Models

To model global common volatility, the authors consider a factor model to model correlated stock movements across countries. We model the inflation-adjusted XLE returns using a GARCH(1,1) model. This is given by:

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1} + \beta_1 \sigma_{t-1}^2$$

We then extract conditional variance predicted by the GARCH model and then take a square root to proxy for volatility. We then add this volatility measure as the outcome variable to a Local Projection IRF (Jordà, 2005). The idea is to consider how shocks to climate change news might affect volatility of the US oil and gas industry. A possible IRF used to calculate the effect of climate change shocks over a forecast horizon specified by h is given by:

$$\hat{\sigma}_{t+h} = \theta_h Index_t + \beta_h controls_t + \nu_{t+h}$$

where $Index_t$ is the climate change concern index. When generating the regressions, we adjust the standard errors using the Newey-West method, which accounts for heteroskedasticity and autocorrelation.

Results

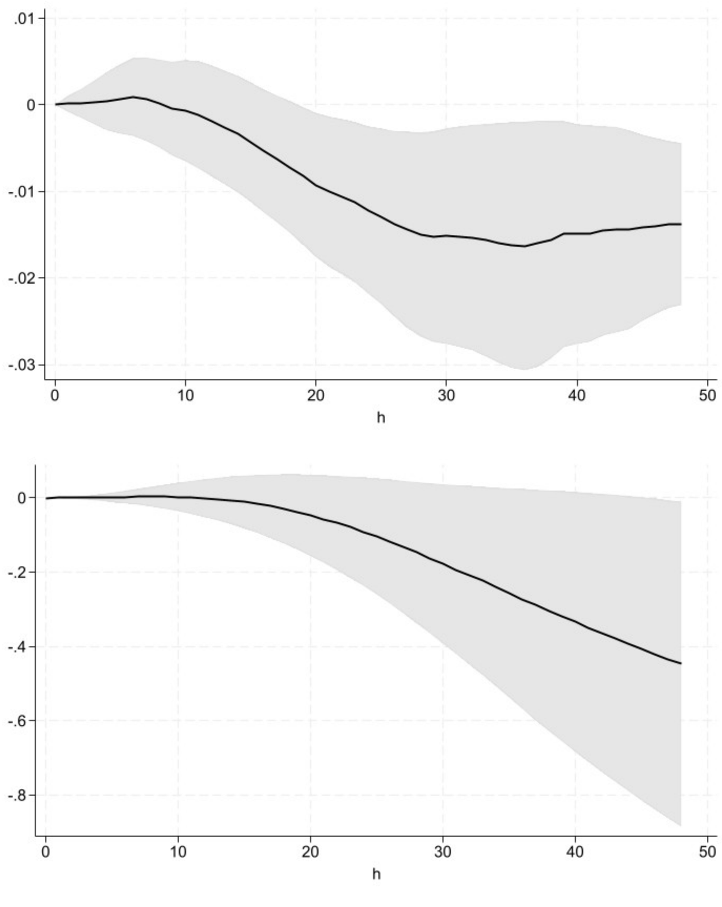

Figure 1: Impulse responses of volatility to a carbon cost shock. Top: Standard response; Bottom: Cumulative response.

Table 1: Impulse Responses to CC_Index Shocks (Selected Horizons)

Forecast Horizon	**Volatility**	**Cumulative Volatility**
F1	-0.0001	0.0001
F2	-0.0002	0.0003
F3	-0.0003	0.0006
⋮	⋮	⋮
⋮	⋮	⋮
F19	-0.0082*	-0.0378
F20	-0.0092*	-0.0470
F21	-0.0100*	-0.0571
⋮	⋮	⋮
⋮	⋮	⋮
F46	-0.0140**	-0.4200
F47	-0.0138**	-0.4338*
F48	-0.0138**	-0.4475*

Note: Significance levels: *p<0.10, **p<0.05, ***p<0.01.

The biggest result we found is that a positive shock on the climate change sentiment will have a negative effect on volatility, which suggests that more negative news on climate change will decrease the volatility of the XLE fund. More specifically, volatility has a significant negative effect after the 19th forecast horizon and remains significant for the remaining forecast horizon. The cumulative effect of a positive shock on climate change sentiment starts positive, but switches to a negative sum on the 12th horizon. It is insignificant throughout most the forecast horizon, until it becomes significant at the 47th and 48th forecast horizon. Since the period-by-period effect on volatility is relatively small, it causes a lack of significant cumulative change for most of the forecast horizon. Although the results are omitted, we also look at the effect of climate change sentiment on the control variables, and find no significant effects at any horizon. This shows robustness of our results as it indicates that no measured factors drive volatility.

Discussion and Conclusion

The effect that global climate change sentiment shocks has on the volatility of the XLE fund contradicts the findings in the Campos-Martins & Hendry paper. Since exchange-traded funds (ETFs) are used to hedge against idiosyncratic risks, this behavior could be isolated to the XLE fund. We believe the decrease in volatility comes from investors and firms hedging risk in order to minimize the effect the news will have on the energy sector. The decrease comes later as the global news would take time to affect American markets directly, either through policy changes or economic barriers. There is literature (Li et al., 2023) that suggests climate sentiment has an effect on the volatility of O&G stocks when compared to "green" stocks, but we do not take the substituting stocks into consideration when showing our change in volatility, as we only study brown stocks.

The results of our research are counterintuitive and suggest that global climate change sentiment reduces volatility among major U.S. O&G firms. This could be the result of stakeholders hedging against risks in anticipation of current negative shocks to climate change news. The results indicate that American O&G firms are more resilient to climate change shocks as we initially hypothesized.

References

Campos-Martins, S., & Hendry, D. F. (2024). Common volatility shocks driven by the global carbon transition. *Journal of Econometrics*, *239*(1), 105472. https://doi.org/10.1016/j.jeconom.2023.05.008

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, *95*(1), 161–182. https://doi.org/10.1257/0002828053822033

Li, H., Bouri, E., Gupta, R., & Fang, L. (2023). Return volatility, correlation, and hedging of green and brown stocks: Is there a role for climate risk factors? *Journal of Cleaner Production*, *414*, 137594. https://doi.org/10.1016/j.jclepro.2023.137594