# Geo-Climate, Geopolitics and the Geo-Volatility of Carbon-Intensive Asset Returns

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**Abstract**

Anthropogenic climate change is due to burning fossil fuels and the consequent release of greenhouse gases. Given current technology, a transition towards low-carbon economies requires investments to shift away from carbon intensive assets. The systemic implications of disruptive technological progress on the prices of such assets are compounded by the geopolitical nature of transition risk. If investors are pricing climate change risk, prices of carbon intensive assets should all be responsive to climate change news. We propose a new modeling approach to analyze to what extent stock markets are reacting to climate change. For modeling the dynamics of volatility comovements at the global scale, we measure global carbon-intensive asset volatility using a novel model of multiplicative volatility factors. The model is applied to the daily stock prices of major oil and gas companies around the world. As the proxy for climate change perception, we use a climate change news index, which is constructed by applying text mining to newspaper content. By linking both sides, financial and climate change, results point out a significant effect of climate change volatility shocks on oil and gas stock return volatilities globally. Even though climate change shocks amplify the effect of crude oil volatility shocks on the oil and gas volatilities, they seem to have no direct effect on the volatility of the crude oil future.

## 1 Introduction

We frequently hear about the urgency of moving investments from brown financial assets to green assets. Brown assets are carbon-intensive and usually associated to fossil fuels

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such as coal, oil and natural gas, which are intrinsically high in carbon. Green assets are associated to cleaner energy and so low in carbon. Anthropogenic climate change is due to burning fossil fuels and its consequent release of greenhouse gases. Carbon dioxide, a greenhouse gas, is probably the most tracked carbon compound. The greenhouse effect of excessive carbon dioxide emissions has been accelerating global warming and disrupting the normal cycle of carbon. In order to reduce the carbon footprint and mitigate the global effects of climate change, a transition to low carbon economies is a work in progress. Given current technology, a shift away from fossil fuels is inevitable for countries to be successful.

Regarding the transmission channels of climate change to the financial sector, climate change risk is usually characterized as either physical or transitional. Even though there are attempts to analyze these risks separately, they are strongly related. The exposure posed by more frequent and severe climate-related disasters is likely to increase awareness and concerns about climate change. Hence, physical risk is likely to spill over and change the expectations about policy responses, especially carbon prices. It can thus amplify the uncertainty about the timing and speed of adjustment towards a low-carbon economy. Moreover, although some regions or countries are not directly exposed to physical risk, they can be indirectly affected by others that are particularly vulnerable through the international relations between the two.

A transition towards low-carbon economies will most certainly come alongside investments shifting away from activities that are carbon intensive. However, countries are still highly dependent on fossil fuels to produce energy. According to the Statistical Review of World Energy (BP, 2020), the distribution of the primary energy consumption by fuel type around the world indicates that, on average, 84% of primary energy is produced by means of fossil fuels (oil, coal and natural gas) and only 16% by non-fossil fuels (hydroelectricity, renewable energy, and nuclear energy). Coal is by far the worst polluter among fossil fuels and yet, in countries such as China and India, more than 50% of their primary energy consumption depends on coal. The effectiveness of changes in investment decisions also depends on the expectations about policy change (e.g. regarding carbon pricing). The systemic implications of disruptive technological progress on the prices of carbon-intensive assets are further compounded by the geopolitical nature of transition risk.

The finance literature on climate change has been focused on the pricing of climate change risks, in particular, on how stock returns reflect investor concerns about climate change. Bolton and Kacperczyk (forthcoming) provides a cross-country analysis of the effects of corporate carbon emissions and a country's transition risk on the stock returns. A company's carbon premium seems to be related to not only its level of emissions (long-run exposure to transition risk) but also changes in its level of emissions (short-run exposure to transition risk). Moreover, the carbon premium tends to be higher (lower) in countries with a higher share of brown (green) sectors (even though it does not seem to reflect physical risk).

If investors are pricing transition risk, one should expect the prices of brown assets to be responsive to climate change news given investor awareness about climate change seems to amplify the level of transition risk (Bolton and Kacperczyk, forthcoming). In order to analyze to what extent financial asset prices are reacting to climate change news, we propose a two-sided procedure. On one side of the analysis we have the brown financial asset prices. A volatility shock to climate change news should affect a wide range of brown assets (if not all) at the same time. Hence, we take financial markets as a whole and measure the comovements of volatilities of financial asset returns using a global volatility factor. On the other side, we control for climate change news. Volatility shocks arising from climate change news are identified and assumed to be an additional determinant of the global volatility factor.

Studies on the impact of climate change on financial markets include the analysis of value at risk associated with climate shocks (Dietz et al., 2016) in which financial losses are aggregated and derived top-down from estimated output losses due to climate change or of climate stress-tests of the financial system as the inter-linkages among financial institutions may amplify both positive and negative shocks (Battiston et al., 2017).

The high uncertainty around future demand for fossil fuels and their role in the transition process towards low carbon economies, make them particularly relevant. Are fossil fuel stock returns responsive to climate change news? If they are exposed to climate change risk posed by policy action such as carbon pricing, they should be. Investing in activities that are not viable in a low carbon economy makes investors less resilient to climate change risks and more exposed to lower financial returns. The most relevant climate change risk in our analysis is transition risk. The uncertainty about the timing and speed of transition towards a low carbon economy is what we mean by transition risk.

If investors are pricing transition risk, this implies prices of high-carbon assets should all be responsive to climate-related policy news. For modeling the dynamics of volatility comovements at the global scale, we use the global volatility factor model of Engle and Campos-Martins (2020). The model was introduced for modeling comovements of idiosyncratic volatilities. When innovations to volatilities are correlated across assets, common volatility shocks can be identified. Economic, political or military events impact volatilities of a wide range of financial assets and move markets. The global volatility factor is thus interpreted as a measure of magnitude of the common volatility shocks and is intended to capture geopolitical risk due to its broad impact on many assets. The global volatility factor model is applied to the daily share prices of oil and gas companies from different countries traded in the NYSE to assure synchronicity of observations. Global oil and gas volatility peaks after the 9/11 terrorist attack, during the global financial crisis in 2008, whereas OPEC announcements and the Saudi drone attack show up as recent extreme global volatility events. As a proxy for climate change risk, we use the climate change news index of Engle et al. (2020). This index is a time series that captures news about long-run climate risk. In particular, we use the innovations in their negative (or bad) news time series which is constructed by using sentiment analysis. Results point out a changing (increasingly positive) effect of climate change volatility shocks to the bad news index on global oil and gas volatility over time. Different oil and gas assets are affected differently by the global volatility factor and this is reflected by the different loadings across assets. The results point out a significant effect of climate change volatility shocks to oil and gas stock return volatilities but not to the oil 1-month future return volatility. Instead, oil and gas volatility shocks driven by oil shocks are amplified by bad climate change news.

The paper is organized as follows. In the following section 2, the global volatility factor model with heterogeneous effects of the factor on the volatilities is summarized and the estimation results are presented for oil and gas stocks. Subsequently, in section 3, we develop the strategy addressed to identify the volatility shocks driven by climate change news and which can affect financial markets. Section 4 links volatility shocks to oil and gas stock returns with volatility shocks to climate change innovations using regression analysis. Finally, section 6 concludes the paper.

## 2 Modeling volatility comovements of stock returns

It is a stylized fact that financial volatilities comove. This is not surprising if asset returns respond to the some factors. Interestingly, whatever factors are extracted from the returns, idiosyncratic volatilities still comove (Herskovic et al., 2016); See also Connor et al. (2006) and Ang et al. (2006) for some references in the literature on idiosyncratic volatility. Engle and Campos-Martins (2020) propose a new model of idiosyncratic volatility comovements based on a multiplicative decomposition of the volatility standardized returns. When many assets respond to the same news at the same time, shocks to volatilities are correlated. The new statistical model is thus able to capture common volatility shocks that make markets move at the same time. We shall now briefly describe this global volatility factor model.

Consider the $(n \times 1)$ vector of returns $\boldsymbol{r}_t = (r_{1t}, \ldots, r_{nt})'$ given by

$$\begin{aligned} \boldsymbol{f}_t &= \boldsymbol{w}'_{t-1}\boldsymbol{r}_t \\ \boldsymbol{r}_t &= r^f + \mathbf{B}\boldsymbol{f}_t + \mathsf{diag}(\sqrt{\boldsymbol{h}_t})\boldsymbol{e}_t, \end{aligned} \tag{1}$$

where $\boldsymbol{w} \equiv (w_1, \ldots, w_n)'$ are weights, $\mathbf{B}$ is an $(n \times p)$ matrix of risk exposures, $\boldsymbol{f}_t$ is a $(p \times 1)$ vector of factors, $\boldsymbol{h}_t \equiv (h_1, \ldots, h_n)'$ contains idiosyncratic conditional variances and $\boldsymbol{e}_t \equiv (e_1, \ldots, e_n)'$ the idiosyncrasies.

Assume factors are sufficient to reduce the contemporaneous correlations to zero such that $\mathbb{E}_{t-1}(\boldsymbol{e}_t\boldsymbol{e}'_t) = \mathbb{I}$. This standard assumption states that the volatility standardized residuals are orthogonal in both times series and cross section with unit variances. This does not mean however that the elements of $\boldsymbol{e}_t$ are independent. The fundamental observation of the model is that the squares of $\boldsymbol{e}_t$ can be correlated in the cross section.

Let $x_t, t = 1, \ldots, T$, denote the global volatility factor, a positive scalar random variable (latent) with mean 1 and variance $\upsilon$ which is independent of $\boldsymbol{\epsilon}_t = (\epsilon_{1t}, \ldots, \epsilon_{nt})'$. The factor loadings are denoted by $s_i, i = 1, \ldots, n$ and interpreted as parameters (fixed effects). The standardized residuals are then assumed to have the multiplicative decomposition

$$e_{it} = \sqrt{g_{it}(s_i, x_t)}\epsilon_{it}, \tag{2}$$

where $g_{it}(s_i, x_t)$ is non-negative for every $t \in [1, T]$ with $\mathbb{E}[g_{it}(s_i, x_t)] = 1$ which satisfies $\mathbb{E}[e_{it}^2] = 1$ for every $i$. Each of the heterogeneous volatility factors is specified as

$$g_{it}(s_i, x_t) \equiv s_i x_t + 1 - s_i, \tag{3}$$

$x_t > 0, t = 1, \ldots, T$, and $0 \leq s_i \leq 1, i = 1, \ldots, n$. Recall that $\mathbb{E}_{t-1}[\boldsymbol{e}_t\boldsymbol{e}_t'] = \mathbb{I}$. But (2) implies $\mathbb{E}_{t-1}[\boldsymbol{e}_t^2(\boldsymbol{e}_t^2)'] = \Psi$. The variance-covariance matrix of the squared standardized residuals $\boldsymbol{e}_t^2$ is assumed as non diagonal with different elements. For further details we refer to Engle and Campos-Martins (2020).

Assuming normality, the log-likelihood function for the volatility standardized residuals is simply

$$\ell(e_{it}, s_i | x_t) = -\frac{1}{2}\left\{\ln 2\pi + \ln g_{it}(s_i, x_t) + \frac{e_{it}^2}{g_{it}(s_i, x_t)}\right\} \tag{4}$$

and the first order conditions are the partial derivatives with respect to the two sets of unknowns $s_i$ and $x_t$,

$$\frac{\partial \sum_{t=1}^{T} \ell(e_{it}, s_i | x_t)}{\partial s_i} = 0$$
$$\frac{\partial \sum_{i=1}^{n} \ell(e_{it}, s_i | x_t)}{\partial x_t} = 0,$$

for all $i$ and $t$. These conditions define the following time-series and cross-sectional heteroskedasticity regressions:

$$\text{Time-Series: } e_{it} = \sqrt{s_i(\hat{x}_t - 1) + 1}\epsilon_{it} \text{ for } i = 1, \ldots, n, \tag{5}$$
$$\text{Cross-Section: } e_{it} = \sqrt{\hat{s}_i(x_t - 1) + 1}\epsilon_{it} \text{ for } t = 1, \ldots, T.$$

Since each partial derivative depends upon the other estimates, a joint maximum can be achieved if the estimation of the two regressions are iterated until convergence in a maximization-maximization procedure (Hastie et al., 2009).

Finally, to detect common volatility shocks, we test the null hypothesis that the squared standardized residuals are uncorrelated. The null hypothesis of no correlation is defined as

$$\mathbb{H}_0 : \Psi = 2\mathbb{I}, \quad \mathbb{E}_{t-1}[\boldsymbol{e}_t^2(\boldsymbol{e}_t^2)'] \equiv \Psi, \tag{6}$$

where $\boldsymbol{e}_t^2 = (e_{1t}^2, \ldots, e_{nt}^2)'$. Without loss of generality, $\boldsymbol{e}_t^2$ are assumed to be equicorrelated under the alternative. Hence, it is straightforward to test $\mathbb{H}_0' : \bar{\rho}_{\boldsymbol{e}^2} = 0$ against $\mathbb{H}_1' : \bar{\rho}_{\boldsymbol{e}^2} > 0$. For $n(n-1)/2$ correlations, the statistic simplifies to

$$\xi = \frac{\sqrt{\frac{nT}{(n-1)/2}} \sum_{i>j,j=1}^{T} \sum_{t=1}^{T} (e_{it}^2 - 1)(e_{jt}^2 - 1)}{\sum_{i=1}^{n} \sum_{t=1}^{T} (e_{it}^2 - 1)^2} \xrightarrow{d} \mathcal{N}(0,1) \text{ under } \mathbb{H}_0'. \tag{7}$$

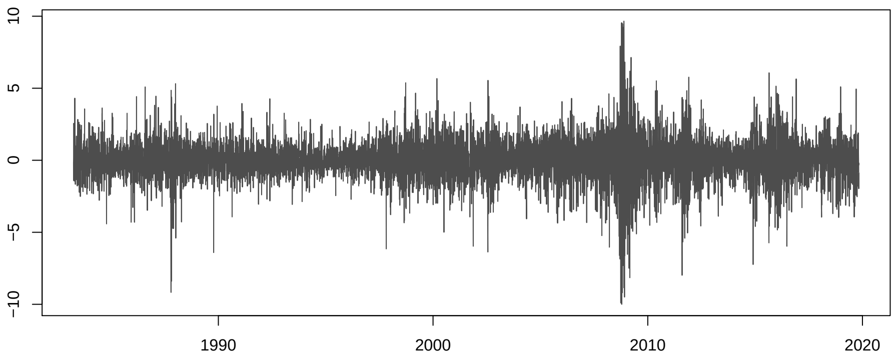
## 2.1 The oil and gas common volatility shocks

For modeling volatility co-movements at the global scale, a volatility factor model is used. Oil and gas global volatility shocks are related to demand shocks (global financial crisis, China slowdown) and supply shocks (e.g. OPEC announcements, which in turn affect oil prices).

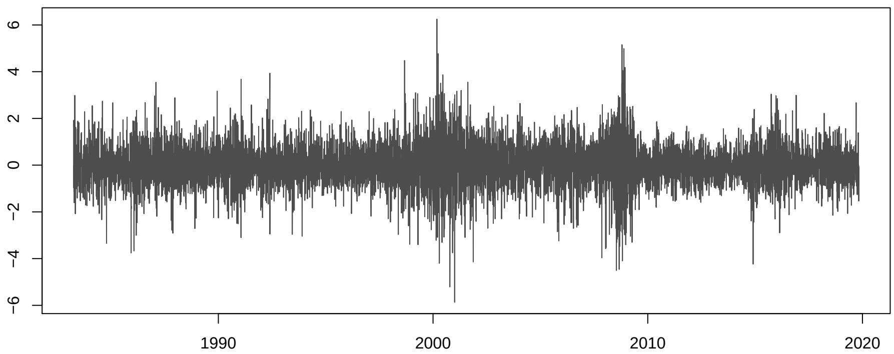
To analyze to what extent climate change news affects financial markets, we use two indicators: one that captures the common shocks to the volatilities of oil and gas stocks returns and the other that works as a proxy for climate change perception or awareness. For a discussion on the climate-policy relevant sectors in the economy we refer to Battiston et al. (2017). On the financial side, we use daily closing prices of shares from twenty major oil and gas companies around the world but traded in the New York Stock Exchange. This way we are guaranteed to have synchronous observations when measuring the comovements. The sample period goes from April 4, 1983 until October 31, 2019. This is an unbalanced panel with a minimum of eight observations per day. Because the time series are not stationary, we convert prices into log-returns. Extreme positive (negative) returns are truncated to ±10%. Our modeling framework starts by estimating a factor model with GARCH errors for each asset. To model the time dependence in the first moment of the data, a first-order autoregressive AR(1) model is fitted when necessary. The choice of the order of the AR model is supported by Ljung-Box AR(1) test. To account for common factors affecting the series of returns, we assume a Fama and French three factor model. We also include the excess returns on the WTI 1-month future price as a covariate. To model the heteroskedasticity behavior of the series, a first order GARCH(1,1) model is assumed for the errors. Both cross-section averaged excess returns and cross-section averaged estimated volatilities are depicted in Figure 1. For comparison, both cross-section averaged estimated volatilities of oil and gas stock returns (black) and the estimated volatility of the excess returns of the S&P 500 index (a), the WTI crude oil future (b) and the energy sector ETF (c) are also shown (blue) in Figure 2.

Even after extracting factors, including the excess returns on the WTI, idiosyncratic volatilities are still correlated. The correlation between the average volatility of oil and gas returns and the volatility of returns on the WTI future is 0.505, on the energy sector ETF (XLE) is 0.666, and on the S&P 500 index is 0.612. Even though the correlations are high, especially for the energy sector ETF, they do not perfectly match the variation captured in the oil and gas returns. The average correlation within oil and gas volatilities is 0.533 and the first principal component accounts around 44% of the total variance of volatilities. Having estimated the series of residuals and volatilities, we compute the vector of standardized residuals $\hat{\boldsymbol{e}}_t, t = 1, \ldots, T$. To detect the presence of significant common volatility shocks over time, we test whether the average correlation of $\boldsymbol{e}_t^2$ is equal to zero. We test $\mathbb{H}_0 : \bar{\rho}_{e^2} = 0$ against the one-sided $\mathbb{H}_0 : \bar{\rho}_{e^2} > 0$. The empirical average correlation $\bar{\rho}_{e^2} = 0.093$. For this sample, the test statistic is $\xi = 110.687$ and we thus strongly reject the hypothesis that the average correlation of the squared standardized residuals is zero. This result provides evidence that the squared standardized residuals are correlated and so we proceed to the estimation of the oil and gas volatility factor in order to capture the common shocks driving the common movements of volatilities.

We shall briefly describe the iterative estimation of the oil and gas volatility factor and corresponding factor loadings. As the starting values for the estimation of $x_t, t = 1, \ldots, T$,

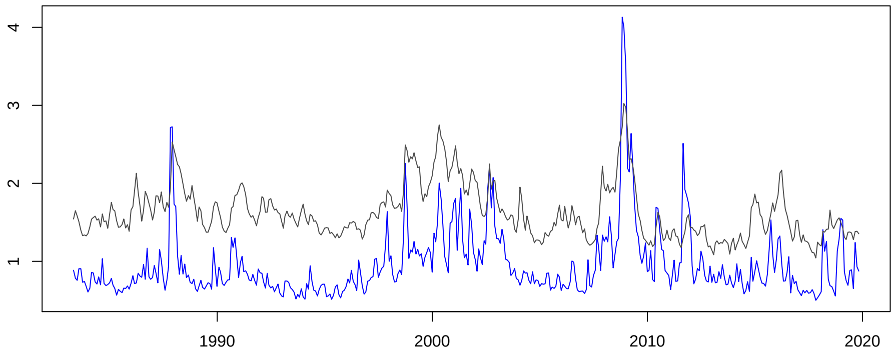



(a) Excess returns.

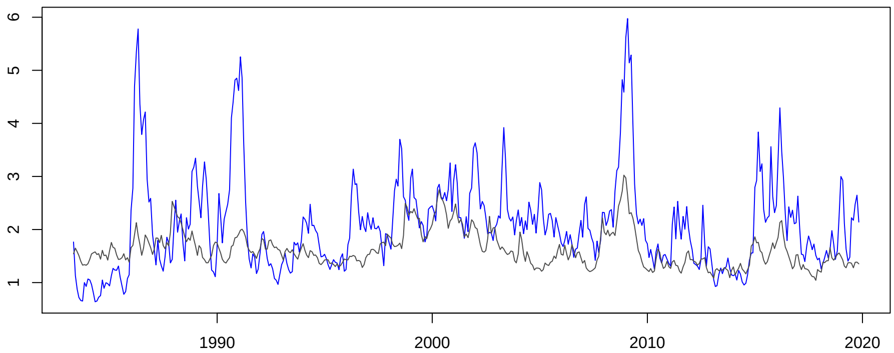



(b) Residuals.

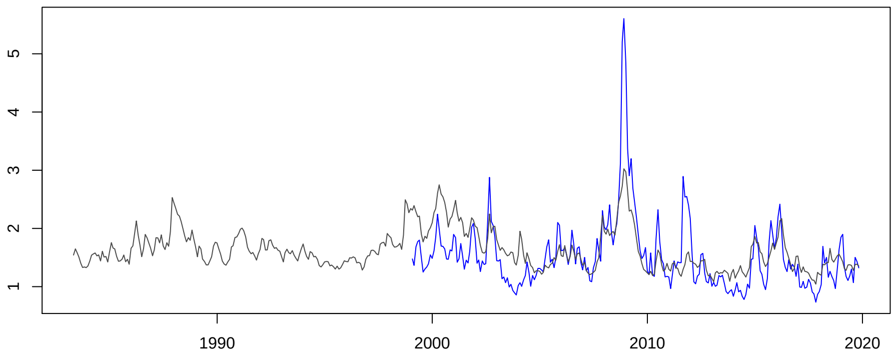
Figure 1: Cross-section averaged oil and gas excess returns and residuals from Fama and French factor model.




(a) S&P 500 index.




(b) WTI crude oil future.




(c) Energy sector ETF.

Figure 2: Monthly means of the cross-section averages of oil and gas idiosyncratic volatilities (gray). For comparison, the monthly average of the volatility of the S&P 500 index, of the 1-month WTI crude oil future, and of the SPDR energy sector ETF are also shown (blue).

record the factor loadings on the first principal component of $\boldsymbol{e}^2$. This is not necessary as the algorithm converges to the same optimal solution when we choose other initial values. Take the estimated standardized residuals as observable and iterate the estimation of the heteroskedasticity regressions defined in (5) until convergence. In each iteration, impose the normalization $x_t/(1/T)\sum_{t=1}^{T} x_t$ and $\sum_{i=1}^{n} s_i^2 = 1$ after estimating, respectively, the cross-section and the time-series regression. For this empirical sample, 15 iterations were performed until the algorithm converged.

The most extreme common oil and gas volatility shocks are summarized in Table 1. For comparison, the returns on the same day are shown for the cross-section average of oil and gas stocks ($\bar{r}_t$), the S&P 500 index ($r_t^{\text{SPX}}$), the crude oil 1-month future ($r_t^{\text{WTI}}$), and the SPDR energy sector ETF ($r_t^{\text{XLE}}$). Several dates are easily recognized as being dates when major events happened affecting financial markets, in general, and not just the oil and gas stocks. Many extreme shocks coincide with large negative returns but we also observe large volatility shocks for some positive returns. The extreme values observed in the global oil and gas volatility factor are strongly correlated with large WTI or XLE returns (or both) and also with the SPX returns. Geopolitical events should affect all assets, asset classes and countries. The last event shown is the day after the 2016 United Kingdom European Union membership referendum in favor of the UK to leave the European Union. This event appears to have caused large negative returns across all the indices showing up in the global volatility factor model as one of the biggest common shocks affecting a wide range of assets (if not all).

The monthly means of the estimated global oil and gas volatility factor are plotted in Figure 3 and some of the largest shocks are labeled. The largest common volatility shocks are financial (stock crashes), economic (global crisis), military (the 9/11 terrorist attack) and political (U.S. Presidential election of Donald Trump or Brexit). These shocks are more likely to affect demand for oil rather than, for instance, OPEC decisions regarding oil production which have effects on the supply side.

The empirical variances and covariances of the squared standardized residuals are not equal across oil and gas stocks. This is likely to be reflecting the fact that different assets have different loadings on the global volatility factor. The factor loadings captures the

Table 1: The largest estimated global shocks and the values of the returns on the same day. $\bar{r}_t$ denotes cross-section average of oil and gas stocks, $r_t^{\mathrm{SPX}}$ the S&P 500 index, $r_t^{\mathrm{WTI}}$ the crude oil 1-month future, and $r_t^{\mathrm{XLE}}$ the SPDR energy sector ETF.

| $t$ | $\hat{x}_t$ | $\bar{r}_t$ | $r_t^{\mathrm{SPX}}$ | $r_t^{\mathrm{WTI}}$ | $r_t^{\mathrm{XLE}}$ |
|---:|---:|---:|---:|---:|---:|
| 1989-10-13 | 43.710 | −6.419 | −6.312 | 2.031 | |
| 2014-11-28 | 32.381 | −8.040 | −0.255 | −10.794 | −6.640 |
| 1987-10-20 | 24.796 | 4.216 | 5.195 | 0.256 | |
| 2000-03-07 | 24.006 | 5.814 | −2.597 | 5.883 | 6.673 |
| 1992-05-26 | 23.427 | 4.024 | −0.632 | 4.938 | |
| 2000-10-13 | 21.893 | −3.405 | 3.284 | −3.012 | −3.900 |
| 2008-07-16 | 21.814 | −1.385 | 2.475 | −3.029 | −2.608 |
| 1998-09-04 | 20.164 | 3.987 | −0.856 | −0.547 | |
| 2001-09-17 | 19.523 | −1.717 | −5.047 | 4.182 | −2.065 |
| 1985-12-09 | 19.449 | −4.270 | 0.619 | −4.374 | |
| 2001-01-03 | 18.998 | −2.370 | 4.888 | 2.862 | −3.101 |
| 2019-04-12 | 18.547 | 1.152 | 0.659 | 0.486 | 0.267 |
| 1984-10-17 | 18.175 | −4.373 | −0.389 | −2.865 | |
| 1987-10-21 | 17.918 | 2.749 | 8.709 | 2.374 | |
| 2010-04-29 | 17.512 | 0.309 | 1.286 | 2.316 | 0.115 |
| 2011-02-22 | 17.170 | −1.522 | −2.074 | 8.204 | −0.979 |
| 1993-06-11 | 16.779 | −3.188 | 0.421 | −1.568 | |
| 1985-07-05 | 16.672 | −0.351 | 0.557 | 0 | |
| 2019-09-16 | 16.613 | 5.130 | −0.314 | 13.694 | 3.301 |
| 2016-11-30 | 16.170 | 6.367 | −0.266 | 8.900 | 4.958 |
| 1985-12-10 | 15.829 | −3.497 | 0.069 | −8.652 | |
| 2001-09-24 | 14.633 | −2.056 | 3.824 | −16.545 | −2.667 |
| 1995-09-21 | 14.545 | 0.307 | −0.645 | −6.237 | |
| 1984-08-02 | 14.441 | 0.907 | 2.506 | 3.287 | |
| 2016-06-24 | 14.326 | −6.162 | −3.658 | −5.055 | −3.285 |

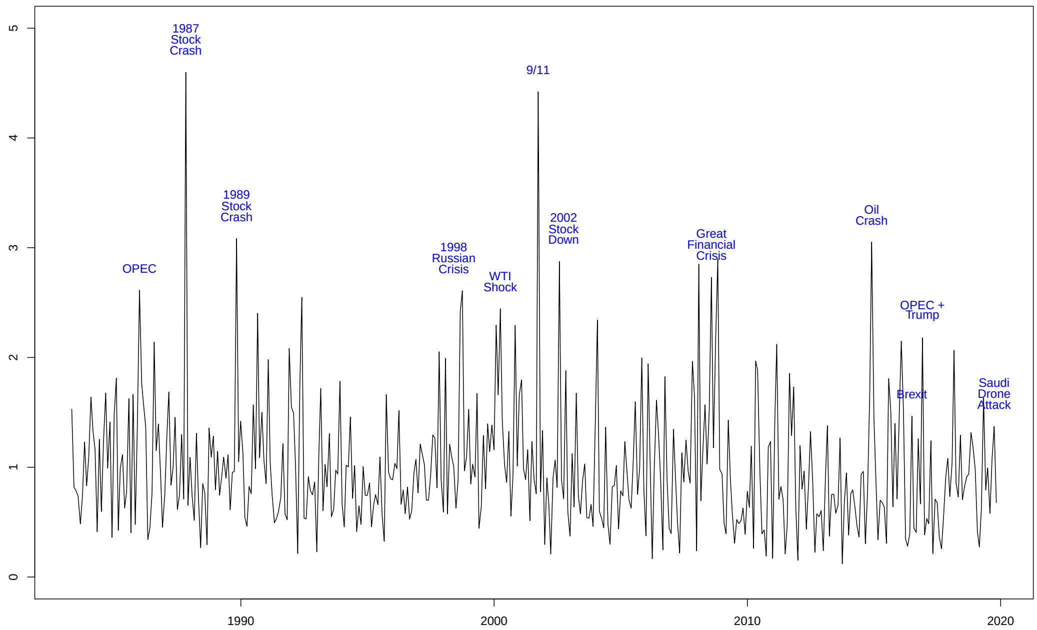



Figure 3: The (monthly) oil and gas global volatility factor.

proportion of the global volatility factor that is affecting the volatility of the asset. The estimated factor loading for the oil and gas assets are presented in Table 2 in descending order. As expected, the effects of the global volatility factor on the volatilities are heterogeneous across assets. These differences in the factor loadings make it possible to hedge against geopolitical risk by using a new criterion for portfolio optimality; See Engle and Campos-Martins (2020) for more details.

As a measure of the goodness of the fit, we re-run the test for common volatility shocks on the standardized residuals, now standardized by the square root of the global

Table 2: The estimated oil and gas factor loadings.

| | $\hat{s}_i$ | | $\hat{s}_i$ |
|---|---|---|---|
| Shell | 0.268 | Suncor | 0.218 |
| BP | 0.262 | Eni | 0.217 |
| Occidental | 0.251 | Devon | 0.212 |
| ConocoPhillips | 0.248 | Repsol | 0.197 |
| Chevron | 0.246 | PetroChina | 0.196 |
| ExxonMobil | 0.229 | Canadian Resources | 0.191 |
| Equinor | 0.226 | Sinopec | 0.189 |
| Schlumberger | 0.225 | CNOOC | 0.177 |
| Total | 0.223 | WTI | 0.168 |
| Halliburton | 0.223 | SPX | 0.128 |
| EOG | 0.218 | Petrobras | 0.097 |

volatility factor. The null hypothesis is re-defined to $\mathbb{H}_{02} : \bar{\rho}_{\boldsymbol{e}^2/\hat{\boldsymbol{x}}} = 0$, where $\boldsymbol{x}$ contains the heterogeneous volatility factors $x_{it} \equiv g_{it}(s_i, x_t)$ defined in (3), $i = 1, \ldots, n$, against the one-sided alternative that the average correlation standardized by the estimated volatility factors is positive. The empirical $\bar{\rho}_{e^2/\hat{x}} = -0.009$ and the test statistic is $-5.745$. This failure to reject the null of no correlation in the square standardized returns $\boldsymbol{e}^2/\hat{\boldsymbol{x}}$, supports the multiplicative decomposition of the standardized residuals and its ability to capture the common volatility shocks driving changes in the financial markets, where we have a particular interest in oil and gas stocks.

The global volatility factor previously denoted by $x$, will for the remaining of the paper be denoted by "GVOL" to make the interpretation of results more intuitive.

# 3 Measuring climate change volatility shocks

Two main transmission channels of climate change risk to financial markets are usually pointed out in the literature. These are referred to as physical and transition risks. Climate change can adversely impact capital stock, economic activities and markets directly as more frequent and severe climate-related disasters occur and are predicted for the upcoming years. Clearly the social, economic and political impact of physical risk is mostly country-specific, but it also has potential systemic implications. A country that is less vulnerable to climate-related events can still have a great indirect exposure to physical risk through international relations with countries that are particularly vulnerable. Financial stability is however most likely to be affected by climate change indirectly through increasing transition risk. As the uncertainty about the timing and the speed of adjustment towards low- or zero-carbon economies increases, so does transition risk. The systemic implications that climate change pose to financial markets are thus most likely to come from transition risk spillovers within carbon-intensive sectors. In order to mitigate the climate change effects, countries have to be aligned in reducing their carbon footprint where there is no room for free riding. For carbon-intensive activities, transition risk includes the impact on the asset prices of policy changes towards carbon pricing, legislation like the UK's Climate Change Act of 2008 and disruptive technological progress.

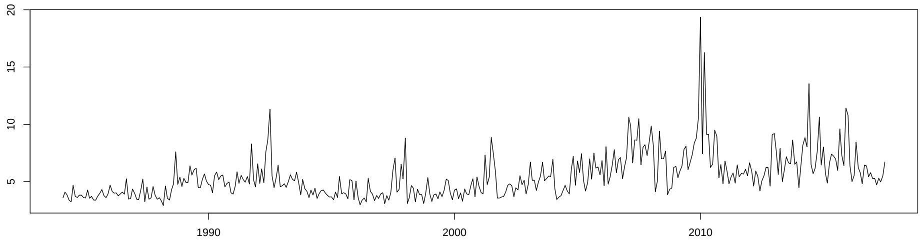
From a cross-country analysis on the impact of climate-related disasters on aggregate stock market indices from 68 developed and emerging countries since 1980, **?** found no significant effect of climate change physical risk on equity valuations. Even though financial losses can be massive and vary widely, they conclude that the reaction of equity prices to large climatic disasters is relatively modest. Other country's characteristics such as a higher rate of insurance penetration and a greater sovereign financial strength seem to explain this low impact and so improved financial stability. Yet, the authors argued that equity investors may not be paying sufficient attention to climate variables. Interestingly, the same study shows that investors in long-term sovereign bonds demanded a premium from countries with high climate risk meaning that investors do appear to be pricing climate change physical risks when making long-term investment decisions.

This seems consistent with Bolton and Kacperczyk (forthcoming) whose findings indicate that stock returns do not reflect physical risks. Because no significantly different carbon premium is found for stocks from countries more exposed to physical risk but it is found for countries associated to higher transition risk, these results suggest that physical risk is not positively correlated with transition risk which appears to be relatively more salient to investors. Possible explanations are provided and include the temporal nature of each type of risk, where physical risk seems to be heavily discounted by investors because of its long-term nature whereas transition risk tends to materialize in a shorter horizon. Griffin et al. (2019) provides evidence that physical risk is being (under) priced by equity investors in the US by matching climate-related events to individual firms. This result suggests physical risk may be local-specific and its financial market effects mostly concentrated in the area affected whereas transition risk can be expected to have wider (global) effects given it is geopolitical by nature. The results also indicate that equity returns seem to respond negatively where the magnitude of the response appears to vary with the cost and duration of the climate-related events. Underpricing is more evident and the increase in equity market volatility is more pronounced for costlier and longer-duration events.

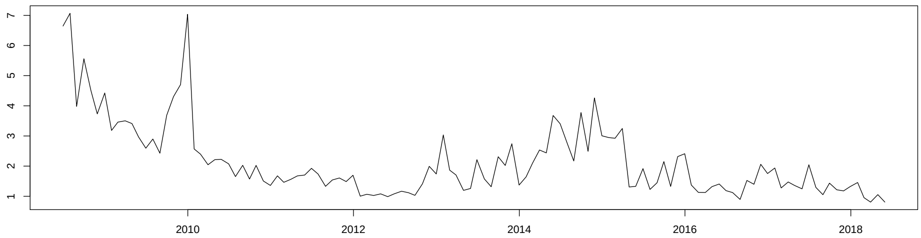
The main goal of this paper is to analyze to what extent climate change risk is affecting financial market volatilities. We are particularly interested in the exposure of financial markets to transition risk arising from the likelihood of economies going low-carbon. In this setting, carbon-intensive assets are expected to be particularly affected. So far we have been focused on the prices of oil and gas companies. Because all prices should be responsive to climate change risk, even though with different magnitudes, we take a measure that captures the magnitude of unexpected volatility shocks common to a wide range of oil and gas prices at the same time. We then consider climate change news as a determinant of common volatility shocks to oil and gas stock prices as climate policies are presumably affecting the value of equity holdings in the fossil sector (Leaton, 2012).

In assessing climate change, much research has relied on rising mean temperature levels. Diebold and Rudebusch (2019) go a step further and propose a novel range-based measure of daily temperature volatility. The new measure of temperature volatility is called the diurnal temperature range and is defined as the difference between the daily maximum and minimum temperatures at a given location. However, when assessing how climate change is affecting financial markets through transitional risk, it is difficult to think that shocks to temperature volatility will impact the volatilities of many asset returns around the world.

Instead, as a proxy for climate change, we use the monthly climate change news index of Engle et al. (2020). Using textual analysis of daily Wall Street Journal (WSJ) newspaper, the climate change news index measures the fraction of its text content dedicated to the topic of climate change. The climate change vocabulary is defined as a set of representative words from relevant texts published by governments and research organizations. To construct the index, a score is assigned to each edition of the WSJ based on the relevance of its climate change content. For instance, a low score is attributed to a particular edition if it has terms that appear in most editions on other days as well. The low score is thus intended to reflect the less informative WSJ content on that particular day. A high score, on the other hand, reflects a text content on a given day with representative terms that appear infrequently overall but frequently in that day's newspaper edition. The index is then computed as the cosine similarity between the scores and each edition of the WSJ. The index ranges between zero - no words on the WSJ match the climate change vocabulary - and unity - if text content of the WSJ shows the same terms in the same proportion as the authoritative texts used to construct the vocabulary. This monthly index is available between 1984/01 and 2017/06. To distinguish between positive news




(a) General CC news index.




(b) Bad CC news index.

Figure 4: The monthly general and the bad or negative climate change news index of Engle et al. (2020).

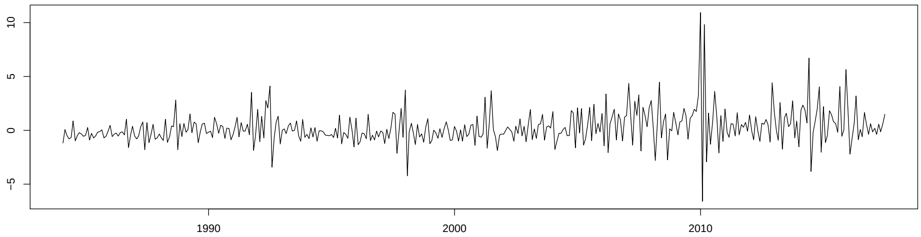
and negative news, a different version of the index is provided. Using sentiment analysis, bad news about climate change can be identified and a climate change bad news index is constructed for the period between 2008/06 and 2017/06. Both indices, general and bad news, are plotted in Figure 4. Notice that the actual values of the index were multiplied by 1000 and then plotted.

Supported by the Ljung-Box AR(1) and ARCH(1) test results, we estimate an AR(1) model with GARCH(1,1) errors for each climate change news index. The innovations and estimated volatilities are depicted, respectively, (a)-(b) and (c)-(d) panels of Figure 5 for general then bad news indices.

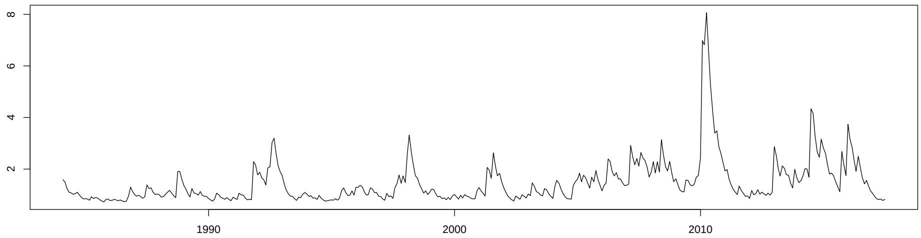
To compute the climate change volatility shocks, we start by modeling the climate change news index $CCI_t, t = 1, \ldots, T$, as an AR(1) process. A climate change volatility shock is then defined as

$$e^2_{CCI,t} - 1 = \frac{(CCI_t - \mu_{CC} - \beta_{CC} CCI_{t-1})^2 - h_{CC,t}}{h_{CC,t}}, \tag{8}$$

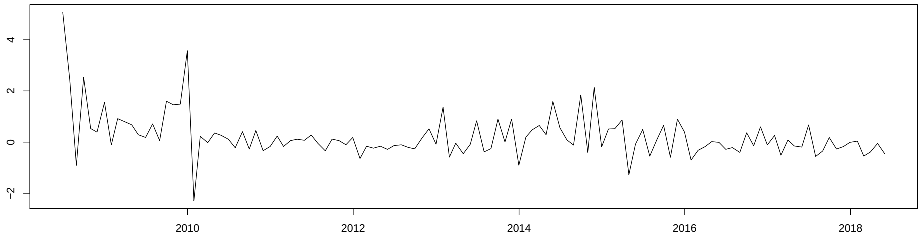
where $\mu_{CC}$ is the intercept in the mean equation, $\beta_{CC}$ is the coefficient of the first-order autoregressive term, and $h_{CC,t}$ is the variance of the residuals from the mean equation



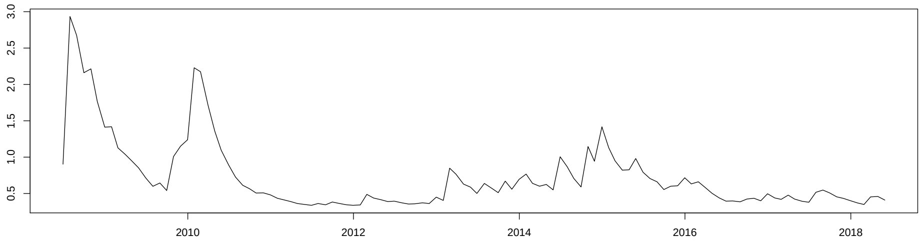

(a) CC: Innovations.




(b) CC: Volatility.




(c) nCC: Innovations.




(d) nCC: Volatility.

Figure 5: The estimated innovations and volatilities of the general (upper) and bad or negative (bottom) climate change news index.

of the climate change news index. The climate change volatility shock represents the proportional difference between the squared innovations in the climate change news index and its expectation. The realized squared innovations are on some days bigger than one and on other days smaller than one. If oil and gas assets have squared innovations bigger than one at the same time, this can be interpreted as a common volatility shock which can be generally associated with geopolitical news. If it coincides with relevant climate change news, then the geopolitical risk on that day is regarded as climate change risk.

# 4 Disentangling the oil and gas volatility shocks

In this section we start by introducing a more general formula to define volatility shocks. The volatility shock to the oil and gas asset $i$,

$$e_{it}^2 - 1 = \frac{(r_{it} - r^f - \boldsymbol{\beta}_i' \boldsymbol{f}_t)^2 - h_{it}}{h_{it}}. \tag{9}$$

This strategy to identify volatility shocks applies to the S&P 500 index and the WTI crude oil 1-month future as well. Moreover, because a common volatility shock to the oil and gas assets may also be driven by relevant volatility shocks to these indices, they are include as determinants of oil and gas volatility shocks.

Common volatility shocks to oil and gas stock returns come from different sources. To analyze to what extent climate change news affects financial markets, we define and compute a climate change volatility shock as before. To control for other relevant shocks affecting these stocks, we also consider volatility shocks to the WTI oil price and the S&P 500 index as sources of unexpected volatility shocks to the oil and gas stock prices. Both stock market and climate change shocks are interpreted as oil and gas volatility shocks coming from the demand side. The volatility shocks arising from oil price shocks are interpreted as supply volatility shocks as they are most likely to be due to OPEC decisions regarding oil production. Naturally, it can be argued that oil price shocks are likely to induce stock market shocks as oil prices tend to affect total output as well.

In Table 3, we present the estimation results for the multiple linear regressions of common oil and gas volatility shocks on the three potential determinants, namely climate change (CC), stock market (SPX) and oil (WTI) volatility shocks. To disentangle between bad and good news on climate change, we use both climate change news indices as determinants of oil and gas volatility shocks. The volatility shocks computed using the complete climate change news index are denoted by "CC" and using the negative climate change news index by "nCC". The sample size for the negative news is limited to the period between 2008/06 until 2017/06. Note also that from 2008/06 the oil and gas panel is balanced (with no missing values).

Table 3: Estimation results for the determinants of oil and gas volatility shocks (monthly averages, $GVOL^m_t$). The regressors include the volatility shocks to the complete ($CC_t$) and negative ($nCC_t$) climate change news index, to the S&P 500 index ($SPX_t$) and the WTI oil 1-month future ($WTI_t$).

| | (1) | (2) | (3) |
|---|---|---|---|
| $GVOL^m_{t-1}$ | 0.224*** | −0.028* | −0.034** |
| | (0.071) | (0.015) | (0.013) |
| $CC_t$ | −0.029** | 0.043* | −0.013 |
| | (0.014) | (0.024) | (0.027) |
| $nCC_t$ | 0.050** | 0.374*** | 0.406*** |
| | (0.023) | (0.106) | (0.095) |
| $SPX_t$ | 0.375*** | 0.623*** | 0.503*** |
| | (0.101) | (0.102) | (0.095) |
| $WTI_t$ | 0.603*** | −0.028 | |
| | (0.097) | (0.055) | |
| $SPX_t \times CC_t$ | | 0.002 | |
| | | (0.055) | |
| $WTI_t \times CC_t$ | | | −0.303*** |
| | | | (0.073) |
| $SPX_t \times nCC_t$ | | | 0.075* |
| | | | (0.038) |
| $WTI_t \times nCC_t$ | | 0.229*** | 0.176** |
| | | (0.071) | (0.067) |
| Constant | 0.677*** | 0.672*** | 0.675*** |
| | (0.076) | (0.077) | (0.071) |
| Observations | 107 | 107 | 107 |
| $R^2$ | 0.481 | 0.486 | 0.561 |
| $\hat{\sigma}$ | 0.432 | 0.434 | 0.401 |
| $\chi^2_{AR}(2)$ | 4.176 | 3.979 | 2.009 |
| | (0.124) | (0.137) | (0.366) |
| $\chi^2_{ARCH}(1)$ | 0.217 | 0.252 | 0.133 |
| | (0.641) | (0.616) | (0.716) |

Notes: The lag of the dependent variable is denoted by $GVOL^m_{t-1}$. The sample period goes from 2008/07 until 2017/06. *p<0.1; **p<0.05; ***p<0.01.

The estimation results for the baseline regression are shown in the first column of Table 3. Volatility shocks to the complete and negative climate change indices have, respectively, negative and positive effects on the volatilities of the stock returns of oil and gas companies. When including both indices in the analysis, we expect to be able to distinguish the effects of each on the global volatility factor. The results provide empirical evidence that both climate change volatility shocks affect the volatilities of oil and gas stock returns. Nevertheless, bad news tends to create larger effects (with higher magnitude) compared to any other news about climate change. The Ljung-Box AR(1) test statistic for the model without the lagged dependent variable is 4.365 (0.037). To model the time dependence in the data we add the oil and gas volatility shocks once lagged in the final estimated model.

The positive coefficient of the bad news index (0.055) indicates that unexpected volatility shocks driven by bad news about climate change are associated with larger oil and gas common volatility shocks. When arising from any other climate change news, the resulting oil and gas volatility shocks are estimated to be smaller ($-0.032$). By including the negative news index, we hope that the complete news index is able to mostly capture the effect of positive news about climate change. This seems to be supported by the negative sign of the estimated coefficient for the general climate change determinant. Good news about climate change makes investors feel more confident about the future of oil and gas leading to smaller oil and gas unexpected volatility shocks. Bad news about climate change is more likely to cause major changes in the stock prices of oil and gas companies as it creates more uncertainty regarding the viability of investments in such assets. This follows the literature on the asymmetric effects of positive and negative news on volatility. It is well known that negative shocks to stock prices produce more volatility than positive shocks. Similarly, the magnitude of the effect of climate change volatility shocks on the volatilities of oil and gas stock returns is greater when the news is bad compared to any other news.

Regarding the other determinants, both stock market and oil volatility shocks can be represented as common shocks moving global oil and gas stock returns. Recall that some of the largest oil and gas common volatility shocks coincide with days when OPEC has made decisions regarding oil production, decisions that have mostly been different from what markets were expecting or hoping for. Moreover, these appear to also coincide with large volatility shocks to the oil returns (as measured by the changes in the price of the WTI 1-month future). Hence, oil volatility shocks (driven mostly by oil supply shocks) tend to cause large unexpected variations in a wide range of stock returns.

In order to analyze if the effects of stock market and oil volatility shocks change when there is simultaneously climate change news affecting the market, we also include interaction terms between these two indicators and each of the climate change news variables. The results are presented in the second and the third column for the interactions terms using, respectively, the complete news and the bad news indicator. Beginning with the oil shocks, it is interesting to observe that bad news on climate change tend to amplify the effects of oil shocks on volatilities. Think about the drone attack to the Saudi Aramco oil facility in Saudi Arabia on November 30, 2016. The disruption in oil production had an immediate impact on oil prices around the world and the effects on the stock prices of major oil companies followed suit. Now imagine that on the same day devastating wildfires hit Australia raising concerns about climate change both in terms of physical and transition risks. The bad climate change news thus amplifies the positive effect of oil volatility shocks on oil and gas volatilities. It seems that when there is a stock market volatility shock and a simultaneous bad climate change news, this shock attenuates the effects of the former. This may be due to the negative correlation ($-0.179$) between the volatility shocks arising from bad climate change news and stock market news.

Interestingly, oil volatility shocks (as measured by the proportional difference between the squared oil idiosyncrasy and its expectation and denoted by WTI) are not determined by the climate change volatility shocks nCC. A linear regression of WTI on both CC and nCC shows no statistically significant effects of climate change on the prices of oil. Instead, investors appear to be reacting to climate change news based only on the investments in oil and gas firms. This is also likely to be reflecting the fact that demand for oil is quite inelastic. The estimation results are presented in Table 4.

As a robustness check, we obtain similar results if the S&P 500 index and WTI 1-month oil future standardized residuals are not included in the sample for estimating the global volatility factor. Also, results are consistent if the WTI 1-month oil future is not included as an additional regressor in the mean equations.

Table 4: Estimation results for the effect of volatility shocks to the complete ($CC_t$) and negative ($nCC_t$) climate change news index on the volatility shocks to the S&P 500 index ($SPX_t$) and the WTI oil 1-month future ($WTI_t$).

| | $SPX_t$ | $WTI_t$ |
|---|---|---|
| $CC_t$ | 0.006 | 0.001 |
| | (0.015) | (0.015) |
| $nCC_t$ | $-0.043^{*}$ | 0.002 |
| | (0.023) | (0.024) |
| Constant | 0.027 | 0.004 |
| | (0.043) | (0.045) |
| Observations | 108 | 108 |
| $R^2$ | 0.034 | 0.000 |
| $\hat{\sigma}$ | 0.447 | 0.464 |
| $\chi^2_{AR}(1)$ | 2.184 | 0.226 |
| | (0.139) | (0.635) |
| $\chi^2_{ARCH}(1)$ | 0.039 | 0.113 |
| | (0.844) | (0.736) |

Notes: The sample period goes from 2008/06 until 2017/06. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

It is commonly thought that climate change is likely to induce structural changes in the financial system (Network for Greening the Financial System, 2019). To allow for richer structures of the global volatility process, including dynamics, structural changes, outliers or time-varying parameters, we apply the indicator saturation approach introduced by Hendry (1999) to the second moment. By applying step indicator saturation (Hendry et al., 2008), climate change is interpreted as a source of structural change affecting the financial system by means of shifts in the global volatility process. To check if some of the spikes in the monthly oil and gas volatility factor are driving spurious relations between the climate change news and the financial market volatility shocks, we re-run regressions (2) and (3) in Table 3 to include impulse indicators as well. Parameter shifts as in the effect of climate change news on the global volatility factor by using multiplicative indicator saturation (Ericsson, 2012) is left for future research.

Including impulse and step indicator saturation (so-called super saturation Ericsson (2012)) seems to improve the empirical results in the new regressions presented in Table 5 as spikes appear to be only introducing noise. The statistically significant impulse

Table 5: Estimation results for the determinants of oil and gas volatility shocks when impulse and step indicator saturation is applied.

| | (1) | (2) |
|---|---|---|
| $CC_t$ | $-0.025^{**}$ | $-0.033^{***}$ |
| | (0.011) | (0.011) |
| $nCC_t$ | 0.025 | $-0.027$ |
| | (0.019) | (0.021) |
| $SPX_t$ | $0.359^{***}$ | $0.289^{***}$ |
| | (0.086) | (0.083) |
| $WTI_t$ | $0.533^{***}$ | $0.440^{***}$ |
| | (0.084) | (0.080) |
| $SPX_t \times CC_t$ | $-0.023$ | |
| | (0.044) | |
| $WTI_t \times CC_t$ | $-0.015$ | |
| | (0.044) | |
| $SPX_t \times nCC_t$ | | $-0.316^{***}$ |
| | | (0.061) |
| $WTI_t \times nCC_t$ | | $0.090^{***}$ |
| | | (0.031) |
| Constant | $0.748^{***}$ | $1.332^{***}$ |
| | (0.080) | (0.238) |
| Observations | 108 | 108 |
| $R^2$ | 0.748 | 0.759 |
| $\hat{\sigma}$ | 0.447 | 0.322 |
| $\chi^2_{AR}(1)$ | 0.149 | 0.005 |
| | (0.699) | (0.942) |
| $\chi^2_{ARCH}(1)$ | 0.209 | 0.146 |
| | (0.648) | (0.703) |

Note: The sample period goes from 2008/05 until 2017/06.
$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

and step indicators are shown in Table 6. These are the selected indicators at the 5% significance level and applying indicator saturation by blocks. Note that indicators only capture effects that are not otherwise accounted for by the regressors.

In order to analyse if the impact of climate change news on global oil and gas volatility changes across different types of news, we use another index to constrict the climate change volatility shocks. The Media Climate Change Concerns (MCCC) index of Ardia et al. (2020) is intended to measure unexpected increases in climate change concerns. It is a daily index constructed by applying text mining to climate change-related news published by major U.S. newspapers. The selected high-reaching (daily circulation of more than 500,000) newspapers are: (i) The Wall Street Journal, (ii) The New York Times, (iii) The Washington Post, (iv) The Los Angeles Times, (v) The Chicago Tribune, (vi) USA

Table 6: The impulse and step indicators in the regressions summarized in Table 5.

| | (1) | (2) |
|---|---|---|
| $IIS_{2008.07}$ | $1.633^{***}$ | $1.078^{***}$ |
| | (0.344) | (0.398) |
| $IIS_{2008.10}$ | $1.960^{***}$ | $1.857^{***}$ |
| | (0.344) | (0.336) |
| $IIS_{2016.11}$ | | $1.055^{***}$ |
| | | (0.342) |
| $SIS_{2008.10}$ | | $-0.643^{**}$ |
| | | (0.249) |
| $SIS_{2010.04}$ | $0.662^{***}$ | $0.554^{***}$ |
| | (0.211) | (0.210) |
| $SIS_{2010.07}$ | $-1.064^{***}$ | $-0.945^{***}$ |
| | (0.276) | (0.268) |
| $SIS_{2010.10}$ | $0.700^{***}$ | $0.486^{**}$ |
| | (0.230) | (0.191) |
| $SIS_{2011.05}$ | $-0.893^{***}$ | |
| | (0.271) | |
| $SIS_{2011.07}$ | $0.652^{**}$ | |
| | (0.249) | |
| $SIS_{2014.10}$ | $1.128^{***}$ | |
| | (0.260) | |
| $SIS_{2014.12}$ | $-1.203^{***}$ | |
| | (0.285) | |
| $SIS_{2015.07}$ | $0.611^{***}$ | $0.506^{***}$ |
| | (0.179) | (0.125) |
| $SIS_{2016.03}$ | $-0.526^{***}$ | $-0.567^{***}$ |
| | (0.152) | (0.146) |
| Constant | $0.748^{***}$ | $1.332^{***}$ |
| | (0.080) | (0.238) |
| Observations | 108 | 108 |
| $R^2$ | 0.748 | 0.759 |
| $\hat{\sigma}$ | 0.447 | 0.322 |
| $\chi^2_{AR}(1)$ | 0.149 | 0.005 |
| | (0.699) | (0.942) |
| $\chi^2_{ARCH}(1)$ | 0.209 | 0.146 |
| | (0.648) | (0.703) |

Note: The sample period goes from 2008/05 until 2017/06.
$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

Today, (vii) New York Daily News, and (viii) The New York Post. The MCCC index is available from January 2, 2003 until June 29, 2018.

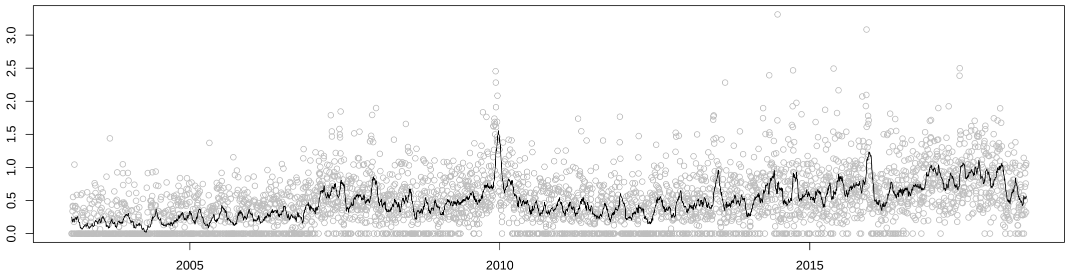



Figure 6: The daily MCCC index (grey) and 22-day rolling window average (black).

In order to compare the climate change daily volatility shocks to the oil and gas global volatility over time, we compute a 22-day rolling window average from the daily point estimates. This averaged series is plotted in figure 7.

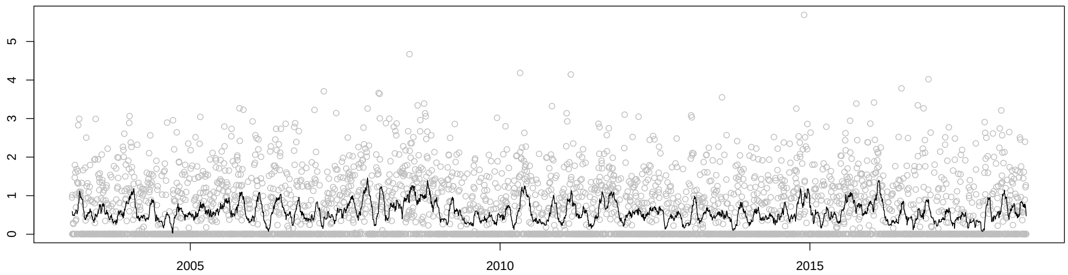



Figure 7: The daily oil and gas global volatility points (grey) and its 22-day rolling window average (black).

We start by computing the first difference of the MCCC index to make the time series stationary. There is strong evidence for time dependence in both first and second moments according to, respectively, the AR and ARCH tests results. By using this new variable as an additional factor in the oil and gas return regressions, it appears there is no statistically significant impact of MCCC on the oil and gas returns over time. These results could also be shown in the paper as they differ from Ardia et al. (2020). However, shocks to the volatility of the MCCC do affect the common volatility driving the oil and gas stock returns as shown in table 7. There is no evidence of time dependence in the first or second moment of the residuals from all regressions. To save space, the results from the AR(2) and ARCH(2) tests are not reported.

Table 7: The effects of MCCC volatility shocks on oil and gas global volatility (GVOL), the dependent variable.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $GVOL_{t-1}$ | $-0.031^{**}$ | $-0.031^{**}$ | $-0.031^{**}$ | $-0.031^{**}$ | $-0.032^{**}$ |
| **$\mathbf{MCCC}_t$** | $0.029^{*}$ | $0.030^{*}$ | $0.027^{*}$ | $0.030^{*}$ | $0.028^{*}$ |
| $WTI_t$ | $0.235^{***}$ | $0.235^{***}$ | $0.233^{***}$ | $0.236^{***}$ | $0.233^{***}$ |
| $XLE_t$ | $0.435^{***}$ | $0.434^{***}$ | $0.432^{***}$ | $0.435^{***}$ | $0.431^{***}$ |
| $SPX_t$ | $-0.024$ | $-0.024$ | $-0.024$ | $-0.025$ | 0.024 |
| $MCCC_t \times WTI_t$ | | $-0.005$ | | | $-0.005$ |
| $MCCC_t \times XLE_t$ | | | $-0.022^{*}$ | | $-0.019$ |
| $MCCC_t \times SPX_t$ | | | | $-0.012$ | $-0.005$ |
| Observations | 3,899 | 3,899 | 3,899 | 3,899 | 3,899 |
| $R^2$ | 0.229 | 0.229 | 0.230 | 0.230 | 0.230 |
| Adjusted $R^2$ | 0.228 | 0.228 | 0.229 | 0.228 | 0.228 |
| Residual Std. Error | 1.636 | 1.636 | 1.636 | 1.635 | 1.636 |
| F Statistic | $231.549^{***}$ | $192.969^{***}$ | $193.680^{***}$ | $193.268^{***}$ | $145.257^{***}$ |

Similarly to the results presented in table 5, by applying impulse and step indicator saturation, we observe a structural increase in the oil and gas global volatility in 2010 and then again in 2017.

Table 8: The effects of MCCC on GVOL over time. $IIS_Y$ is a yearly impulse indicator assuming value 1 when return in observed in year $Y$. $SIS_Y$ is a yearly step indicator taking value 0 when returns are observed in a year previous to year $Y$ and 1 when observed in and after year $Y$. Showing only the statistically significant coefficients.

| | |
|---|---|
| $GVOL_{t-1}$ | $-0.038^{***}$ |
| $WTI_t$ | $0.235^{***}$ |
| $XLE_t$ | $0.418^{***}$ |
| $IIS_{2008}$ | $0.401^{***}$ |
| MCCC | 0.048 |
| $MCCC \times SIS_{2010}$ | $0.197^{**}$ |
| $MCCC \times SIS_{2017}$ | $0.169^{*}$ |
| Observations | 3,899 |
| $R^2$ | 0.236 |
| Adjusted $R^2$ | 0.229 |
| Res. Std. Error | 1.635 |
| F Statistic | $35.117^{***}$ |

Investors in fossil fuel companies are now pricing climate change risks. Using world's major oil and gas stock prices, our empirical evidence shows that investors are reacting to climate change news, especially when the news is bad. Aggregating news by topics and themes provides a more comprehensive analysis of the impact of different news on the oil and gas stock prices. In particular, investors in fossil fuel companies around the world seem to be more volatile following news on the agricultural impact of climate change (Table 9, first column) where the effect of news involving livestock (topic 20 in the second column of Table 9) on the oil and gas global equity market is particularly pronounced. Similar effects are expected on agri-business assets, where increased attention and pressure have been raised due to climate-damaging practices in agriculture [1]. For a similar analysis by theme including indicators to account for outliers and structural changes in GVOL, and structural changes in the relationship between GVOL and MCCC see Appendix A.

Table 9: The effects of MCCC on GVOL by theme. MCCC themes were computed as the average of the topics included in each theme following the classification proposed by Ardia et al. (2020).

| | | | |
|---|---|---|---|
| $GVOL_{t-1}$ | $-0.033^{**}$ | | $-0.035^{**}$ |
| $WTI_t$ | $0.236^{***}$ | | $0.238^{***}$ |
| $XLE_t$ | $0.420^{***}$ | | $0.422^{***}$ |
| Financial & Regulation | $0.029^{*}$ | topic11 | $0.020^{**}$ |
| Agreement & Summit | $-0.005$ | topic20 | $0.013^{***}$ |
| Public Impact | $0.025^{*}$ | topic25 | $0.011^{*}$ |
| Research | $-0.005$ | topic31 | $0.015^{***}$ |
| Disaster | $-0.019^{*}$ | topic33 | $-0.008^{*}$ |
| Environmental Impact | $-0.015$ | topic34 | $0.008^{**}$ |
| Agricultural Impact | $0.022^{***}$ | topic40 | $0.018^{***}$ |
| Observations | 3,899 | | 3,899 |
| $R^2$ | 0.232 | | 0.242 |
| Adjusted $R^2$ | 0.230 | | 0.233 |
| Res. Std. Error | 1.634 | | 1.631 |
| F Statistic | $117.589^{***}$ | | $28.592^{***}$ |

The ten words with the highest probability for selected topics (only the statistical significant topics as shown in table 9) in each theme are the following:

- Financial & Regulation

  **topic40** project, technology, plant, cost, coal, carbon_dioxide, power_plant, facility, scale, carbon.

[1] Using stock prices of the largest US meat processing company, the American Tyson Foods, climate change bad news has an adverse (positive) effect on the volatility of the Tyson Foods stock price and climate change general news appears to exacerbate the effects of stock market shocks.

**topic31** oil, tax, fuel, price, carbon_tax, production, taxis, cost, ethanol, revenue.

**topic25** money, program, budget, development, fund, funding, effort, initiative, aid, poverty.

- Public Impact

**topic34** poll, survey, majority, public, pew, penguin, concern, opinion, result, support.

**topic11** child, school, student, family, woman, life, street, art, event, police.

- Disaster

**topic33** fire, wildfire, insurance, risk, home, property, disaster, loss, flood, zone.

- Agricultural Impact

**topic20** food, animal, meet, cow, cattle, farm, ski, resort, beef, diet.

For more details and other topics, we refer to Ardia et al. (2020).

# 5 Policy implications and future work

Co-movements of financial market volatilities are caused by global shocks which can originate from political (e.g. the *Brexit*) and regulatory (carbon prices) actions, pandemics (COVID-19) or natural disasters. Climate change requires global action and global energy transition. Given this geopolitical nature of climate change transitional (and physical) risk we propose an approach based on a global volatility factor of carbon intensive asset returns to measure and hedge against geo-climatic risk. The novel approach allows us to analyze whether and to what extent the prices of a very wide range of carbon intensive assets traded in a particular stock exchange (to avoid asynchronicity) react to the arrival of new information related to climate change. Results also provide the means to bridge the co-movements of financial asset volatilities (or geopolitics whose risk is measured by the common shocks that drive all markets to move at the same time) to climate change news with global impact (geo-climate).

As time for an orderly transition to low carbon economies runs out, the likelihood of extreme and global climate-related shocks to carbon-intensive asset prices rises and so does the likelihood of huge unexpected losses. It is well known that oil global shocks impact the real economy with effects across all sectors of activity and countries around the world. Financial markets are however not prepared to cope with such shocks where a wide range of assets are affected at the same time, including not only high but also low carbon due indirectly to the aggregate demand effects. There is a remarkably high uncertainty around future demand for fossil fuels due to climate change and, more recently, the COVID-19 pandemic (when for the first time in history, oil futures were trading at negative prices showing how global shocks can have unprecedented effects on oil prices) as well as future supply following the Saudi Arabia and Russia price war. By their political power, wealth, and expertise, fossil fuel companies should be proactive in the transition process towards low-carbon economies. Because the incentives (mostly moral) to shareholders are not enough, governments in countries highly dependent on fossil fuels shall pressure them by applying carbon taxes, taking legal action, financing green activities in order to make them more competitive, and greening their financial systems.

Some challenges may difficult the transition process and once again policy action will be determinant. Country data shows that it is possible to reduce CO2 emissions and experience economic growth. But history has also shown that CO2 emissions tend to rise after economic or financial crises. Moreover, oil prices have been remarkably low and oil companies are among the highest dividend payers meaning transition to clean energies will be even more challenging as non-fossil fuels become relatively less competitive. As demand for oil starts giving signs of stagnation in some developed countries, there is a need to regulate oil companies from shifting to developing countries such as India and China and investing in oil exploration and production capacity. Because emissions are likely to grow elsewhere, especially in developing countries, it may be desirable to identify the connections of firms to the rest of the world through international relations, trade and financial contracts. Investors and risk managers from firms everywhere will be able to see how important e.g. OPEC or government plans announcements are and how effective hedging strategies can be. We thus expect to provide valuable information for banks, pension fund managers (there seems to be smaller exposure of top banks relatively to pension funds), insurers and investors to hedge against global risk arising from climate change. The global volatility model can also be analyzed for other major carbon-intensive companies around the world (car manufacturers, aerospace corporations, construction companies) and analyze the relationship between the magnitude of the factor loadings and the structure and composition of oil production and demand.

Virtually all assets are exposed to transition risk with different magnitudes meaning some assets are more responsive than others. Thus, assets with bigger volatility factor loadings are expected to be the more exposed to climate change risk because the more uncertain investors are regarding the profitability of their investments, and the more volatility shocks can be attributed to climate-related common events. Because volatilities are correlated, a common shock will sharply increase the volatility of a portfolio. Although it is not possible in this framework to predict when such a shock will occur (even tough we can predict future scenarios), it is possible to form portfolios with reduced impact. This important feature of the global volatility model leads to a new criterion for portfolio optimality, intended to reduce the exposure to this type of risk. Hence, if the index loadings on assets or sectors differ, it is possible to reduce (but not eliminate) the exposure to this form of risk. A stable portfolio should be relatively insensitive to climate global volatility and would prevent market turmoil during the transition process. As the probability of a disordered transition increases, uncertainty is likely to drive financial market turmoil and pose increased risks to financial stability. Investors are already pricing climate change risks but to what extent are companies or firms reacting and changing accordingly? This would give insight on when and how policy makers should take action. As a policy instrument, the government and central banks can take positions on the geo-climate volatility index and help investors to diversify their portfolios during the transition process. At the global scale, it would improve responses to tackle climate change as agreed by the Paris agreement. The role of the financial system in managing climate-related risks and mobilizing capital for low-risk investments is crucial (Network for Greening the Financial

System, 2019). Our contribution to identifying the high and low risk assets, designing financial regulations and guiding capital flows seems promising.

At the national level we can consider financial assets traded, for instance, in the London Stock Exchange. As a proxy for climate change risks, a news index similar to the ones used in this paper can be constructed by applying text mining to high-reaching newspaper's content such as, for instance, The Financial Times for the United Kingdom. This is particularly relevant given the pressure for a green COVID-19 recovery and the United Kingdom's government 10-point green plan to build back better including to make London "the global centre of green finance" (Department for Business, Energy & Industrial Strategy, 2020). Information about the exposure of companies to common, global or geo-climatic risks is scarce. To promote more informed investing, lending, and insurance underwriting decisions, organizations across all sectors are recommended to disclose climate-related financial information (Task Force on Climate-related Financial Disclosures, 2017). But interpret and draw comparisons out of such load of non-harmonized information is difficult.

Given mostly large companies are publicly traded, results can then be extended to virtually all companies in a country by matching the ones that run similar business activities using standard industrial classification. Matching allows us to identify companies at different levels of climate change risk, to assess potential financial losses, to analyze the structure of vulnerable employment, and to define the scale of adjustment towards a resilient financial and economic systems in the pandemic and net-zero era. This allows us to define the scale of adjustment that will need to be undertaken to build and maintain a resilient financial system in the future. It would also help in targeting the financial and non-financial organizations with public debt or equity more exposed to climate risk and focusing efforts in implementing recommendations listed in Task Force on Climate-related Financial Disclosures (2017). This includes asset managers and asset owners, public- and private-sector pension plans, endowments, and foundations. The results can give insight about the structure of vulnerable labor and on how design readjustment policies to help employees at risk entering the changing labor market.

Investing in activities that are not viable in a low carbon economy makes investors less resilient to climate change risks and more exposed to financial losses. Missed sustainable activities due to the reluctance arising from the lack of information on the exposure to climate-related risks, which would otherwise be profitable, create employment and generate income are also likely in a low-carbon transition scenario. It is important to properly but efficiently identify entities at different levels of risk, to consider climate risks into governance and to run scenario analyses to explore the financial risks posed by climate change, including the resilience of the current business models of the largest banks, insurers and the financial system. Models of common volatility shocks in conjunction with climate change shocks could be used to assess the vulnerability or resilience of the financial system as well as study the predictability of such shocks and how they might propagate both across assets and over time. These results provide a valuable contribution of national importance and international standing to achieve a resilient financial services sector to climate-related risks.

# 6 Conclusions

Climate change risk, specifically transition risk, is regarded as a source of geopolitical risk. Climate change news affecting financial markets is expected to affect the volatilities of all brown assets. We take a sample of oil and gas stock prices and apply a model of global volatility factors to capture common volatility shocks affecting simultaneously all assets. To analyze to what extent climate change news is affecting financial markets, we then link the common volatility shocks to climate change volatility shocks while controlling for other types of volatility shocks, namely stock market and oil shocks. We find strong evidence that climate change news drives volatility surprises for the oil and gas assets but the same is not found for the oil 1-month future. Instead, it seems that the effects of climate change on oil prices are masked by the oil and gas companies. This is due to the fact that volatility shocks driven by climate change news amplify the effects of volatility shocks arising from the crude oil price.

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# A MCCC and GVOL by theme over time.

Table 10: The effects of MCCC on GVOL by theme over time.

| | Financial & Regulation | Agreement & Summit | Public Impact | Research | Disaster | Environmental Impact | Agricultural Impact |
|---|---|---|---|---|---|---|---|
| $GVOL_{t-1}$ | $-0.039^{***}$ | $-0.038^{***}$ | $-0.038^{***}$ | $-0.039^{***}$ | $-0.039^{***}$ | $-0.039^{***}$ | $-0.038^{***}$ |
| $WTI_t$ | $0.236^{***}$ | $0.235^{***}$ | $0.235^{***}$ | $0.235^{***}$ | $0.235^{***}$ | $0.234^{***}$ | $0.236^{***}$ |
| $XLE_t$ | $0.415^{***}$ | $0.417^{***}$ | $0.418^{***}$ | $0.416^{***}$ | $0.417^{***}$ | $0.420^{***}$ | $0.417^{***}$ |
| theme | 0.113 | 0.033 | 0.105 | $-0.004$ | $0.159^{**}$ | $0.113^{**}$ | 0.007 |
| theme $\times$ $SIS_{2004}$ | 0.089 | 0.174 | 0.062 | 0.006 | $-0.160^{**}$ | $-0.089$ | $0.118^{*}$ |
| theme $\times$ $SIS_{2005}$ | $-0.277^{**}$ | $-0.159$ | $-0.169^{*}$ | 0.045 | $-0.021$ | $-0.030$ | $-0.152^{***}$ |
| theme $\times$ $SIS_{2006}$ | 0.133 | $-0.044$ | $-0.020$ | $-0.006$ | 0.001 | $-0.030$ | 0.019 |
| theme $\times$ $SIS_{2007}$ | $-0.105$ | $-0.026$ | 0.036 | 0.031 | 0.037 | 0.070 | 0.034 |
| theme $\times$ $SIS_{2008}$ | 0.025 | 0.112 | 0.001 | $-0.098$ | $-0.007$ | $-0.125^{**}$ | $-0.062$ |
| theme $\times$ $SIS_{2009}$ | 0.007 | $-0.085$ | $-0.074$ | 0.068 | $-0.016$ | 0.050 | 0.040 |
| theme $\times$ $SIS_{2010}$ | 0.015 | 0.077 | 0.162 | $-0.056$ | $-0.050$ | 0.072 | $-0.006$ |
| theme $\times$ $SIS_{2011}$ | $-0.025$ | $-0.091^{**}$ | $-0.074$ | 0.008 | 0.054 | $-0.011$ | $-0.010$ |
| theme $\times$ $SIS_{2012}$ | $-0.013$ | $-0.018$ | 0.045 | $-0.002$ | 0.004 | $-0.042$ | $0.102^{***}$ |
| theme $\times$ $SIS_{2013}$ | 0.087 | $-0.032$ | $-0.180^{**}$ | $-0.020$ | $-0.034$ | $-0.026$ | $-0.136^{***}$ |
| theme $\times$ $SIS_{2014}$ | 0.024 | 0.094 | $0.191^{***}$ | $0.106^{*}$ | 0.006 | 0.031 | $0.073^{*}$ |
| theme $\times$ $SIS_{2015}$ | $-0.027$ | $-0.074$ | $-0.090$ | $-0.111^{**}$ | 0.001 | 0.021 | $-0.043$ |
| theme $\times$ $SIS_{2016}$ | $-0.076$ | $-0.004$ | $-0.046$ | $-0.065$ | $-0.021$ | $-0.006$ | $0.100^{***}$ |
| theme $\times$ $SIS_{2017}$ | $0.155^{*}$ | 0.021 | 0.130 | 0.057 | 0.048 | $-0.029$ | $-0.020$ |
| theme $\times$ $SIS_{2018}$ | $-0.128$ | 0.008 | $-0.008$ | $-0.027$ | 0.008 | 0.029 | $-0.087$ |
| Observations | 3,899 | 3,899 | 3,899 | 3,899 | 3,899 | 3,899 | 3,899 |
| $R^2$ | 0.236 | 0.235 | 0.237 | 0.235 | 0.234 | 0.235 | 0.243 |
| Adjusted $R^2$ | 0.230 | 0.229 | 0.230 | 0.228 | 0.227 | 0.228 | 0.236 |
| Res. Std. Error | 1.635 | 1.635 | 1.634 | 1.636 | 1.637 | 1.636 | 1.627 |
| F Statistic | $35.175^{***}$ | $35.003^{***}$ | $35.226^{***}$ | $34.923^{***}$ | $34.726^{***}$ | $34.961^{***}$ | $36.477^{***}$ |

Impulse indicators (IIS) are not shown to save space but are included in all regressions.