# Common volatility shocks in the global carbon transition

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**Abstract**

We propose a novel approach to measure the global effects of climate change news on financial markets. For that purpose, we first study the global common volatility of the oil and gas industry, and then project it on climate-related shocks. We show that rising concerns about the energy transition make oil and gas share prices move at the global scale, controlling for shocks to the oil price, US and world stock markets. Despite the clear exposure of oil and gas companies to carbon transition risk, not all geoclimatic shocks are alike. The sign and magnitude of the impact differs across topics and themes of climate-related concerns. Regarding sentiment, climate change news tends to create turmoil only when the news is negative. Furthermore, the adverse effect is amplified by oil price movements but weakened by stock market shocks. Finally, our findings point out climate news materialises when it reaches the global scale, supporting the relevance of modelling geoclimatic volatility.

*Keywords*: Geoclimatic volatility shocks, Global common volatility, Multiplicative factor models, Climate transition risk, Oil and gas industry.
*JEL classification*: C38, C58, C31, C32, G15

## 1 Introduction

Anthropogenic climate change is mainly due to burning fossil fuels, namely coal, oil and natural gas, and the consequent release of greenhouse gases such as carbon dioxide.

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Human influence is unequivocal in causing climate change (IPCC, 2021). To reduce carbon emissions and mitigate the effects of global warming and climate change, a low-carbon energy transition is under way. The ever growing pressure to divest from fossil fuels is reflected in the pledges to reach net-zero emissions that are surging in the climate agenda of not only governments but also large companies and hedge fund firms everywhere. Climate targets now represent 61% of the global greenhouse gas emissions, 68% of the gross domestic product globally and 56% of the world's population (Black et al., 2021).

Various factors may hinder the energy transition making credible plans to achieve climate targets difficult to design. Given current technology, the move away from fossil fuels can take decades. If many industrialised countries are working to find alternative energy sources, their emerging counterparts are reluctant to make the move from (cheap) fossil fuels. 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 comes from coal. The total carbon footprint is similar among fossil fuel types. Though coal is the dirtiest per unit of energy produced, oil accounts a similar share of emissions and natural gas will play a big role in the energy transition. Moreover, coal use has been declining in the world's largest emitting countries, while other fossil fuels continue growing close to historical rates. In China, for instance, coal may have already peaked whereas the consumption of all other energy sources is growing strongly. Forward-looking policy should be thus focusing on the oil and gas (O&G) industry; For a discussion on the climate-policy relevant sectors in the economy we refer to Battiston et al. (2017).

Financial regulators have recently recognised climate change as a new source of financial risk. They are worried about the extent to which stock markets are inefficiently pricing climate-related risks (Hong et al., 2019). Investors may be overestimating the value of fossil fuels stocks and possibly creating a 'carbon bubble' Leaton (2011), Leaton et al. (2013). However, the view that climate-related risks are not relevant to decisions made today has begun to change. Investment decisions are starting to reflect ethical motivations—we have seen a revolt of investors pressing for a retreat on fossil fuel—and expectations about policy change, regulation, and carbon prices. To build climate resilience, regulators have become more interested in identifying climate-related shocks to financial institutions such as banks or insurers, and integrating climate risk management into business practices and financial decision making (UNFCCC, 2014). Climate risk posed to financial markets might come from two sources. Physical risk arises from the exposure to more frequent and severe climate-related disasters, where the resulting health and economic welfare losses from physical climate events can be very large. Carbon transition risk, on the other hand, reflects the uncertainty around the timing and speed of the low-carbon transition, which is likely to lead to unanticipated and sudden adjustments of asset prices. Even though there are attempts to analyze these risks separately, they are strongly related. Although some regions or countries are not directly exposed to physical risk, they can be indirectly affected by others that are particularly vulnerable through international relations. Moreover, physical risk is likely to spill over and change expectations about policy responses, especially about carbon prices. Investors' expectations about climate policies, technology and physical risk can thus contribute to the exposure of firms to transition risk as they can prompt a reassessment of the value of a large range of assets (Carney, 2015).

Both climate-related risks carry huge uncertainty about policy and behavioural responses and technological developments. The speed at which the re-pricing occurs is also uncertain and can have great implications for financial stability. In a disorderly transition, investors may fail to anticipate and incorporate the impact of climate policies in their business models (Monasterolo and Battiston, 2020). Transition risk will thus be higher if moving to low-carbon energy sources ends being disorderly, precipitating large falls in profits and assets across a wide range of existing businesses. Moreover, the adverse effects of the green transition to the economy can be amplified by the interconnectedness of the financial system (Battiston et al., 2017) and rising investor awareness (Bolton and Kacperczyk, 2021b). Obviously, carbon-intensive activities are not viable in a low-carbon economy. These businesses are less resilient to climate risks, their investors may experience lower financial returns and large losses, and their assets and workers may become stranded (Leaton, 2011, Van der Ploeg and Rezai, 2020). The resulting falling property values, for instance, could lead to widespread mortgage defaults (which led to the Great Recession). Many central banks and financial regulators are adopting climate-based strategies to monitor and stabilise the financial system.

To compensate for their exposure, investors are pricing carbon transition risk. Using a cross-section of US stock returns, Bolton and Kacperczyk (2021a) find strong evidence for a carbon premium with emissions positively affecting stock returns. At the global level, Bolton and Kacperczyk (2021b) show the cross-country effects of corporate carbon emissions and a country's level of transition risk on stock returns. A company's carbon premium seems to be associated with 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), the larger is the country's share of brown (green) sectors. It does not seem to reflect physical risk though.

Political insecurity and uncertainty can have a great impact on global energy markets. Increasing O&G prices in turn can jeopardise economic growth, shake international security and test the political stability of energy importing countries. We have seen the role Russia played in European geopolitics during the Crimea crisis and, more recently, with its invasion of Ukraine. Russia is the largest natural gas exporter and one of the major producers of crude oil. Europe's dependence on Russian energy makes it thus a central international issue to political, economic and financial stability. In comparison with macroeconomic news, geopolitical news has a strong immediate impact and generates greater uncertainty and trading activity in crude oil markets (Brandt and Gao, 2019). Geopolitics has been defined as the way political activity in a country affects other countries in the world. In the most conventional view, the power of a country is mostly determined by its geographic location and control over territory. Strongly related to military risk is the geopolitical risk index of Caldara and Iacoviello (2022); see also Brandt and Gao (2019) for its relation to crude oil markets. Recent history has shown that wars over trade, oil price or even territory are not won in a battle field. Geopolitical tensions between Russia and the West following the invasion of Ukraine are reflected in the threats of a ban on Russian oil and other sanctions aimed at disrupting the country's economy by causing its stock market to falter and its currency to devalue, and ultimately at changing policy and possibly even the regime in Russia. Regardless of being successful, this geo-strategy affected almost immediately the globalised and digitised financial system by shaking global markets, in particular, the oil market. Issues such as climate change and the energy transition were quickly dominated by geopolitics, record high oil prices and dividends, and O&G share buybacks. In this paper, we adopt this broader definition of geopolitics to understand how not only politics but also international and intergovernmental organizations such as the Organization of the Petroleum Exporting Countries (OPEC), multinational companies and, more importantly, mass media make energy markets move. In particular, by broad geopolitical risk we mean the exposure of a wide range of O&G share prices to adverse geopolitical events.

Companies operating in carbon-intensive industries, such as oil and gas, are particularly exposed and vulnerable to climate transition risk. Given the geopolitical nature of both the O&G industry and climate transition risk, factors at the country-level seem relatively more relevant than sector- or company-specific. Climate policy stringency and regulation can differ greatly across the countries a company operates and the O&G carbon footprint can be very different if we think in terms of ownership or their physical location. As we focus on the O&G industry, responsibility to become sustainable in a low-carbon economy lies with industrialising countries and western investors. Notwithstanding, we expect a reassessment of the value of a large range of carbon-intensive assets globally in response to climate change news, rising concerns and tighter policies regardless of their origin.

We propose a novel methodology to measure common movements of the O&G industry and to identify those which have been driven by unexpected increases in climate change concerns. The model of global common volatility developed by Engle and Campos-Martins (2020), and which can be interpreted as a measure of broad geopolitical risk, is applied to the daily share prices of O&G companies from various countries and regions of the world. We show the common events that have made the O&G equity prices move at the same time and that have had the greatest impact on the industry since 1983. O&G global common volatility peaks during the COVID-19 pandemic, after the 9/11 terrorist attack, Black Monday in 1987, and during the Great Recession of 2007-2009. Also, announcements by OPEC or the drone attack on the Saudi Aramco production facilities in 2019 show up as broad geopolitical events driving changes in the global O&G equity market as well. As a proxy for climate risk, we use the daily media climate change concerns index of Ardia et al. (2020) and the monthly climate change news index of Engle et al. (2020). Each index is a time-series that captures news about climate risk, constructed by applying text mining to the content of internationally relevant United States newspapers. We find strong evidence that climate change news and concerns do make the O&G stock prices move at the global scale, controlling for shocks to the oil price, US and world stock markets. This variation of the O&G global common volatility driven by climate change news is called geoclimatic volatility. But not all geoclimatic shocks are alike. The signs and magnitudes of the impacts differ across topics and themes, and whether the news is negative or positive. Our empirical results also point out climate-related news materialises when it reaches the global scale. The systemic implications of the carbon transition seem thus to reflect the geopolitical nature of both the O&G industry and transition risk.

The paper is organised as follows. In Section 2, the global common volatility model and the estimation procedure are briefly described. The results from the empirical application of the model to global O&G stock returns, including a detailed analysis of the major common events affecting the industry over time, are shown in this section as well. Subsequently, in Section 3, we develop the strategy addressed to identify the common volatility shocks that are driven by climate change concerns or news. First we introduce the measures used as proxies for climate change concerns and news. Then, we present the results showing evidence for geoclimatic shocks by projecting the O&G global common variance shocks onto climate change variance shocks. Section 4 is devoted to discussing and highlighting the policy implications of the results. Finally, Section 5 concludes the paper.

# 2 Modelling global common variance

Economic, financial or political events impact volatilities and move markets globally. O&G volatility co-movements at the global scale can be driven by various geopolitical events. Smales (2021) studied the impact of geopolitical events on oil and stock markets, and found that geopolitical risk drives oil price and stock market volatility. In particular, an increase in geopolitical risk is associated with higher volatility in both markets. To analyze to what extent global events affecting the O&G industry fall in the category of climate change, we propose a two step approach. In this section, we measure O&G global common volatility, which can be interpreted as a broad measure of the magnitude of geopolitical events to a wide range of O&G equities, countries and regions of the world. Then, in the next section, we identify the common volatility shocks that are driven by climate change news using regression analysis.

## 2.1 Measuring common variance shocks

It is a stylised fact that financial volatilities co-move. This is not surprising when asset returns respond to the same factors. Interestingly, whatever factors are extracted from the returns, idiosyncratic volatilities still co-move (Herskovic et al., 2016). When many assets, markets and countries respond to the same news at the same time, shocks to volatilities are correlated (Engle and Campos-Martins, 2020). To measure common shocks to the volatilities of a wide range of assets, they propose a new model of global common volatility based on a multiplicative volatility factor decomposition of the standardised residuals. We shall briefly explain how we apply the model to study volatility co-movements in the global O&G equity market (we will use O&G to denote the industry as a whole).

Consider the $(N \times 1)$ vector of O&G equity returns $\boldsymbol{r}_t = (r_{1,t}, \ldots, r_{N,t})'$ given by

$$\boldsymbol{r}_t - r_{f,t} = \mathbf{B}\boldsymbol{f}_t + \mathsf{diag}\left\{\sqrt{\boldsymbol{h}_t}\right\}\boldsymbol{e}_t, \tag{1}$$

where $r_{f,t}$ is the risk-free return, $\mathbf{B}$ is an $(N \times p)$ matrix of risk exposures, $\boldsymbol{f}_t$ is a $(p \times 1)$ vector of risk factors, $\boldsymbol{h}_t \equiv (h_{1,t}, \ldots, h_{N,t})'$ contains idiosyncratic conditional variances and $\boldsymbol{e}_t \equiv (e_{1,t}, \ldots, e_{N,t})'$ the idiosyncrasies.

Assuming factors are sufficient to reduce the contemporaneous correlations of returns to zero, this implies the volatility standardised residuals $\boldsymbol{e}_t$ will have zero covariances and unit variances. We denote the variance-covariance matrix of $\boldsymbol{e}_t$ by $\Sigma_{e,t}$, whose $(i,j)$ entry is the covariance between the zero-mean random variables $e_{i,t}$ and $e_{j,t}$, i.e., $\Sigma_{e,t}^{i,j} = cov[e_{i,t}, e_{j,t}] = \mathbb{E}_{t-1}[e_{i,t}e_{j,t}], i,j = 1,\ldots,N$, so $\Sigma_{e,t} = \mathbb{I}_N$, the identity matrix of order $N$. This assumption does not mean that residuals are independent in the cross-section, merely uncorrelated. To reduce the contemporaneous correlations of returns to zero, the cross-sectional mean returns may be used as a factor in model (1).

The fundamental observation of the model presented is that, even though the standardised residuals are orthogonal with unit variance, their squares (or absolute values) are likely to be correlated in the cross-section. Since volatility is well known to be predictable, the co-movement of volatilities is most likely caused by the positive correlation between shocks to those volatilities (Engle and Campos-Martins, 2020).

We define a variance shock to the $i$th O&G equity as follows:

$$\phi_{i,t}^{\sigma} \equiv e_{i,t}^2 - 1, \tag{2}$$

$i = 1, \ldots, N$, where $e_{i,t}^2 = (r_{i,t} - r_{f,t} - \boldsymbol{\beta}_i' \boldsymbol{f}_t)^2 / h_{i,t}$ generally denotes the squared standardised residual from a factor model. We use the Greek letter $\sigma$ (*sigma*) to emphasize that these are volatility shocks[1]. In this setting, the variance shock $\phi_{i,t}^{\sigma}$ can be interpreted as the proportional difference between the squared idiosyncrasy and its expectation. For each equity, the realised squared idiosyncrasy is on some days larger than usual (unity) and on other days smaller than usual. If many O&G equities around the world have squared idiosyncrasies larger than usual at the same time, this can be interpreted as a common variance shock to the global O&G industry. As we will show, these global common events are associated with geopolitical news that we will later identify as climate common volatility shocks.

Let's introduce some additional notation. We denote the global O&G variance (latent) factor by $f_{\text{O\&G},t}^{\sigma}, t = 1, \ldots, T$, a positive scalar random variable with $\mathbb{E}[f_{\text{O\&G},t}^{\sigma}] = 1$. Moreover, $f_{\text{O\&G},t}^{\sigma}$ is independent of $\boldsymbol{\epsilon}_t = (\epsilon_{1,t}, \ldots, \epsilon_{N,t})'$, where $\epsilon_{i,t} \sim \text{IIN}(0,1)$ i.e., independently and identically normally distributed with zero mean and unit variance, $i = 1, \ldots, N$. The factor loadings are denoted by $s_i, i = 1, \ldots, N$. These are interpreted as parameters (or fixed effects). The standardised residuals are then assumed to have the multiplicative decomposition of Engle and Campos-Martins (2020),

$$e_{i,t} = \sqrt{g(s_i, f_{\text{O\&G},t}^{\sigma})}\, \epsilon_{i,t}, \tag{3}$$

where

$$g(s_i, f_{\text{O\&G},t}^{\sigma}) \equiv s_i (f_{\text{O\&G},t}^{\sigma} - 1) + 1, \tag{4}$$

$f_{\text{O\&G},t}^{\sigma} > 0, t = 1, \ldots, T$, and $0 \leq s_i \leq 1, i = 1, \ldots, N$. By choosing specification (4), $g(s_i, f_{\text{O\&G},t}^{\sigma})$ is non-negative for every $t \in [1, T]$ and by assuming $\mathbb{E}[g(s_i, f_{\text{O\&G},t}^{\sigma})] = 1$, $\mathbb{E}[e_{i,t}^2] = 1$ is satisfied for every $i$.

Assuming $f_{\text{O\&G},t}^{\sigma}$ has strictly positive variance, the specification (3) implies the squared standardised residuals are positively correlated. Hence, the variance-covariance

[1] These are, in fact, variance shocks. Because volatility is simply the standard deviation, i.e., the square root of the variance, when interpreting results, these two terms can be used interchangeably.

matrix of the squared standardised residuals, $\Sigma_{e^2,t}$, will not be diagonal due to the cross-sectional dependence in the volatility standardised residuals. It is then straightforward to test for common variance shocks by testing whether $\Sigma_{e^2,t}$ is diagonal. In practice, this null hypothesis is tested by calculating the empirical variance-covariance matrix using the squared estimated volatility standardised residuals. We will use the test statistic proposed by Engle and Campos-Martins (2020), which follows in distribution a standard normal under the null hypothesis. Under the alternative, $f^{\sigma}_{\text{O\&G},t}$ varies over time inducing co-movements and positive correlations between the squared standardised residuals. Note that the $(i,j)$ entry of $\Sigma_{e^2,t}$ is the covariance between the squared random variables $e^2_{i,t}$ and $e^2_{j,t}$, i.e., $\Sigma^{i,j}_{e^2,t} = cov[e^2_{i,t}, e^2_{j,t}] = \mathbb{E}_{t-1}[(e^2_{i,t} - 1)(e^2_{j,t} - 1)], i,j = 1,\ldots,N$. Positive correlations mean that the off-diagonal elements of $\Sigma_{e^2,t}$ will also be positive. Moreover, we assume $s_i = 1, i = 1,\ldots,N$, under the alternative meaning all equities are equally affected by a shock. This means all pairwise correlations will be the same. The problem can thus be reduced to checking whether the equicorrelation of the squared standardised residuals, denoted by $\rho_{e^2}$, is positive. For further details, we refer to Engle and Campos-Martins (2020).

Because the data generating process is multiplicative between two sets of unknowns $f^{\sigma}_{\text{O\&G},t}, t = 1,\ldots,T$ and $s_i, i = 1,\ldots,N$, we estimate each conditional on the other by maximum likelihood. The first order conditions with respect to each set of unknowns give two heteroscedasticity relationships:

$$\text{Cross-Section: } e_{i,t} = \epsilon_{i,t}\sqrt{\hat{s}_i\left(f^{\sigma}_{\text{O\&G},t} - 1\right) + 1} \text{ for } t = 1,\ldots,T, \tag{5}$$

$$\text{Time-Series: } e_{i,t} = \epsilon_{i,t}\sqrt{s_i\left(\hat{f}^{\sigma}_{\text{O\&G},t} - 1\right) + 1} \text{ for } i = 1,\ldots,N.$$

The cross-sectional regression allows us to estimate the unobserved value of $f^{\sigma}_{\text{O\&G},t}, t = 1,\ldots,T$, (using some initial values for the factor loadings) and then the time-series regression allows us to obtain estimates for $s_i, i = 1,\ldots,N$, conditional on the estimates for the latent variable. There is thus an estimator for each $s_i, i = 1,\ldots,N$, given $\hat{f}^{\sigma}_{\text{O\&G},t}, t = 1,\ldots,T$, using time-series and another estimator for each $f^{\sigma}_{\text{O\&G},t}, t = 1,\ldots,T$, given estimated $\hat{s}_i, i = 1,\ldots,N$, for each cross-section. To gain efficiency, we iterate the estimation of the time-series and cross-sectional regressions until convergence. At that point, both first order conditions are satisfied and a joint maximum can be achieved.

## 2.2 The dataset

We use the daily closing prices of shares from 25 major O&G companies around the world extracted from the data platform Datastream[2]. The full list of equities used can be found in Appendix A. These are all traded on the NYSE ensuring synchronous observations when measuring volatility co-movements. The sample period goes from January 12, 1983 until January 29, 2021. This is an unbalanced panel (equities were launched on different dates) with a minimum of eight observations per day. To remove any stochastic trend, we convert prices into log-returns. Our modelling framework starts by estimating a factor model with generalised auto-regressive conditional heteroscedastic (GARCH) errors for each series of O&G excess returns. Extreme returns are truncated to $\pm 10\%$ to avoid problems in the estimation of the GARCH models and to prevent outliers from showing up as global common events. For modelling the time dependence observed in the first moment of the data, a first-order autoregressive (AR) component is added to the pricing factor models. This is supported by Ljung-Box AR(1) tests. To account for common factors affecting the series of O&G returns, we choose $p = 4$. We consider the classic framework of Fama and French with three factors, namely the size of firms (small minus big), book-to-market values (high minus low), and excess return of the market (the portfolio's return less the risk-free rate of return). To control for oil price shocks, we also include the excess returns of the West Texas Intermediate (WTI) crude oil 1-month future as an additional factor in the pricing model (1). To model the heteroscedasticity behaviour of the series, a first order GARCH model is assumed for the errors. The choice of a GARCH(1,1) model is supported by Ljung-Box ARCH(1) tests and sufficient to capture the heteroscedastic behaviour of each series. The summary statistics including the results from the tests of time-independence in the first and second moments of each O&G return series are presented in Appendix B.

The cross-sectional mean O&G residuals from the factor models is depicted in the top panel of Figure 1 and the estimated conditional volatilities in the middle and bottom panels. For comparison, the estimated volatility of the excess returns of the WTI crude oil future and the Standard & Poor's 500 index (SPX) and of the Standard & Poor's Depository Receipt (SPDR) energy select sector fund (XLE) are also shown in, respectively, the middle and bottom panels. The XLE series, available from December 21, 1998, reflects the exposure to mostly oil, gas and consumable fuel companies in the US. Even though they share some US-based constituents, our sample includes O&G companies from all over the world. A first observation from the top

[2]A limitation of using coal stock prices has to due with the data availability. Few purely coal mining companies are quoted or traded on the NYSE. For instance, Peabody went bankrupt in 2016 but re-entered in 2017. Most non-state controlled coal is from general mining companies. BHP, the world's largest mining company, is a mining, metals and petroleum company. It would be hard to separate what role coal transition risk played.

panel is that O&G returns are heteroscedastic with larger movements during periods of market distress, namely the Early 2000s Recession, the 2007-2009 Great Recession, the oil price plunge of 2014-2016, and, more recently, the COVID-19 Pandemic. Despite O&G returns being on average more volatile than the XLE or the SPX, the middle and bottom panels show the WTI crude oil future is the most volatile. Another interesting observation from those panels is that all volatilities depicted tend to co-move over time, especially in the periods of higher uncertainty and market turmoil.

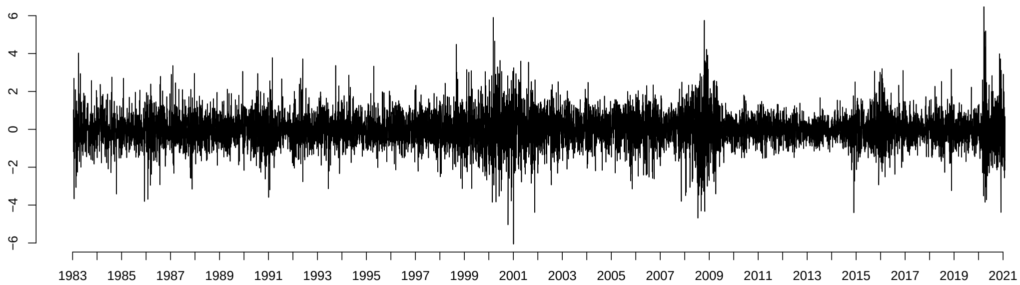
Having extracted the pricing factors, the idiosyncratic volatilities are still correlated. Their cross-sectional mean correlation is 0.583 and their first principal component accounts for around 65% of their total variance. The correlation between the cross-sectional mean O&G volatility and that of the WTI oil future is 0.554, of the energy sector XLE is 0.913, and of the SPX is 0.643. Though highly correlated, neither each nor all of them seem to fully capture the variation in the global O&G equity market. When it comes to variance shocks, these correlations are even lower. The correlation between the cross-sectional mean O&G variance shocks and those to the WTI future is only 0.188, to the energy sector XLE is 0.648, and to the SPX is 0.099.

## 2.3 The Oil & Gas variance factor

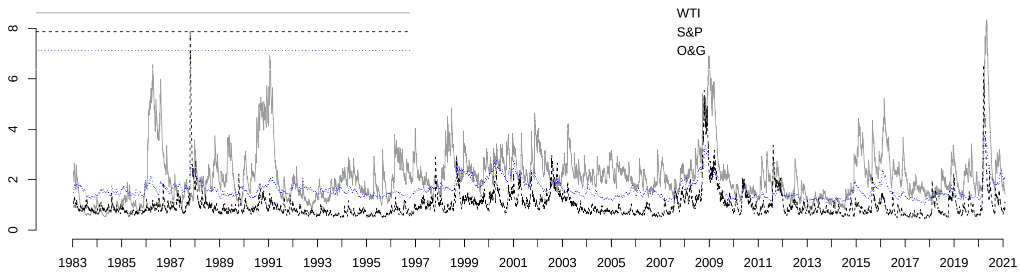
After estimating the factor pricing models, we compute the vector of volatility standardised residuals $\hat{\boldsymbol{e}}_t, t = 1, \ldots, T$. Before estimating the O&G global common variance, we have to test the null hypothesis of no common variance shocks. As explained above, we need to test whether $\Sigma_{e^2,t}$ is diagonal against the one sided alternative that its off-diagonal elements are positive. The empirical counterpart of the equicorrelation $\rho_{e^2}$ is computed based on the squared estimated volatility standardised residuals and denoted by $\rho_{\hat{e}^2}$. For this sample, $\rho_{\hat{e}^2} = 0.096$ and the test statistic is $\xi_{\hat{e}^2} = 141.3$ ($p-$value $= 0.000$). The null hypothesis that the squared standardised residuals are uncorrelated is thus strongly rejected. This result provides evidence that the squared standardised residuals are, in fact, positively correlated and we can then proceed to the estimation of the O&G global common variance. To help estimating $f^{\sigma}_{\mathrm{O\&G},t}$, we also use the cross-sectional mean O&G standardised residuals. The sample size then becomes $N = 26$.

We shall briefly describe the iterative estimation of $f^{\sigma}_{\mathrm{O\&G},t}$ and corresponding factor loadings. As the starting values for the estimation of the O&G variance factor we choose the factor loadings on the first principal component of the squared standardised residuals[3]. Then, we take the estimated standardised residuals as observable

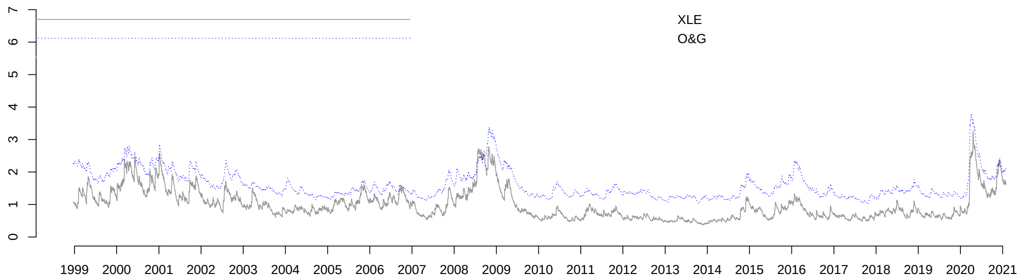
[3]Despite the factor loadings on the first principal component being natural values for the initial estimates of the O&G factor loadings, the algorithm seems to converge to the same optimal solution when we choose other initial values. The estimator does not seem to be sensitive to the choice of the initial values.




(a) O&G returns




(b) Conditional volatilities of O&G versus WTI and SPX




(c) Conditional volatilities of O&G versus XLE

Figure 1: Cross-sectional mean O&G residuals (top) and estimated conditional volatilities (middle and bottom). For comparison, the volatility of the 1-month WTI crude oil future and of the S&P 500 index (SPX) are also shown in the middle panel and of the SPDR energy sector fund (XLE) in the bottom panel. The XLE series is available from December 21, 1998.

and iterate the estimation of the cross-sectional and time-series regressions (5) until convergence. In each iteration, in order to identify the variance-covariance matrix of the squared standardised residuals, we impose the normalizations $\sum_{i=1}^{N} s_i^2 = 1$ and $f^{\sigma}_{\text{O\&G},t}/\bar{f}^{\sigma}_{\text{O\&G}}$, where $\bar{f}^{\sigma}_{\text{O\&G}} = (1/T)\sum_{t=1}^{T} f^{\sigma}_{\text{O\&G},t}$. This is done after estimating, respectively, each time-series and cross-section regression. For this empirical sample, 15 iterations were performed until the algorithm converged.

The most extreme common O&G variance shocks captured by $\hat{f}^{\sigma}_{\text{O\&G},t}$ are summarised in Table 1. For comparison, the excess returns on the same day are shown for the cross-section average of O&G stocks ($\bar{r}_t^{\text{O\&G}}$), the S&P 500 index ($r_t^{\text{SPX}}$), the crude WTI oil 1-month future ($r_t^{\text{WTI}}$), and the SPDR energy sector fund ($r_t^{\text{XLE}}$). Note that the excess returns of O&G stocks have been truncated. Several dates are easily recognised as when major events happened affecting global financial markets, including the O&G equity market. Many extreme common variance shocks as measured by $\hat{f}^{\sigma}_{\text{O\&G},t}$ coincide with large negative returns to the O&G industry. Negative shocks thus appear to have higher potential to have a global effect than positive ones. However, they may or may not be matched by large negative shocks to the WTI, XLE and/or SPX. For instance, on March 20, 2020 when the returns of the US stock market and the commodity price of oil had both been negative, that of the O&G industry had actually been positive. Or even when the NYSE reopened after the 9/11 on September 17, 2001, and the returns of US stock market and the O&G industry had both been negative, the returns of the WTI crude oil had been positive. This difference also gives some insight on the nature of these shocks with some appearing to be stock or energy market specific and others commodities exchange specific. Hence, using individual prices such as WTI or XLE rather than the co-movements of multiple financial stock prices at the global scale to analyse the exposure to transition risk may not be the most appropriate. As we will see below, transition risk seems to materialise only when it has a global impact and this can be captured by using the model of common variance shocks to equities of companies operating in different countries and parts of the world.

Global events, such as economic or financial, political elections, climate policy changes or terrorist attacks are likely to reflect changes in global oil demand primarily. Recently, these include pandemics (many events during the COVID-19 pandemic such as the day after the US relief package was signed on March 20, 2020, which also ended the worst weekly performance for all three major US stock indices, namely Dow, S&P 500 and Nasdaq Composite, since October 2008), financial crashes and crises (such as the Great Recession of 2007-2009), military (the day on which the NYSE opened after the 9/11 terrorist attacks on September 17, 2001) and political (the day after the UK European Union membership referendum with its decision in favor of the *Brexit* on June 23, 2016, on the days after US presidential elections in 2016 and 2020, and during

Table 1: The largest estimated global shocks and the values of the returns on the same day. $\bar{r}_t^{O\&G}$ denotes the cross-sectional mean oil and gas truncated excess return, $r_t^{\mathrm{SPX}}$ the return of the S&P 500 index, $r_t^{\mathrm{WTI}}$ the return of the WTI crude oil 1-month future, and $r_t^{\mathrm{XLE}}$ the return of the SPDR energy sector fund.

| $t$ | $\hat{f}^{\sigma}_{\mathrm{O\&G},t}$ | $\bar{r}_t^{\mathrm{O\&G}}$ | $r_t^{\mathrm{SPX}}$ | $r_t^{\mathrm{WTI}}$ | $r_t^{\mathrm{XLE}}$ |
|---|---|---|---|---|---|
| 2020-03-20 | 42.915 | 1.519 | −4.433 | −11.724 | 0.971 |
| 2014-11-28 | 35.934 | −7.218 | −0.255 | −10.726 | −6.640 |
| 1987-10-20 | 28.158 | 3.276 | 5.195 | 0.101 | |
| 1993-09-29 | 26.473 | 3.212 | −0.308 | −0.167 | |
| 1985-12-09 | 25.085 | −4.301 | 0.619 | −4.338 | |
| 2008-07-16 | 23.811 | −1.402 | 2.475 | −3.029 | −2.608 |
| 2000-03-07 | 23.642 | 5.492 | −2.597 | 5.883 | 6.673 |
| 1995-04-20 | 23.505 | 2.164 | 0.073 | −6.732 | |
| 2020-03-23 | 22.859 | −1.779 | −2.973 | −9.683 | −9.272 |
| 1998-09-04 | 22.729 | 3.645 | −0.856 | −0.684 | |
| 2000-10-13 | 22.576 | −3.320 | 3.284 | −3.096 | −3.900 |
| 1992-05-26 | 22.018 | 4.010 | −0.632 | 4.943 | |
| 1993-06-11 | 21.264 | −3.200 | 0.421 | −1.413 | |
| 2020-03-17 | 21.229 | −0.167 | 5.823 | −6.291 | 0.681 |
| 1984-10-17 | 21.084 | −4.416 | −0.389 | −2.653 | |
| 2019-04-12 | 21.024 | 0.241 | 0.659 | 0.486 | 0.267 |
| 1985-07-05 | 19.748 | −0.379 | 0.557 | 0 | |
| 2020-11-09 | 19.430 | 8.913 | 1.163 | 8.179 | 13.344 |
| 2010-04-29 | 18.930 | 0.322 | 1.286 | 2.316 | 0.115 |
| 2001-01-03 | 18.542 | −2.598 | 4.888 | 2.896 | −3.101 |
| 1985-12-10 | 17.288 | −3.528 | 0.069 | −1.170 | |
| 1983-03-31 | 16.997 | 3.806 | −0.281 | 0 | |
| 2016-11-30 | 16.627 | 5.538 | −0.266 | 8.900 | 4.958 |
| 2001-09-17 | 16.400 | −1.637 | −5.047 | 4.251 | −2.065 |
| 1986-01-27 | 16.370 | −2.014 | 0.464 | 7.226 | |

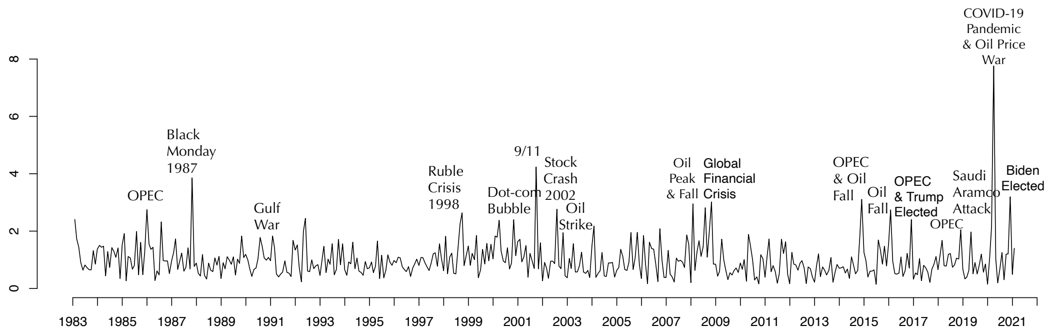



Figure 2: The (monthly averaged) O&G global common variance index. Note: 'OPEC' indicates an announcement and 'Peak' or 'Fall' indicates oil price peak or fall, respectively.

trade wars). Shocks that are likely to reflect oil supply shocks involve announcements from OPEC such as on November 28, 2014, when Saudi Arabia blocked its output cut, crashing oil prices and driving shares of oil and gas companies around the world to follow suit; oil spills such as on April 29th, 2010 when the magnitude of the Deepwater Horizon disaster that had occurred a week earlier finally sank in with investors; oil strikes such as the Venezuelan general strike that took place late in 2002; or even air strikes like the drone attack to the Saudi Aramco oil production facilities on September 14, 2019, which caused its biggest disruption ever. Given the NYSE was closed on this day combined with the threat of new attacks and an official statement, the effects only materialised when the stock exchange reopened on September 16, 2019. Oil shocks can be supply shocks, shocks to the global demand for all industrial commodities, and demand shocks specific to the global crude oil market. Kilian (2009) interpreted the latter as precautionary oil demand shocks. In anticipation of an expected oil shortage, traders buy and store crude oil with the expectation of selling it later at a profit. Killian and Murphy (2014) later augmented the model to explicitly include speculative oil demand shocks using data on oil inventories. The new model revealed a larger role for supply shocks at the expense of speculative trading, which remained the main driver of earlier oil price surges. More recent episodes seemed to have however been largely and persistently caused by unexpected increases in world oil consumption driven by global business cycle fluctuations. Regarding O&G variance shocks, we also expect these to be more demand rather than supply driven.

All the geopolitical events discussed above caused large returns across the global O&G equities at the same time showing up in the global common volatility factor as some of the biggest common shocks affecting the O&G industry. The monthly averaged estimated O&G global common variance factor, $\hat{f}^{\sigma}_{\text{O\&G},m}$, where $m$ indicates the calendar month, is plotted in Figure 2 where some of the major events affecting the O&G industry are labelled.

The empirical variances and covariances of the squared standardised residuals are, in fact, not equal across O&G equities. This reflects the fact that different equities have different loadings on $f^{\sigma}_{\text{O\&G},t}$. The estimated O&G loadings are presented in Table 2 in descending order of magnitude. These values capture the proportion of $f^{\sigma}_{\text{O\&G},t}$ that affects each asset variance. Because the impact of $f^{\sigma}_{\text{O\&G},t}$ is heterogeneous across equities, O&G companies have different exposures to common variance shocks. This heterogeneity may reflect country-level as well as company-specific factors. When assessing the geopolitical nature of both the O&G industry and climate transition risk, factors at the country-level are more relevant than sector- or company-specific. Concerning transition risk, climate policy stringency, for instance, may explain differences between companies based in the US, China or Europe. Greener policies in the markets or countries a company operates make it more exposed to climate transition risk. One would then expect companies operating in the UK, France or Norway to be more exposed than those in the US or China. Taking such conclusions from the results provided in Table 2 can be misleading though. The loadings shown do not solely reflect exposure to climate transition risks, but to all sorts of shocks that make all O&G companies move at the same time. It is then not surprising that some of the *supermajors*, namely Shell (RDS), BP, Chevron (CVX), ConocoPhillips (COP) and ExxonMobil (XOM), are the top companies with largest exposure to these shocks.

By construction of functions $g(s_i, f^{\sigma}_{\text{O\&G},t}), i = 1, \ldots, N$, the loading $s_i$ measures the exposure of company $i$ to any common volatility shock. An important implication of the difference in the O&G loadings is that it makes possible to reduce the exposure to broad geopolitical risk. For more details on portfolio optimality in the presence of common volatility shocks, we refer to Engle and Campos-Martins (2020). Exploring the heterogeneity of loadings further, in particular from the climate viewpoint, is surely relevant and interesting. We use regression analysis to disentangle the overall exposure of the O&G industry to climate transition risk in the next section. To analyse individual exposure to climate-related common volatility shocks, an extension of the model would be needed. For instance, including an observable climate change variable as an additional common variance factor would allow us to directly estimate the individual loadings on this climate factor. Extending the model of common volatility to the multi-factor level is beyond the scope of the paper though. Nevertheless, it highlights new ways of modelling climate common volatility.

Finally, as an indicator of the goodness of the fit, we re-run the test for common variance shocks on $\boldsymbol{e}^2_t$ further standardised by the functions of $s_i$ and $f^{\sigma}_{\text{O\&G},t}$. These are denoted by $\boldsymbol{\epsilon}^2_t = (\epsilon^2_{1,t}, \ldots, \epsilon^2_{N,t})'$, where $\epsilon^2_{i,t} = e^2_{i,t}/g(s_i, f^{\sigma}_{\text{O\&G},t}), i = 1, \ldots, N$. The empirical $\rho_{\hat{\epsilon}^2} = -0.004$ and the test statistic (assuming the model is correctly specified) becomes $\xi_{\hat{\epsilon}^2} = -0.522$ ($p-$value $= 0.699$). This failure to reject the null means that the squared standardised residuals become uncorrelated by removing the common shocks. This result not only supports the multiplicative decomposition (3)-(4) but also the

Table 2: The estimated oil and gas global common variance factor loadings.

| | $\hat{s}_i$ | | $\hat{s}_i$ |
|---|---|---|---|
| O&G | 0.329 | EQNR | 0.199 |
| RDS | 0.241 | TOT | 0.198 |
| BP | 0.228 | CNQ | 0.185 |
| CVX | 0.228 | E | 0.180 |
| COP | 0.226 | PTR | 0.171 |
| APC | 0.223 | KMI | 0.162 |
| OXY | 0.216 | REPYY | 0.159 |
| EOG | 0.214 | CEO | 0.153 |
| SLB | 0.212 | SNP | 0.151 |
| HAL | 0.209 | EC | 0.151 |
| XOM | 0.208 | PSX | 0.105 |
| SU | 0.204 | PBR | 0.091 |
| DVN | 0.202 | EPD | 0.084 |

A glossary can be found in Appendix A.

ability of the global common variance factor to capture the shocks driving movements in the global O&G market.

# 3 Disentangling geoclimatic variance

The global O&G equity market is geopolitical by nature. The OPEC's 'price war' that erupted between Saudi Arabia and Russia in the first quarter of 2020 rapidly spilled over to the global stock market. This is a good example of tail risk that can have major implications for the global economy. The global common volatility model provides a way of systematically modelling how geopolitics can affect global markets. By measuring common large volatility shocks, our results support the view that global events such as the one just described make the O&G equity prices move at the same time. It is an important result to assessing the systemic nature of broad geopolitical risk affecting the O&G industry. Global events shaking the O&G companies might come from different sources. We are interested in identifying which of those arise from climate change media concerns or news. This variation driven by climate change geopolitical news with global impact is called geoclimatic volatility.

## 3.1 Proxying climate shocks

The main goal of this paper is to analyze to what extent climate change news is fuelling an additional source of risk by making financial markets move. We are particularly interested in the exposure of carbon-intensive capital markets to the risk arising from the energy transition towards low-carbon economies. In what follows, we now consider climate change news as a determinant of those O&G common variance shocks as the low-carbon transition is expected to have a great impact on the value of O&G equity holdings.

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. The former relates to how 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. Though physical risk seems to have mostly local effects, companies in a country that is less vulnerable to climate-related events can still have a great indirect exposure to physical risk through international relations with those that are particularly vulnerable. Financial stability is however most likely to be affected by climate change indirectly through increasing transition risk. This type of climate change risk arises from the uncertainty about the timing and the speed of adjustment toward green economies. It includes the impact of policy changes towards carbon pricing, legislation like the UK's Climate Change Act of 2008 and disruptive technological progress. The systemic implications of climate change to financial markets are thus most likely to come from the exposure to transition risk, in particular, of companies in carbon-intensive sectors. Moreover, as the likelihood of a disorderly transition increases, so does climate transition risk.

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 articles. The MCCC index thus captures climate change concerns portrayed in the news media by combining attention and information. It reflect both uncertainty and sentiment about climate change. The selected major (daily circulation of more than 500,000) US 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 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. The MCCC index is plotted in Figure 3 and is available at https://www.dropbox.com/s/way43an9xntvqwn/Sentometrics_US_Media_Climate_Change_Index.csv?dl=1. It is clear how concerns peak around the United Nations climate change conferences such as in late 2009 (Copenhagen, COP15) and in late 2015 (Paris, COP21) when the Paris Agreement, a legally binding international treaty adopted by 196 parties to limit global warming to below 2 degrees Celsius compared to pre-industrial levels, was sealed.

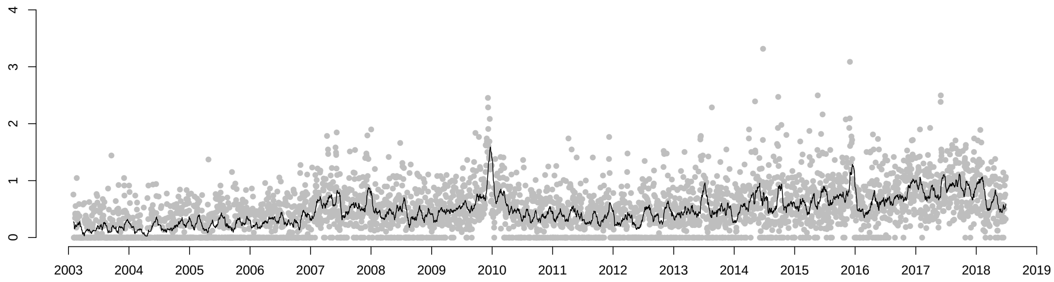



Figure 3: The daily MCCC index (gray) and its 20-day rolling window average (black).

Aggregating news by themes and topics provides a more comprehensive analysis of the impact of climate change on the global O&G equity market. Ardia et al. (2020) constructed climate change concerns indices for 40 different topics and 8 aggregate themes. The most common words associated to each of the statistically significant topics in our analysis are presented in Appendix C; for other topics, we refer to Ardia et al. (2020). Similarly, we construct variance shocks for each topic and then aggregate them by theme. We excluded category 'Other' which resulted in 7 themes and 38 topics. For that purpose, we compute the cross-sectional mean of the relevant topics (without repetition) for each theme. For instance, theme 'Research' is obtained by averaging the variance shocks to three topics and theme 'Financial & Regulation' by averaging the variance shocks to other eleven topics.

The impact of climate change concerns on financial markets may reflect changes in firms' future cash flows or in climate risk *appetite*. Investors may be willing to accept higher levels of risk (for the same expected return) if their climate taste changes. Some themes may affect either or both channels. According to Ardia et al. (2020), 'Financial & Regulation' primarily affects the cash flow channel whereas 'Disaster', 'Research' or 'Societal Impact' is more likely to affect the tastes channel. 'Agreement & Summit', 'Environmental impact' or Agricultural Impact' can alter both. Regulations can change firms' future cash flows, but discussions about the consequences of climate action failure may increase investors' distaste for climate change.

To assess whether the impact of negative climate change news differs from positive news, we use the two monthly climate change news indices proposed by (Engle et al., 2020). By applying textual analysis to the daily Wall Street Journal (WSJ), the *generic* 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.

As an attempt to distinguish the effect of purely negative climate change news, we will also use a different version of the climate change news index which uses sentiment analysis. The WSJ-based index described above has been constructed under the assumption that the number of news articles about climate change increases when climate transition risk is high. However, it may be spuriously capturing positive climate news about, for instance, new mitigation technologies, as increases in climate transition risk. By applying sentiment analysis to the climate-related articles, it is possible to measure the intensity of negative climate news in a given month. The index is proposed by Engle et al. (2020) based on the services of a data analytics provider and news media from not only the WSJ, but others such as Reuters, BBC, CNN, and Yahoo News. In order to find negative climate change news, they filter the news articles using search phrase *climate change* and then select those with negative content. This index thus measures the share of all news articles that have been both about climate change and assigned to the negative sentiment category; for more details we refer to Engle et al. (2020). The negative climate change news index is only available from 2008/06. For that reason, we restrict our sample to the time period between 2008/06 (first observation available of the negative index) and 2017/06 (last observation available of the generic index). In order to visualize and compare the two indices, Figure 4 plots the time series of the generic climate change news index (solid line) and the negative climate change news index (dashed line). To make the series interpretable, we multiply each by 1000. Both indices can be downloaded from `http://pages.stern.nyu.edu/~jstroebe/Data/EGLKS_data.xlsx`.

Overall, the level of the generic index tends to be higher than that of the negative index. The two indices tend to move together and both spike around climate summits. However, as pointed out by Engle et al. (2020), there are a few exceptions when the generic index spikes but the negative index does not. In particular, the one observed in early 2010 when the WSJ extensively reported on the Climatic Research Unit email controversy known as *Climategate*. Hacked emails from a server at the Climatic Research Unit at the University of East Anglia were used by climate change

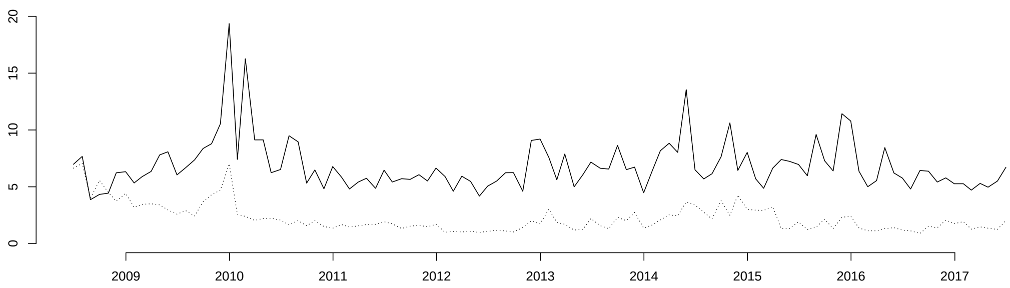



Figure 4: The monthly generic (solid line) and negative (dashed line) climate change news index (multiplied by 1000).

deniers who accused scientists of manipulating data and alleged global warming to be a scientific conspiracy. If investors' beliefs about climate change have been shaken by this news and in the light of climate transition risk, the Climategate controversy can hardly be regarded as negative news. Hence, we interpret the difference between the two indices as containing news about climate change that is either positive or, at least, not negative.

As proxies for climate change volatility shocks, we compute the variance shock $\phi^{\sigma}_{\text{MCCC},t}$ to the media climate change concerns index at time $t$, $\phi^{\sigma}_{\text{CC}^+,m}$ to the generic climate change news index (CC$^+$) and $\phi^{\sigma}_{\text{CC}^-,m}$ to the negative climate change news index (CC$^-$) in a given month $m$. Each of the variables have then been constructed similarly to the variance shocks to the O&G equity prices explained in Section 2.1; see Equation (2). If O&G common variance shocks coincide with relevant climate change news, then the risk posed by the global event is regarded as geoclimatic risk. The strategy just described to identify variance shocks is applied to the other determinants of O&G global common variance considered below.

## 3.2 Interpreting climate shocks to Oil & Gas

To measure to what extent climate change news is driving common variance shocks to the O&G industry, we carry out a regression analysis. In practice, we use a centred dependent variable, so no constant is included in the regressions. To control for the time dependence in the data, we add lagged values of the dependent variable. There is no time dependence left in the first or second moment of the residuals from all regressions at the 5% significance level.

Table 3 shows the estimation results for the simplest regressions of the O&G global common variance $f^{\sigma}_{\text{O\&G},t}$ (centred around its mean) on the variance shocks to the MCCC index $\phi^{\sigma}_{\text{MCCC},t}$. The regression in column (1) provides evidence that variance shocks to the MCCC index explain movements in the O&G global common variance.

Evidence of daily O&G geoclimatic volatility is supported by the positive and statistically significant coefficient associated to $\phi^{\sigma}_{\text{MCCC},t}$.

Many other shocks are also likely to affect the global O&G equity market. To control for volatility shocks affecting the O&G industry other than those arising from climate change news, we also include as covariates the variance shocks to the 1-month future WTI crude oil price, $\phi^{\sigma}_{\text{WTI},t}$, the SPDR S&P 500 exchange traded fund (SPY), $\phi^{\sigma}_{\text{SPY},t}$, and the all country world index (ACWI), $\phi^{\sigma}_{\text{ACWI},t}$, at time $t$. Each of the above variables is constructed as the proportional difference between the squared residual from a conditional mean model and its expected value (i.e. conditional variance), similarly to Equation (2).

The WTI crude oil price is a global benchmark index that reflects oil shocks. As discussed in Section 2.3, we expect the oil variance shocks $\phi^{\sigma}_{\text{WTI},t}$ to mostly reflect changes in the expectations of future oil demand rather than future oil supply. The SPY index is intended to track the S&P 500 index, which comprises 500 large- and mid-cap US stocks and is one of the main benchmarks of the US equity market. Given equities in our sample are all traded on the NYSE and given the relevance of US markets in the global financial system, $\phi^{\sigma}_{\text{SPY}}$ is used to capture US-based equity market shocks as well as control for the financial health and stability of the US economy. The ACWI is a global equity index designed to measure the global equity-market performance, including stocks from developed and emerging markets. $\phi^{\sigma}_{\text{ACWI}}$ is intended to capture global equity market variance shocks. Disentangling these sources of common variance shocks to the global O&G equity market is challenging. For instance, oil price shocks affecting the global O&G equity market might also affect the US and the global equity markets. We circumvent this identification problem by including all control variables in each regression.

As expected, all the above control variables seem to move O&G equity prices. The statistically significantly positive coefficients shown in column (2) of Table 3 mean that variance shocks to the oil price, US or global equity market are all likely to affect the O&G industry. Or put differently, the volatilities of the global oil market, the US equity market, and the global equity market, and that of the global O&G equity market all move together. Some of the largest O&G global common variance shocks happen on days when OPEC announced its decisions regarding oil production. Many of these decisions have frequently been different from what markets were expecting or hoping for. Also O&G global common variance tends to peak during economic or financial crises when global consumption is declining. Hence, the oil variance shocks measured by $\phi^{\sigma}_{\text{WTI}}$ tend to drive unexpected changes in O&G share prices, be they demand- or supply-based. The US and the global equity markets also affect O&G global common variance. The higher economic uncertainty, locally and globally, is reflected in higher demand-based uncertainty around O&G equities. Considering that

Table 3: Projecting the O&G global common variance ($f^{\sigma}_{\text{O\&G},t}$) on the variance shocks to the media climate change concerns index ($\phi^{\sigma}_{\text{MCCC},t}$).

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $\phi^{\sigma}_{\text{MCCC},t}$ | 0.045*** | 0.045*** | 0.041*** | 0.040** | 0.039*** |
| | (0.015) | (0.015) | (0.015) | (0.016) | (0.015) |
| $\phi^{\sigma}_{\text{WTI},t}$ | | 0.091*** | 0.064*** | 0.090*** | 0.064*** |
| | | (0.013) | (0.013) | (0.013) | (0.013) |
| $\phi^{\sigma}_{\text{SPY},t}$ | | 0.042** | | 0.038** | |
| | | (0.018) | | (0.018) | |
| $\phi^{\sigma}_{\text{ACWI},t}$ | | 0.104*** | 0.102*** | 0.103*** | 0.102*** |
| | | (0.014) | (0.013) | (0.014) | (0.013) |
| $\phi^{\sigma}_{\text{XLE},t}$ | | | 0.251*** | | 0.250*** |
| | | | (0.016) | | (0.016) |
| $\phi^{\sigma}_{\text{WTI},t} \times \phi^{\sigma}_{\text{MCCC},t}$ | | | | −0.007 | −0.008 |
| | | | | (0.009) | (0.008) |
| $\phi^{\sigma}_{\text{SPY},t} \times \phi^{\sigma}_{\text{MCCC},t}$ | | | | −0.023 | |
| | | | | (0.014) | |
| $\phi^{\sigma}_{\text{ACWI},t} \times \phi^{\sigma}_{\text{MCCC},t}$ | | | | −0.007 | −0.004 |
| | | | | (0.009) | (0.009) |
| $\phi^{\sigma}_{\text{XLE},t} \times \phi^{\sigma}_{\text{MCCC},t}$ | | | | | 0.025** |
| | | | | | (0.011) |
| $f^{\sigma}_{\text{O\&G},t-1}$ | 0.120*** | 0.110*** | 0.107*** | 0.110*** | 0.108*** |
| | (0.016) | (0.016) | (0.015) | (0.016) | (0.015) |
| $f^{\sigma}_{\text{O\&G},t-2}$ | 0.088*** | 0.086*** | 0.081*** | 0.086*** | 0.078*** |
| | (0.016) | (0.016) | (0.015) | (0.016) | (0.015) |
| $f^{\sigma}_{\text{O\&G},t-3}$ | 0.060*** | 0.055*** | 0.051*** | 0.055*** | 0.052*** |
| | (0.016) | (0.016) | (0.015) | (0.016) | (0.015) |
| Observations | 3,898 | 3,898 | 3,898 | 3,898 | 3,898 |
| Adj. $R^2$ | 0.033 | 0.064 | 0.116 | 0.065 | 0.117 |
| $\hat{\sigma}$ | 1.630 | 1.604 | 1.558 | 1.603 | 1.558 |
| F Statistic | 34.402*** | 39.377*** | 74.377*** | 28.046*** | 52.686*** |

Note: *$p$-value < 0.1; **$p$-value < 0.05; ***$p$-value < 0.01.

the volatility is higher and volatility shocks are larger during periods of economic crisis (when output is falling), it may be argued that O&G global common variance is, in general, counter-cyclical, a phenomenon also found by Engle and Campos-Martins (2020).

The US-based O&G companies used in this study are also the top holdings of the energy sector fund XLE. As of 2021, the constituents of XLE were all based in the US and around 90% belonged to the Oil, Gas & Consumable Fuels Industry. Our O&G dataset covers around 70% of the fund's holdings. Given no other country has such representation in our dataset and given the importance of the US in the geopolitical panorama, it is relevant to check whether there is a US effect in the model. To control for volatility shocks arising from the US energy sector, variance shocks to the energy select sector SPDR fund will be denoted by $\phi^{\sigma}_{\mathrm{XLE},t}$. Because they are strongly correlated, we replace $\phi^{\sigma}_{\mathrm{SPY},m}$ by $\phi^{\sigma}_{\mathrm{XLE}}$, as the US explanatory variable in column (3). Results seem robust with climate change concerns driving O&G geoclimatic variance after accounting for shocks arising from the US energy sector. The impact is, however, slightly lower. Moreover, note that the effect of climate-related shocks would not change if we were to keep all four control variables. The gains in terms of goodness of the fit by including $\phi^{\sigma}_{\mathrm{SPY},m}$ as well were negligible though.

The effect of climate change news seems to persist even after controlling for other shocks with global impact. Adding control variables makes the effect of climate change concerns more pronounced. To check how relevant climate-related variance shocks compare to these other shocks, we also add interaction terms between the climate change variance shocks and each of the other three control variables. The interaction terms between $\phi^{\sigma}_{\mathrm{MCCC},t}$ and each of $\phi^{\sigma}_{\mathrm{WTI},t}$, $\phi^{\sigma}_{\mathrm{SPY},t}$ and $\phi^{\sigma}_{\mathrm{ACWI},t}$ are presented in column (4). None is statistically significant. Interestingly, when we replace the control variable $\phi^{\sigma}_{\mathrm{SPY},m}$ by $\phi^{\sigma}_{\mathrm{XLE}}$ and the interaction term in column (5), climate change risk seems to become more of a concern to O&G investors when there is turmoil in the US energy market. For instance, during the recent Russia's invasion of Ukraine, some argued that long-term issues such as climate change and the energy transition have been quickly dominated by geopolitics, record high oil prices and dividends, and O&G share buybacks. At least in the short term, oil exploration and production is still seen as profitable, creating incentives to continue holding shares in O&G companies instead of moving to other less polluting investments. This means investors are still focused on returns, perhaps more than sustainability. But it does not mean they are not concerned about their exposure to climate change. Especially when countries such as the members of the European Union seem so committed to become less dependent on Russian oil and gas by ramping up renewables and increasing energy efficiency.

When running regressions similar to those shown above for variance shocks to individual equities (rather than for the common variance shocks as measured by $f^{\sigma}_{\mathrm{O\&G},t}$),

we find little evidence of climate change concerns affecting the O&G industry at the individual level. Similarly to Ardia et al. (2020), we also used the (first difference of the) MCCC index as an additional factor in the O&G pricing models discussed in Section 2.1. Surprisingly, we found no evidence that it affects the O&G equity returns. Combined, these results suggest that the effects of climate change concerns on financial markets are more intricate and systemic than one might have expected and more complex volatility or factor models of higher moments, such as the global common volatility model, are necessary to capture them.

Aggregating news by themes and topics allows us to disentangle the effects of climate change news on financial markets and to better understand the mechanisms through which climate change can impact them. The estimation results from studying the impact of climate change concerns by theme are presented in Table 4 and by topic in Table 5.

In addition to the control variables, we start by using in column (6) and column (7) of Table 4 the variance shocks to all seven thematic indices. The difference between the two regressions lies in the choice of the measure used to capture US-based shocks., i.e., $\phi^{\sigma}_{\mathrm{SPY},t}$ or $\phi^{\sigma}_{\mathrm{XLE},t}$. The stock prices of O&G companies around the world seem to be more volatile following climate-related news on either Financial & Regulation, Public Impact or Agricultural Impact. If using the MCCC index raised some doubts of whether this index was truly capturing carbon transition and regulatory risks, the statistically significant positive coefficient associated to the variance shocks relating to Financial & Regulation reinforces the results shown in the previous regressions. News on disasters appears to rather decrease O&G global common volatility.

Evidence on whether markets are pricing physical risks is mixed. A cross-country analysis of the impact of climate-related disasters on aggregate stock market indices by International Monetary Fund (2020) suggested no significant effect of physical risk on equity valuations. This is consistent with Bolton and Kacperczyk (2021b), who found no carbon premium for stocks from countries more exposed to physical risk (only for countries associated with higher transition risk). If we consider only extreme events, results change. Griffin et al. (2019) find that investors are recognizing but underpricing physical risk by matching climate-related extreme events to the location of firms' headquarters. Dietz et al. (2016) finds much of the climate value at risk of global financial assets to be in the tail. News on a particular disaster thus seems to have mostly local effects and so is unlikely to have a global impact on financial markets unless natural disasters become too frequent, costly and widespread, increasing concerns about transition risk. 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.

Some news may impact financial markets only indirectly and through mechanisms that are not very explicit. In addition to the variables in column (7), we add interaction

Table 4: Projecting the O&G global common variance ($f^{\sigma}_{\text{O\&G},t}$) on the variance shocks to media climate change concerns by theme. In addition to the control variables, the seven themes have been included in each regression. In column (8), in addition to controls and themes, interaction terms between each theme and $\phi^{\sigma}_{\text{XLE},t}$ have been added as regressors.

| | (6) | (7) | (8) | |
|---|---|---|---|---|
| | $\times 1$ | $\times 1$ | $\times 1$ | $\times \phi^{\sigma}_{\text{XLE},t}$ |
| $\phi^{\sigma}_{\text{WTI},t}$ | 0.091*** | 0.063*** | 0.065*** | |
| | (0.013) | (0.013) | (0.013) | |
| $\phi^{\sigma}_{\text{SPY},t}$ | 0.043** | | | |
| | (0.018) | | | |
| $\phi^{\sigma}_{\text{ACWI},t}$ | 0.104*** | 0.102*** | 0.101*** | |
| | (0.014) | (0.013) | (0.013) | |
| $\phi^{\sigma}_{\text{XLE},t}$ | | 0.252*** | 0.250*** | |
| | | (0.016) | (0.017) | |
| $\phi^{\sigma}_{\text{Financial \& Regulation},t}\times$ | 0.053*** | 0.057*** | 0.046*** | −0.012 |
| | (0.014) | (0.014) | (0.015) | (0.013) |
| $\phi^{\sigma}_{\text{Agreement \& Summit},t}\times$ | −0.012 | −0.013 | −0.005 | 0.029*** |
| | (0.013) | (0.013) | (0.013) | (0.011) |
| $\phi^{\sigma}_{\text{Public Impact},t}\times$ | 0.041** | 0.043** | 0.045** | 0.002 |
| | (0.018) | (0.017) | (0.018) | (0.015) |
| $\phi^{\sigma}_{\text{Research},t}\times$ | −0.007 | −0.008 | −0.007 | 0.003 |
| | (0.006) | (0.006) | (0.007) | (0.006) |
| $\phi^{\sigma}_{\text{Disaster},t}\times$ | −0.034*** | −0.035*** | −0.033*** | −0.006 |
| | (0.012) | (0.011) | (0.012) | (0.009) |
| $\phi^{\sigma}_{\text{Environmental Impact},t}\times$ | −0.015 | −0.012 | −0.016 | −0.006 |
| | (0.011) | (0.010) | (0.011) | (0.010) |
| $\phi^{\sigma}_{\text{Agricultural Impact},t}\times$ | 0.031*** | 0.026*** | 0.029*** | −0.017*** |
| | (0.009) | (0.009) | (0.009) | (0.006) |
| $f^{\sigma}_{\text{O\&G},t-1}$ | 0.109*** | 0.106*** | 0.106*** | |
| | (0.016) | (0.015) | (0.015) | |
| $f^{\sigma}_{\text{O\&G},t-2}$ | 0.088*** | 0.082*** | 0.082*** | |
| | (0.016) | (0.015) | (0.015) | |
| $f^{\sigma}_{\text{O\&G},t-3}$ | 0.056*** | 0.052*** | 0.052*** | |
| | (0.016) | (0.015) | (0.015) | |
| Observations | 3,898 | 3,898 | 3,899 | |
| Adjusted $R^2$ | 0.072 | 0.124 | 0.126 | |
| $\hat{\sigma}$ | 1.597 | 1.552 | 1.550 | |
| F Statistic | 24.099*** | 43.358*** | 29.202*** | |

Note: *$p$-value < 0.1; **$p$-value < 0.05; ***$p$-value < 0.01.

terms between the variance shocks by theme and those to the XLE in column (8). A striking yet not surprising result shows up with this regression. Shocks to the US energy sector appear to be amplified by unexpected increases in concerns on Agreement & Summit (0.029). This is clear evidence for the impact that climate summits and agreements such as the Paris accord that was sealed during the UN climate summit in late 2015. The adverse effect of shocks driven by climate negotiations seems to be indirect with the US playing an important role. This is presumably due to the withdrawal of the US from the Paris agreement during the administration of President Donald Trump and then the rejoin when President Joe Biden was elected. Overall, this finding highlights how discussions about climate policies can disrupt global markets.

To better understand the transmission mechanisms of climate change concerns to the O&G industry, have a closer look at the topics that constitute these themes. In Table 5, we summarise the estimation results by topic, presenting only the ones that make O&G stock prices move globally. As a robustness check, we present estimation results for either $\phi^{\sigma}_{\mathrm{SPY},t}$ or $\phi^{\sigma}_{\mathrm{XLE},t}$. For the most common words for the topics listed, see Appendix C.

When it comes to Financial & Regulation, news with explicit mentions of the fossil fuel industry and carbon pricing (topic 31) or of carbon and technological disruption (topic 40) drives global O&G variance shocks, creating turmoil around this carbon-intensive industry. Surprisingly, at least at first, topic 6 which is one of the closest topics to measuring unexpected increases in concerns about litigation (its most common words are *rule*, *administration*, *agency*, *regulation*, *law*, *court*, *decision*) seems to have no impact. According to a recent policy report by Setzer and Higham (2021), most cases of climate change litigation were filed before courts and have been brought against governments (and their support to the fossil fuel industry). Only a small, but increasingly significant, number of cases are targeted at companies. It seems litigation may, in fact, be weakening or undermining climate action by challenging the way in which it is being carried out.

Concerning agricultural impact, concerns involving droughts and livestock, respectively topic 4 and 20 shown, has a particularly pronounced effect. Variance effects similar to those found in this paper for the O&G industry are thus to be expected if our approach is applied to agri-business assets[4]. The increased attention and pressure that have been raised due to climate-damaging agricultural practices appears to cause higher uncertainty around carbon-intensive assets and to spill over to the O&G industry. Interestingly, a specific topic associated with societal impact seems to also affect the O&G industry. As it relates to science, truth, and presumably the consequences

[4]In fact, using stock prices of the largest US meat processing company, the American Tyson Foods, we observe that climate-related variance shocks are associated with those to the Tyson Foods stock returns

Table 5: Projecting the O&G global common variance ($f^{\sigma}_{\text{O\&G},t}$) on the variance shocks to media climate change concerns by topic. The most common words per topic shown are listed in Appendix C.

| | (9) | (10) |
|---|---|---|
| $\phi^{\sigma}_{\text{WTI},t}$ | 0.093*** | 0.066*** |
| | (0.013) | (0.013) |
| $\phi^{\sigma}_{\text{SPY},t}$ | 0.042** | |
| | (0.018) | |
| $\phi^{\sigma}_{\text{XLE},t}$ | | 0.253*** |
| | | (0.016) |
| $\phi^{\sigma}_{\text{ACWI},t}$ | 0.107*** | 0.105*** |
| | (0.014) | (0.013) |
| $\phi^{\sigma}_{\text{Topic 4},t}$ | 0.020** | 0.019** |
| | (0.009) | (0.008) |
| $\phi^{\sigma}_{\text{Topic 8},t}$ | 0.033** | 0.035*** |
| | (0.013) | (0.013) |
| $\phi^{\sigma}_{\text{Topic 20},t}$ | 0.012** | 0.010** |
| | (0.005) | (0.005) |
| $\phi^{\sigma}_{\text{Topic 31},t}$ | 0.013** | 0.012** |
| | (0.005) | (0.005) |
| $\phi^{\sigma}_{\text{Topic 33},t}$ | −0.010* | −0.009* |
| | (0.005) | (0.005) |
| $\phi^{\sigma}_{\text{Topic 34},t}$ | 0.018*** | 0.020*** |
| | (0.005) | (0.005) |
| $\phi^{\sigma}_{\text{Topic 40},t}$ | 0.019** | 0.021** |
| | (0.009) | (0.009) |
| $f^{\sigma}_{\text{O\&G},t-1}$ | 0.111*** | 0.107*** |
| | (0.016) | (0.015) |
| $f^{\sigma}_{\text{O\&G},t-2}$ | 0.087*** | 0.081*** |
| | (0.016) | (0.015) |
| $f^{\sigma}_{\text{O\&G},t-3}$ | 0.055*** | 0.051*** |
| | (0.016) | (0.015) |
| Observations | 3,898 | 3,898 |
| Adjusted $R^2$ | 0.075 | 0.128 |
| $\hat{\sigma}$ | 1.595 | 1.548 |
| F Statistic | 8.183*** | 14.018*** |

Note: *$p$-value $< 0.1$; **$p$-value $< 0.05$; ***$p$-value $< 0.01$.

of climate action failure, this topic is likely to alter investors' taste for climate change and create pressure on the O&G industry.

Negative news about climate change is more likely to cause major changes in the O&G equity returns as it creates more uncertainty regarding the viability of investments in carbon-intensive assets and activities in a low-carbon economy. This is consistent with the asymmetric effects of good and bad news on financial volatility. It is well known that negative shocks to stock prices produce more volatility than positive shocks. Similarly, the magnitude of climate-related volatility shocks is expected to be greater when the news is bad compared to generic news. When only the generic news is included in the regression, no statistically significant effect is found. This may be due to the fact that positive and negative news affect O&G global common volatility in opposite directions, and presumably cancel out. Only when both indices are included, we are able to disentangle the two effects and show that only negative news has the potential to disrupt the global O&G equity market.To analyze the impact of sentiment of the climate change news on the volatility of the global O&G equity market, in Table 6, we present the estimation results for the multiple linear regressions using two climate change indicators, namely the volatility shocks arising from climate change generic news ($CC^+$) and climate change negative news ($CC^-$). In order to distinguish the impact on O&G global common volatility of positive and negative climate change news, we estimate a regression including variance shocks to both as explanatory variables. According to the estimation results shown in column (1) in Table 6, variance shocks to the generic and negative climate change news index have, respectively, a negative ($-0.031$) and positive ($0.046$) effect on O&G global common variance. The impact of purely negative news, as measured by $CC^-$, tends to make the O&G equity returns move more and beyond expected. Positive or good news about climate change reflected in $CC^+$ makes investors more confident about the future of O&G leading to less uncertainty and lower O&G global common variance. We view this asymmetry of the O&G geoclimatic variance as empirical support for including both indices in the regressions.

Overall, the control variance shocks seem to make the global O&G equity market move. Evidence is not as strong as when using daily variance shocks to the US equity market though. Only the variance shocks to the oil price ($\phi^{\sigma}_{\mathrm{WTI},m}$) and to the global equity market ($\phi^{\sigma}_{\mathrm{ACWI},m}$) seem to be strongly relevant. Evidence is mixed for variance shocks to the US equity market, $\phi^{\sigma}_{\mathrm{SPY},m}$.

In order to analyze if the impact of climate change news differs when there is simultaneously a shock to the control variables, we also include interaction terms between controls and either $\phi^{\sigma}_{\mathrm{CC}^+,m}$ or $\phi^{\sigma}_{\mathrm{CC}^-,m}$. As we find no interacted effect when the news is positive, these results are not shown. However, it is interesting to observe that negative climate change news amplifies the effects of oil variance shocks (0.111)

Table 6: Projecting the O&G global common variance averaged over the calendar month ($f^{\sigma}_{\mathrm{O\&G},m}$) on the generic ($\phi^{\sigma}_{\mathrm{CC}^{+},m}$) and negative ($\phi^{\sigma}_{\mathrm{CC}^{-},m}$) climate change news index. For comparison, the variance shocks to the US energy sector fund ($\phi^{\sigma}_{\mathrm{XLE},m}$) are also used as an explanatory variable in (3) and as the dependent variable in the last column.

| | $f^{\sigma}_{\mathrm{O\&G},m}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | $\phi^{\sigma}_{\mathrm{XLE},m}$ |
| $\phi^{\sigma}_{\mathrm{CC}^{+},m}$ | $-0.031^{**}$ | $-0.037^{**}$ | $-0.028^{**}$ | $-0.0005$ |
| | (0.016) | (0.017) | (0.012) | (0.009) |
| $\phi^{\sigma}_{\mathrm{CC}^{-},m}$ | $0.046^{*}$ | $-0.023$ | $0.050^{***}$ | $-0.002$ |
| | (0.024) | (0.034) | (0.018) | (0.014) |
| $\phi^{\sigma}_{\mathrm{WTI},m}$ | $0.509^{***}$ | $0.409^{***}$ | $0.169^{*}$ | $0.336^{***}$ |
| | (0.104) | (0.104) | (0.089) | (0.063) |
| $\phi^{\sigma}_{\mathrm{SPY},m}$ | 0.179 | $0.258^{*}$ | | 0.098 |
| | (0.152) | (0.148) | | (0.091) |
| $\phi^{\sigma}_{\mathrm{ACWI},m}$ | $0.212^{*}$ | $0.216^{*}$ | $0.204^{**}$ | 0.031 |
| | (0.123) | (0.119) | (0.084) | (0.075) |
| $\phi^{\sigma}_{\mathrm{XLE},m}$ | | | $1.062^{***}$ | |
| | | | (0.123) | |
| $\phi^{\sigma}_{\mathrm{WTI},m} \times \phi^{\sigma}_{\mathrm{CC}^{-},m}$ | | $0.111^{***}$ | | |
| | | (0.042) | | |
| $\phi^{\sigma}_{\mathrm{SPY},m} \times \phi^{\sigma}_{\mathrm{CC}^{-},m}$ | | $-0.054$ | | |
| | | (0.092) | | |
| $\phi^{\sigma}_{\mathrm{ACWI},m} \times \phi^{\sigma}_{\mathrm{CC}^{-},m}$ | | $-0.250^{***}$ | | |
| | | (0.093) | | |
| $f^{\sigma}_{\mathrm{O\&G},m-1}$ | $0.191^{**}$ | $0.141^{*}$ | $0.221^{***}$ | |
| | (0.078) | (0.076) | (0.059) | |
| Observations | 107 | 107 | 107 | 108 |
| Adj. $R^2$ | 0.325 | 0.385 | 0.607 | 0.235 |
| $\hat{\sigma}$ | 0.467 | 0.445 | 0.356 | 0.285 |
| F Statistic | $9.578^{***}$ | $8.434^{***}$ | $28.570^{***}$ | $7.620^{***}$ |

Note: $^{*}p$-value $< 0.1$; $^{**}p$-value $< 0.05$; $^{***}p$-value $< 0.01$.

in column (2). As an example, consider oil spills such as the Deepwater Horizon disaster in 2010. It had an impact on oil, raising at the same time concerns about its environmental impact. Turmoil in the oil market seemed thus amplified by the increased uncertainty around the future viability of the O&G industry. Regarding the relative relevance of equity market sentiment and climate change sentiment, it seems that a variance shock to the global equity market attenuates ($-0.250$) the effect of a simultaneous negative climate change news. This may be due to the fact that global equity market shocks are still seen as more relevant than the implications of climate change. Global markets (and investors) appear to react more to political and economic news, which are inherently short-term compared to climate change, still seen by many as a long-term problem. Thus, when the news moving global markets is climate, it is not surprising that its effect is relatively smaller.

We also check whether results change when the variance shocks to the XLE, $\phi^{\sigma}_{\text{XLE}}$, are included in the regressions. The estimation results are shown in column (3) of Table 6. There appears to be a large effect on the O&G global common variance of shocks to the US energy sector after controlling for other variance shocks with global impact. Nevertheless, the increased (decreased) O&G global common variance following negative (positive) climate change news seems to be robust to shocks arising from the US energy sector.

Finally, we regress the idiosyncratic variance shocks to XLE on the same explanatory variables as in (1) of Table 6. Notice that we are using the univariate XLE series to compute the variance shocks and so no cross-sectional (or cross-country) information is being used as we did to estimate the O&G global common variance. The results from this regression are shown in the last column of Table 6. Only oil variance shocks seem to explain why the squared returns of XLE are larger than usual in a given month. By using only US-based O&G companies, we are not able to find evidence that climate change news drives some of these variance shocks. From the historical denial and scepticism about climate change to the withdrawal from the Paris agreement during the administration of President Donald Trump, this result is hardly surprising. However, it sheds some light on the transmission mechanism of global climate change news. It seems to only materialise when the news is global. From a methodological point of view, it seems more difficult to capture geoclimatic variance shocks when the modelling framework does not incorporate cross-country information. In terms of economic intuition, this is likely to reflect the geopolitical nature of both transition risk and the global O&G equity market. Applying a carbon tax locally is not likely to be global material news–unless the economy is sufficiently large as for the climate measure to be effective in reducing global emissions–and so to affect the global O&G industry. Less concerned state-owned oil giants such as Saudi Aramco would easily find unethical investors elsewhere. Only when the most polluting firms and economies are committed to achieve a common and global climate goal, news on the carbon transition shakes the O&G industry. This reinforces both how a common climate policy can be important and why the negotiations during climate summits can disrupt global markets.

A similar regression has been estimated using $\phi^{\sigma}_{\mathrm{WTI},m}$ as the dependent variable to check whether variance shocks to oil prices are driven by climate change news. We find no statistically significant effect for either $\phi^{\sigma}_{\mathrm{CC}^{+},m}$ or $\phi^{\sigma}_{\mathrm{CC}^{-},m}$. Investors appear to be pricing climate change risks in O&G stocks rather than the commodities. This is likely to be reflecting the short-term optimism about O&G and the long-term nature of climate change risks, which start showing signs of affecting today's investment decisions. We address this further in the discussion below. Another explanation may be related to the carbon footprints of oil producers and consumers and how they are perceived. Carbon emissions from a company's operations can occur directly (scope 1) and indirectly from the consumption of purchased energy (scope 2). Both are widely reported. Data on indirect emissions related to products purchased and, more importantly, sold by a company (scope 3) are not widely available. As we move from scope 1 to scope 3 emissions, the ability of O&G companies to reduce their carbon footprint becomes more limited. No wonder commitments from major O&G producers have been made only to reduce their scope 1 and 2 emissions. But that is only a small portion of their carbon footprint. For O&G consumers, it would be the other way round as they could have a great impact on scope 3 emissions. However, demand for oil is quite inelastic as consumers are unable to substitute fossil fuels quickly or easily when prices change. Most people do not have access to charging points, let alone afford an electric car. Pressure has thus been put on companies rather than on consumers of fossil fuels despite the efforts and attempts of O&G majors to divert the attention to them.

# 4 Discussion

The energy transition is underway and investors are paying attention. The views that markets are not pricing the climate-related risks and that they are not necessarily relevant to investment decisions made today have begun to change. Some may still incorrectly view the implications of climate change to be relevant only in the long run. They expect the industry to remain strong at least in the short term and so are reluctant to divest from O&G. Despite being more focused on returns than sustainability, investors are however becoming more concerned that companies may expose them to possible future climate-related financial losses. This is what we call the profitability-sustainability dilemma of O&G investors.

A recent survey by BCG (2021) of 250 institutional investors in the O&G industry confirms both divides and convergence with climate goals. Despite 78% of investors either factoring climate risks into their O&G valuations or considering doing it, 70% of those who are doing it do not believe they impact valuations. These investors are optimistic that oil prices (returns) will remain high (strong) in the short term despite the recent oil price wars and the global energy crisis amid the COVID-19 pandemic. If so, what then explains the movements in the O&G industry in response to climate-related news and rising concerns? According to our results, the long-term uncertainty around the sustainability of the O&G industry seems to be already impacting valuations. The strategical move stems perhaps from the pressure of environmental activists, and governmental and regulatory climate action that seem to be sinking in with investors and reflected in managerial change. Even though optimistic about the short-term future of O&G, investors are less so when it comes to the long-term viability of the industry. Interestingly, the survey showed that key stakeholders see value creation in the energy transition. They agree that O&G needs to become environmentally sustainable by reducing its carbon emissions and finding low-carbon portfolio alternatives. For instance, we have recently seen O&G major Exxon Mobil losing board seats to an activist hedge fund forcing the company to align with global climate goals on the same day activism won over another major, this time Royal Dutch Shell, by having the company ordered by a Dutch court to drastically cut its greenhouse gas emissions. The more uncertain is the environment in which a company operates, the more investors will scrutinize its investment decisions and demand for immediate evidence of returns.

Other factors may impact the O&G industry and hinder the energy transition process. Climate policy and action can be crucial. The uncertainty around future demand for fossil fuels is very high due to not only climate change but also 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). The future of oil supply is also uncertain given the recent wars over oil price and territory. By their political power, wealth, and expertise, fossil fuel companies should be proactive in the transition process towards low-carbon economies. However, current incentives to shareholders may not be enough. Before the COVID-19 pandemic, oil prices have been remarkably low and oil companies are among the highest dividend payers. This means the transition to clean energies will be even more challenging as non-fossil fuels become relatively less competitive. Hence, governments in countries highly dependent on fossil fuels must pressure them to produce greener by applying carbon taxes, taking legal action and financing green activities in order to make them more competitive. As demand for oil starts showing signs of stagnation in some developed countries, there is a need to regulate oil companies from both shifting to developing countries such as India or China, and from investing in oil exploration and production capacity. It is possible to reduce greenhouse gas emissions and experience economic growth. But history has also shown that they tend in fact to rise after economic or financial crises. Because emissions are likely to grow elsewhere in the aftermath of the COVID-19 pandemic, especially in developing countries, it is also important to identify international relations, trade and financial contracts between firms in low and high carbon economies.

The time to incorporate changes is critical as the window for an orderly adjustment towards low-carbon economies becomes narrower. So is the speed of technological progress which has become evermore important. If fire sales of carbon-intensive assets, liquidity problems and financial instability are all expected in a disorderly transition, a gradual repricing of assets and early action could avoid massive unexpected losses. If moving away from O&G is complex and slow, the energy transition from coal can be sharp and quick with far higher gains in terms of emissions reduction. Policy action should then be devoted to put an end on coal and to the social and economic implications of disrupting the coal system so that more time could be attributed to the O&G transition.

Disclosure of climate-related information is another concern as it is still scarce, which makes it difficult to assess the risk of holding shares of carbon-intensive assets as the world moves away from fossil fuels. The approach we propose here based on how financial asset prices react to climate change news and rising concerns can help to identify, and target companies and countries that are more exposed to climate risk during the process of decarbonising the global energy system. Measuring the exposure to geoclimatic risk can help in designing financial regulations, guiding capital flows and supporting global climate action. Although it is difficult to predict when climate-related shocks will occur, geoclimatic volatility can be useful to reduce their global economic impacts.

# 5 Conclusion

Carbon transition risk and O&G markets are by nature geopolitical. Climate-related material news is thus expected to impact the volatilities of a wide range of O&G equities at the global scale. Using daily prices of world major O&G companies, we propose a novel approach for modelling geoclimatic variance. The method involves two steps. First, we measure the variance shocks that make the broad range of O&G stock prices move. Then, in the second step, we project the O&G global common variance onto the space of climate-related shocks, proxied by a climate change news index. In this setting, we are able to identify O&G global common movements due to climate-related unanticipated events as geoclimatic shocks.

Climate-related news does make O&G equities around the world move. This finding prevails when controlling for shocks to the oil price, US and world stock markets. But not all geoclimatic shocks are alike. Notwithstanding fossil fuels companies being exposed to carbon transition risk, the sign and magnitude of the impact differs across topics and themes of climate-related concerns. Moreover, climate change news seems to create turmoil in the carbon-intensive industry only when the news is negative, which tends to be amplified by oil price movements. Surprisingly, the results point out geoclimatic news materialises only when it reaches the global scale.

With the results provided in this paper, we hope to shed some light on the national and international exposure of carbon-intensive assets to climate transition risk. The results should be regarded cautiously though. At the global scale, they can be used to improve responses to tackle climate change as agreed by the Paris agreement. But it is difficult to find an association between individual or country stocks and global climate change news in the current setting. Geoclimatic volatility could be further studied by including climate information at the individual or country level in the model. Differences in exposures could be related to climate policy stringency, activism, geological events or carbon emissions. For instance, the effects of natural disasters seem to be mostly local. Incorporating granular climate data (which may be difficulty to find at the monthly frequency) could help disentangle individual from global effects of climate change news. This opens ways of improving our understanding of how climate change news is making financial markets move.

Finally, we expect governments and companies to assess their climate pledges and to rethink the way they publicize or politicise them. The announcement of an infeasible net-zero goal or a carbon price that is too low or ineffective, may not (only) damage a firm's or country's competitiveness individually, but may (also) disrupt global markets. The stability and resilience of the financial system will be crucial in managing climate-related risks and mobilizing capital for low-risk green investments.

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# A List of Oil & Gas stocks

Table A1: The world's major fossil fuel companies included in the estimation of O&G global common variance. These stocks are all traded on the NYSE.

| | Company | Country |
|---|---|---|
| APC | Anadarko Petroleum* | United States |
| BP | BP | United Kingdom |
| CEO | China National Offshore Oil Corp. | China |
| CNQ | Canadian Natural Resources | Canada |
| COP | ConocoPhillips | United States |
| CVX | Chevron | United States |
| DVN | Devon Energy | United States |
| E | Eni | Italy |
| EC | Ecopetrol | Colombia |
| EOG | EOG Resources | United States |
| EPD | Enterprise Products | United States |
| EQNR | Equinor | Norway |
| HAL | Halliburton | United States |
| KMI | Kinder Morgan | United States |
| OXY | Occidental Petroleum | United States |
| PBR | Petrobras | Brazil |
| PSX | Phillips 66 | United States |
| PTR | PetroChina | China |
| RDS | Royal Dutch Shell | The Netherlands<br>United Kingdom |
| REPYY | Repsol | Spain |
| SLB | Schlumberger | United States |
| SNP | China Petroleum & Chemical Corp. | China |
| SU | Suncor Energy | Canada |
| TOT | Total | France |
| XOM | ExxonMobil | United States |

*Acquired by Occidental Petroleum in 2019.

# B Summary statistics

Table A2: Summary statistics of oil and gas stock returns. Results from the tests of time-independence (see Jarque and Bera (1980)) in the first moment and second moment denoted, respectively, as AR(1) and ARCH(1), are also shown. Rob. Kr. and Rob. Sk. represent, respectively, the robust kurtosis and robust skewness (see Kim and White (2004)).

| | APC | BP | CEO | CNQ | COP |
|---|---|---|---|---|---|
| Min. | −10 | −10 | −10 | −10 | −10 |
| Mean | 0.022 | 0.005 | 0.032 | 0.044 | 0.013 |
| Max. | 10 | 10 | 10 | 10 | 10 |
| S.D. | 2.236 | 1.692 | 2.368 | 2.484 | 1.969 |
| Rob. Kr | 0.256 | 0.161 | 0.102 | 0.161 | 0.147 |
| Rob. Sk | 0.031 | 0.017 | −0.015 | 0.017 | 0.042 |
| AR(1) | 3.308 | 33.400 | 0.087 | 6.746 | 0.666 |
| $p-$value | 0.069 | 0.000 | 0.768 | 0.009 | 0.414 |
| ARCH(1) | 193.939 | 360.807 | 85.575 | 82.367 | 380.222 |
| $p-$value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

| | CVX | DVN | E | EC | EOG |
|---|---|---|---|---|---|
| Min. | −10 | −10 | −10 | −10 | −10 |
| Mean | 0.013 | −0.004 | 0.002 | −0.015 | 0.030 |
| Max. | 10 | 10 | 10 | 10 | 10 |
| S.D. | 1.613 | 2.545 | 1.860 | 2.460 | 2.370 |
| Rob. Kr | 0.137 | 0.222 | 0.131 | 0.190 | 0.117 |
| Rob. Sk | 0.040 | 0.018 | −0.017 | 0.002 | 0.037 |
| AR(1) | 0.578 | 1.978 | 0.034 | 19.403 | 0.232 |
| $p-$value | 0.447 | 0.160 | 0.854 | 0.000 | 0.630 |
| ARCH(1) | 255.600 | 453.623 | 151.127 | 275.096 | 192.139 |
| $p-$value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

| | EPD | EQNR | HAL | KMI | OXY |
|---|---|---|---|---|---|
| Min. | −10 | −10 | −10 | −10 | −10 |
| Mean | 0.018 | 0.021 | 0.005 | −0.025 | 0.000 |
| Max. | 10 | 10 | 10 | 10 | 10 |
| S.D. | 1.716 | 2.176 | 2.484 | 1.855 | 2.019 |
| Rob .Kr | 0.254 | 0.134 | 0.147 | 0.261 | 0.157 |
| Rob. Sk | −0.018 | 0.025 | 0.020 | −0.004 | 0.035 |
| AR(1) | 5.709 | 0.837 | 10.921 | 0.117 | 1.267 |
| $p-$value | 0.017 | 0.360 | 0.001 | 0.732 | 0.260 |
| ARCH(1) | 393.875 | 121.329 | 373.105 | 434.295 | 436.300 |
| $p-$value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Table A10: Continued from previous page.

| | PBR | PSX | PTR | RDS | REPYY |
|---|---|---|---|---|---|
| Min. | −10 | −10 | −10 | −10 | −10 |
| Mean | 0.026 | 0.030 | 0.005 | 0.011 | −0.002 |
| Max. | 10 | 10 | 10 | 10 | 10 |
| S.D. | 3.098 | 2.017 | 2.213 | 1.599 | 1.930 |
| Rob. Kr | 0.140 | 0.271 | 0.157 | 0.182 | 0.169 |
| Rob. Sk | −0.016 | −0.071 | 0.021 | 0.009 | 0.038 |
| AR(1) | 5.271 | 0.765 | 0.378 | 4.327 | 4.302 |
| $p-$value | 0.022 | 0.382 | 0.539 | 0.038 | 0.038 |
| ARCH(1) | 315.547 | 95.340 | 154.356 | 898.501 | 325.131 |
| $p-$value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | **SLB** | **SNP** | **SU** | **TOT** | **XOM** |
| Min. | −10 | −10 | −10 | −10 | −10 |
| Mean | 0.001 | 0.012 | 0.035 | 0.012 | 0.013 |
| Max. | 10 | 10 | 10 | 10 | 10 |
| S.D. | 2.157 | 2.335 | 2.205 | 1.777 | 1.510 |
| Rob. Kr | 0.125 | 0.177 | 0.271 | 0.106 | 0.102 |
| Rob. Sk | −0.005 | −0.017 | 0.037 | 0.042 | 0.048 |
| AR(1) | 0.261 | 6.484 | 5.532 | 4.694 | 0.499 |
| $p-$value | 0.609 | 0.011 | 0.019 | 0.030 | 0.480 |
| ARCH(1) | 337.858 | 233.194 | 247.009 | 526.754 | 322.265 |
| $p-$value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

# C Most common words for selected topics

The ten words with the highest probability for each statistically significant topic shown in Table 5 are the following:

Theme: Financial & Regulation

Topic 31: oil, tax, fuel, price, carbon_tax, production, taxis, cost, ethanol, revenue.

Topic 40: project, technology, plant, cost, coal, carbon_dioxide, power_plant, facility, scale, carbon.

Theme: Public Impact

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

Theme: Societal Impact

topic8 science, book, story, truth, film, news, movie, medium, reader.

Theme: Disaster

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

Theme: Agricultural Impact

Topic 4: drought, region, river, rain, desert, lake, dam, rainfall, water_supply, mountain.

Topic 20: food, animal, meat, cow, cattle, farm, ski, resort, beef, diet.

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