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Common volatility shocks driven by 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 calculate the global common volatility of the oil and gas industry. Then we project it on climate-related shocks constructed using text-based proxies of climate change news. 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 signs and magnitudes of the impacts differ across climate risk drivers. Regarding sentiment, climate change news tends to create turmoil only when the news is negative. Moreover, 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.

1. Introduction

Anthropogenic climate change is from burning fossil fuels, namely coal, oil and natural gas which currently release 36 gigatons/year CO_2 emissions globally (IPCC, 2021). To reduce greenhouse gas (GHG) emissions and mitigate the effects of global warming and climate change, a low-carbon energy transition is under way. The increasing pressure to divest from fossil fuels is reflected in ever more pledges to reach net-zero emissions by governments, large companies and finance firms everywhere. Black et al. (2021) estimate climate targets now represent 61% of global GHG emissions, 68% of gross domestic product globally and 56% of the world's population.

However, the energy transition is slow: while many industrialised countries are expanding non-GHG energy sources, emerging countries continue to exploit (cheap) fossil fuels. According to the Statistical Review of World Energy (BP, 2022), in 2021, on average 82% of global primary energy comes from fossil fuels (oil, coal and natural gas) and only 18% from non-fossil fuels (hydroelectric, renewable energy, and nuclear). Coal is the worst polluter per unit of energy among fossil fuels yet in China and India produces more than 50% of their primary energy. Although coal use has been declining in the world's largest GHG emitting countries, other fossil fuels are continuing to grow close to historical rates. Indeed, oil accounts for a similar global share of GHG emissions, and natural gas will play a big role in the energy transition so

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leakages must be tightly controlled as methane is about 20 times as powerful as CO_2 as a GHG. Consequently, forward-looking policy must focus on the oil and gas (O&G) industry: (Battiston et al., 2017) discuss the climate-policy relevant sectors of economies.

Financial regulators now recognise climate change as a source of financial risk and are concerned about stock markets inefficiently pricing climate-related risks (Hong et al., 2019). Investors may be overestimating the value of fossil fuels stocks, possibly creating a 'carbon bubble' (Leaton, 2011; Leaton et al., 2013). Investment decisions are starting to reflect climate-related risks as well as ethical motivations, shown by investors pressing for a retreat from fossil fuel amid expectations about policy change, regulation, and carbon prices. To build climate resilience, regulators are identifying potential 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 risks 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 can be very large. *Carbon transition risk* reflects uncertainty around the timing and speed of the low-carbon transition, which could lead to sudden unanticipated adjustments of asset prices. These risks are actually strongly related. Even regions or countries not directly exposed to physical risk can be indirectly affected through international relations by others that are particularly vulnerable. 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 by prompting a reassessment of the value of many assets (Carney, 2015).

Both climate-related risks face considerable uncertainty about policy and behavioural responses and technological developments. The speed of re-pricing is also uncertain, with implications for financial stability. A disorderly transition to low-carbon energy sources will result if investors fail to anticipate and incorporate stringent climate policies in their business models, precipitating large falls in asset values (Monasterolo and Battiston, 2020). These adverse effects will be amplified by the interconnectedness of the financial system (Battiston et al., 2017) and rising investor awareness (Bolton and Kacperczyk, 2021a). Carbon-intensive businesses are less resilient to climate risks, so their assets and workers may become 'stranded' (Leaton, 2011; Van der Ploeg and Rezai, 2020), and falling property values could lead to widespread mortgage defaults (creating another Great Recession). Consequently, central banks and financial regulators are adopting climate-based strategies to monitor and stabilise the financial system.

Investors must price carbon transition risk to compensate for their exposure. Bolton and Kacperczyk (2021b) find strong evidence for a carbon premium with emissions positively affecting stock returns in a cross-section of US stock returns. At the global level, Bolton and Kacperczyk (2021a) 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 both long-run and short-run exposure to transition risk through its level of and changes in GHG emissions. This carbon premium tends to be higher (lower), the larger a country's share of brown (green) sectors, but does not seem to reflect physical risk.

Political insecurity and uncertainty also impact global energy markets. Increasing O&G prices in turn can jeopardise economic growth, reduce international security and test the political stability of energy importing countries. Although Russia is the largest natural gas exporter and a major crude oil producer, Europe's dependence on Russian energy did not transpire to be irrevocable following Russia's invasion of Ukraine. Geopolitics has been defined as how political activity in one country affects other countries, determined by its geographic location and control over territory. The geopolitical risk index of Caldara and Iacoviello (2022), for instance, is a text-based news index strongly related to military risk. Compared to macroeconomic news, geopolitical news has a strong immediate impact and generates greater uncertainty and trading activity in crude oil markets (Brandt and Gao, 2019). Geopolitical tensions between Russia and the West following the invasion of Ukraine almost immediately affected the globalised financial system by shaking global markets, especially the O&G market putting climate change and the energy transition on hold. We adopt a broad definition of geopolitical risk to understand how politics, international and intergovernmental organisations such as the Organisation of the Petroleum Exporting Countries (OPEC), multinational companies and mass media move a wide range of O&G share prices after adverse geopolitical events.

Climate policy stringency and regulation can differ greatly over time and across the countries in which any company operates and its O&G carbon footprint can differ in terms of ownership and physical location. Given the geopolitical nature of both the O&G industry and climate transition risk, factors at the country-level seem more relevant than sector or company-specific. Although the drive to become sustainable in a low-carbon economy currently lies with industrialised countries and western investors, we expect the reassessment of the value of a large range of carbon-intensive assets in response to climate change news, rising concerns and tighter policies to be global 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 in Engle and Campos-Martins (2023), 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. We establish 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 2007–2009 Great Recession. Announcements by OPEC and the 2019 drone attack on the Saudi Aramco production facilities also show up as geopolitical events driving changes in the global O&G equity market. 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) as proxies for climate risk. Each index is a text-based time-series of news about climate risk, constructed by text mining the content of internationally-relevant United States (US) newspapers. Climate change news and concerns make O&G stock prices move at the global scale, controlling for shocks to the oil price, US and world stock markets. This variation in the O&G global common volatility driven by climate change news is called geoclimatic volatility. Not all geoclimatic shocks are alike as the signs and magnitudes of the impacts differ across topics and themes, and whether the news is negative or positive. Our empirical results also show climate-related news materialises when it reaches the global scale. Thus the systemic implications of the carbon transition seem 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 and testing procedures are described in Section 2.1 together with results from its empirical application to global O&G stock returns in Section 2.2, including a detailed analysis in Section 2.3 of the major events triggering shocks to the industry. In Section 3, we develop the econometric framework to identify the common volatility shocks that are driven by climate change concerns and news. First, Section 3.1 introduces the text-based proxies for climate change news. Then, Section 3.2 presents the results showing evidence for geoclimatic shocks by projecting the O&G global common variance shocks onto climate-related variance shocks. Section 3.3 considers climate risk drivers and Section 3.4 climate sentiment mitigating and amplifying effects. Section 4 highlights the policy implications of these results. Section 5 concludes the paper.

2. Common volatility of the oil and gas industry

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) found that an increase in geopolitical risk is associated with higher volatility in both oil prices and stock markets. We propose a two-step approach to analyse the extent to which global events affecting the O&G industry are due to climate change news. First, we measure O&G common volatility (a broad measure of the magnitude of geopolitical events) for a wide range of O&G equities, countries and regions of the world. In Section 3, using regression analysis we identify which common volatility shocks to the O&G industry are driven by climate change news.

2.1. Modelling global common volatility

When many assets, markets and countries respond to the same news at the same time, shocks to volatilities are correlated. Interestingly, whatever factors are extracted from returns, idiosyncratic volatilities still co-move (Herskovic et al., 2016). To measure common shocks to the volatilities of a wide range of assets, Engle and Campos-Martins (2023) propose a model of global common volatility based on a multiplicative volatility factor decomposition of the standardised residuals. We briefly introduce the general model, then explain how we apply it to study volatility co-movements in the global O&G equity market (we use O&G to denote the industry as a whole).

Consider the vector of O&G equity excess returns $\boldsymbol{r}_t = (r_{1,t}, \dots, r_{N,t})'$ where $r_{i,t} = \tilde{r}_{i,t} - r_{f,t}$, $\tilde{r}_{i,t}$ is the observed return and $r_{f,t}$ is the risk-free return, $i = 1, \dots, N$. In practice, we specify a factor model with AR(1)-GARCH(1,1) errors for each time series $i = 1, \dots, N$, of excess returns as follows:

$$r_{i,t} = c_i + \delta_i r_{i,t-1} + \boldsymbol{\beta}_i' \boldsymbol{f}_t + u_{i,t}, \quad |\delta_i| < 1, \tag{1}$$

where c_i is a constant, δ_i is the first-order auto-regressive (AR) coefficient, $\boldsymbol{\beta}_i$ is a $(p \times 1)$ vector of risk exposures, $\boldsymbol{f}_t$ is a $(p \times 1)$ vector of risk factors and $u_{i,t}$ is an error term. For each equity, $u_{i,t}$ is assumed to follow the first-order generalised auto-regressive conditional heteroscedastic (GARCH) model (Bollerslev, 1986). In this setting, $u_{i,t}$ is decomposed multiplicatively as $u_{i,t} = h_{i,t} e_{i,t}$, where

$$h_{i,t} = \omega_i + \alpha_{i,1} u_{i,t-1}^2 + \beta_{i,1} h_{i,t-1}, \quad \omega_i, \alpha_{i,1} > 0, \beta_{i,1} \geq 0, \alpha_{i,1} + \beta_{i,1} < 1. \tag{2}$$

Assuming factors are sufficient to reduce the contemporaneous correlations of returns to zero,[1] this implies the volatility standardised residuals $\boldsymbol{e}_t = (e_{1,t}, \dots, e_{N,t})'$ 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., $\Sigma_{e,t}^{i,j} = cov[e_{i,t}, e_{j,t}] = \mathbb{E}_{t-1}[e_{i,t} e_{j,t}]$, $i, j = 1, \dots, N$, 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.

The key insight of the model is that, although 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 partly predictable, the co-movement of volatilities is most likely caused by the positive correlation between shocks to those volatilities (Engle and Campos-Martins, 2023).

We define a variance shock to the ith O&G equity as follows:

$$\phi_{i,t}^{\sigma} \equiv \frac{u_{i,t}^2 - h_{i,t}}{h_{it}} = e_{i,t}^2 - 1, \tag{3}$$

[1] To reduce the contemporaneous correlations of returns to zero, the cross-sectional mean returns may be used as a factor in model (1).

where $e_{i,t}^2 = u_{i,t}^2/h_{i,t}$, $i = 1, \ldots, N$, generally denotes the squared standardised innovation, in this setting from factor model (1). We use the superscript σ to emphasise that these are *volatility* shocks.[2] The variance shock $\phi_{i,t}^{\sigma}$ is 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. 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. These global common events are associated with geopolitical news that we will later identify as climate common volatility shocks.

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, $i = 1, \ldots, N$, and interpreted as parameters (or fixed effects). The standardised residuals are then assumed to have the multiplicative decomposition of Engle and Campos-Martins (2023),

$$e_{i,t} = \sqrt{g(s_i, f_{\text{O\&G},t}^{\sigma})}\epsilon_{i,t}, \tag{4}$$

where

$$g(s_i, f_{\text{O\&G},t}^{\sigma}) \equiv s_i(f_{\text{O\&G},t}^{\sigma} - 1) + 1, \tag{5}$$

$f_{\text{O\&G},t}^{\sigma} > 0, t = 1, \ldots, T$, and $0 \leq s_i \leq 1, i = 1, \ldots, N$. By choosing specification (5), $g(s_i, f_{\text{O\&G},t}^{\sigma})$ is positive 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, (4) implies $\boldsymbol{e}^2$ are positively correlated. Hence, the variance–covariance matrix of $\boldsymbol{e}^2$ averaged over t, Σ_{e^2}, will not be diagonal due to the cross-sectional dependence in $\boldsymbol{e}$. It is then straightforward to test for common variance shocks by testing whether Σ_{e^2} is diagonal. Under the alternative, $f_{\text{O\&G},t}^{\sigma}$ varies over time inducing co-movements and positive correlations of $\boldsymbol{e}^2$. Note that the (i, j) entry of $\Sigma_{e^2,t}$ is the covariance between the squared random variables $e_{i,t}^2$ and $e_{j,t}^2$, i.e., $\Sigma_{e^2,t}^{i,j} = cov[e_{i,t}^2, e_{j,t}^2] = \mathbb{E}_{t-1}[(e_{i,t}^2 - 1)(e_{j,t}^2 - 1)], i, j = 1, \ldots, N$. 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 $N(N-1)/2$ unique pairwise correlations will be the same. The null hypothesis is thus reduced to $\mathbb{H}_0 : \rho_{e^2} = 0$, where ρ_{e^2} is the equicorrelation of the squared standardised residuals, and tested against the alternative that this is positive i.e., $\mathbb{H}_1 : \rho_{e^2} > 0$. For that purpose, we will use the test statistic proposed by Engle and Campos-Martins (2023),

$$\xi_{e^2} = \frac{\sqrt{\dfrac{NT}{(N-1)/2}} \sum_{i>j,j=1}^{N} \sum_{t=1}^{T} (e_{it}^2 - 1)(e_{jt}^2 - 1)}{\sum_{i=1}^{N} \sum_{t=1}^{T} (e_{it}^2 - 1)^2}, \tag{6}$$

which has a standard normal distribution under $\mathbb{H}_0$. Using Monte Carlo simulations the test has been shown to have good size and power in various settings. For the finite-sample properties of the test and further details, we refer to Engle and Campos-Martins (2023). In practice, the null hypothesis is tested by calculating the empirical variance–covariance matrix $\Sigma_{\hat{e}^2}$.

Assuming normality, the likelihood is constructed as if $f_{\text{O\&G},t}^{\sigma}$ were observed and given by

$$L(s, f_{\text{O\&G}}^{\sigma}; e) = -\frac{1}{2} \sum_{i=1,t=1}^{N,T} \left\{ \log g(s_i, f_{\text{O\&G},t}^{\sigma}) + \frac{e_{i,t}^2}{g(s_i, f_{\text{O\&G},t}^{\sigma})} \right\}. \tag{7}$$

Because the model formulation is multiplicative between two sets of unknowns $f_{\text{O\&G},t}^{\sigma}$, $t = 1, \ldots, T$, and s_i, $i = 1, \ldots, N$, we estimate each conditional on the other by maximum likelihood as follows. The first-order conditions,

$$\frac{\partial L(s, f_{\text{O\&G},t}^{\sigma}; e)}{\partial s_i} = 0, \quad \frac{\partial L(s, f_{\text{O\&G}}^{\sigma}; e)}{\partial f_{\text{O\&G},t}^{\sigma}} = 0,$$

give two heteroscedasticity relationships:

$$\begin{aligned} \text{Cross-Section: } e_{i,t} &= \epsilon_{i,t}\sqrt{\hat{s}_i\left(f_{\text{O\&G},t}^{\sigma} - 1\right) + 1} \text{ for } t = 1, \ldots, T, \\ \text{Time-Series: } e_{i,t} &= \epsilon_{i,t}\sqrt{s_i\left(\hat{f}_{\text{O\&G},t}^{\sigma} - 1\right) + 1} \text{ for } i = 1, \ldots, N. \end{aligned} \tag{8}$$

The cross-sectional regression allows us to estimate the unobserved value of $f_{\text{O\&G},t}^{\sigma}$, $t = 1, \ldots, T$, using (e.g.) the loadings on the first principal component of the squared standardised residuals as initial values.[3] Then the time-series regression

2 Because volatility is the square root of the variance these two terms can be used interchangeably when interpreting results.

3 Despite the factor loadings on the first principal component being natural values for the initial estimates of the O&G factor loadings, the estimator does not seem to be sensitive to the choice of the initial values.

provides estimates for $s_i, i = 1, \dots, N$, conditional on the estimates of the latent variable. There is thus an estimator for each $s_i, i = 1, \dots, N$, given $\hat{f}^{\sigma}_{\mathrm{O\&G},t}, t = 1, \dots, T$, using time-series and another estimator for each $f^{\sigma}_{\mathrm{O\&G},t}, t = 1, \dots, T$, given estimated $\hat{s}_i, i = 1, \dots, N$, for each cross-section. To gain efficiency, we iterate the estimation of the time-series and cross-sectional regressions until convergence.[4] At that point, both first-order conditions are satisfied and a joint maximum can be achieved.

2.2. The oil and gas stock returns

We use the daily closing prices of shares from January 12, 1983 until January 29, 2021 for 25 major global O&G companies extracted from the data platform Datastream.[5] Appendix A records the full list of equities, all of which are traded on the NYSE ensuring synchronous observations for measuring volatility co-movements. This is an unbalanced panel (equities were launched on different dates) with a minimum of eight observations per day. The algorithm has been developed so that at each point in time we estimate the value of the global common factor using all the available observations in that cross section.[6] Prices are converted to log-returns to remove stochastic trends.

We first estimate a factor model for each series of O&G excess returns. Extreme returns are truncated to $\pm 10\%$ to avoid problems in estimating GARCH models and to prevent outliers from showing up as global common events. Appendix B presents summary statistics for truncated returns. We use the three factors framework of Fama and French for O&G returns, 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) so $p = 4$. Each factor model includes a lagged dependent variable and assumes GARCH(1,1) errors: Ljung–Box AR(1) and ARCH(1) tests of time independence in the first and second moments reported in Appendix B confirm these are necessary to capture time dependence.

The cross-sectional mean O&G residuals from the factor models are shown in the top panel of Fig. 1, and the estimated conditional volatilities in the middle and bottom panels with the estimated volatility of the excess returns of the WTI crude oil future and the Standard & Poor's (S&P) 500 index, and of Standard & Poor's Depository Receipt (SPDR) energy select sector fund (XLE), respectively, for comparison. O&G returns are heteroscedastic with large movements during periods of market distress, namely the early 2000s recession, the 2007–2009 Great Recession, the oil price plunge of 2014–2016, and the COVID-19 pandemic. Though the WTI crude oil future is the most volatile, the volatilities tend to co-move especially during market turmoil.

Having extracted the pricing factors, the estimated 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 correlations between the cross-sectional mean O&G volatility and that of the WTI oil future, energy sector XLE, and S&P500 are 0.554, 0.913 and 0.643, though none of these, nor all combined, fully capture the variation in the global O&G equity market. The correlations are even lower between the cross-sectional mean O&G variance shocks and those to the WTI future, energy sector XLE, and S&P500 are only 0.188, 0.648, and 0.099. This motivates applying the global common volatility model to many assets from all over the world rather than using a single index.

After estimating the factor pricing models, we compute the vector of volatility standardised residuals $\hat{\boldsymbol{e}}_t, t = 1, \dots, T$. Before estimating the O&G global common variance, we test the null hypothesis of no common variance shocks as explained in Section 2.1. The empirical counterpart of the equicorrelation ρ_{e^2} is computed from the squared estimated volatility standardised residuals, averaged across all pairwise correlations, denoted $\rho_{\hat{e}^2}$. 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, so we can proceed to estimate 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, so the sample size becomes $N = 26$. Estimating and testing for global common volatility can be done using the R package *geovol* (Campos-Martins, 2021).

2.3. Events shaking the oil and gas industry

The model is estimated as described in Section 2.1. For this empirical sample, 15 iterations were performed until the algorithm converged. The estimated most extreme common O&G variance shocks captured by $\hat{f}^{\sigma}_{\mathrm{O\&G},t}$ are summarised in Table 1. For comparison, the (truncated) excess returns on the same day are shown for the cross-section average of O&G stocks ($\bar{r}^{\mathrm{O\&G}}_t$), the S&P 500 index ($r^{\mathrm{S\&P500}}_t$), the crude WTI oil 1-month future (r^{WTI}_t), and the SPDR energy sector fund (r^{XLE}_t).

[4] In each iteration, in order to identify the variance–covariance matrix of the squared standardised residuals, we impose the normalisations $\sum_{i=1}^{N} s_i^2 = 1$ and $f^{\sigma}_{\mathrm{O\&G},t}/\bar{f}^{\sigma}_{\mathrm{O\&G}}$, where $\bar{f}^{\sigma}_{\mathrm{O\&G}} = (1/T)\sum_{t=1}^{T} f^{\sigma}_{\mathrm{O\&G},t}$. This is done after estimating, respectively, each time-series and cross-section regression.

[5] Coal stock prices have limited data availability as few purely coal mining companies are quoted or traded on the NYSE. Peabody went bankrupt in 2016 but re-entered in 2017. Most non-state controlled coal is from general mining companies. BHP, for instance, is a mining, metals and petroleum company so it is unclear what role coal transition risk plays.

[6] The presence of missing values is not an issue because not only the initial sample period which includes most missing values is not considered in the geoclimatic volatility analysis presented in Section 3 but also both the estimator and test perform well even with a small number of assets (Engle and Campos-Martins, 2023).

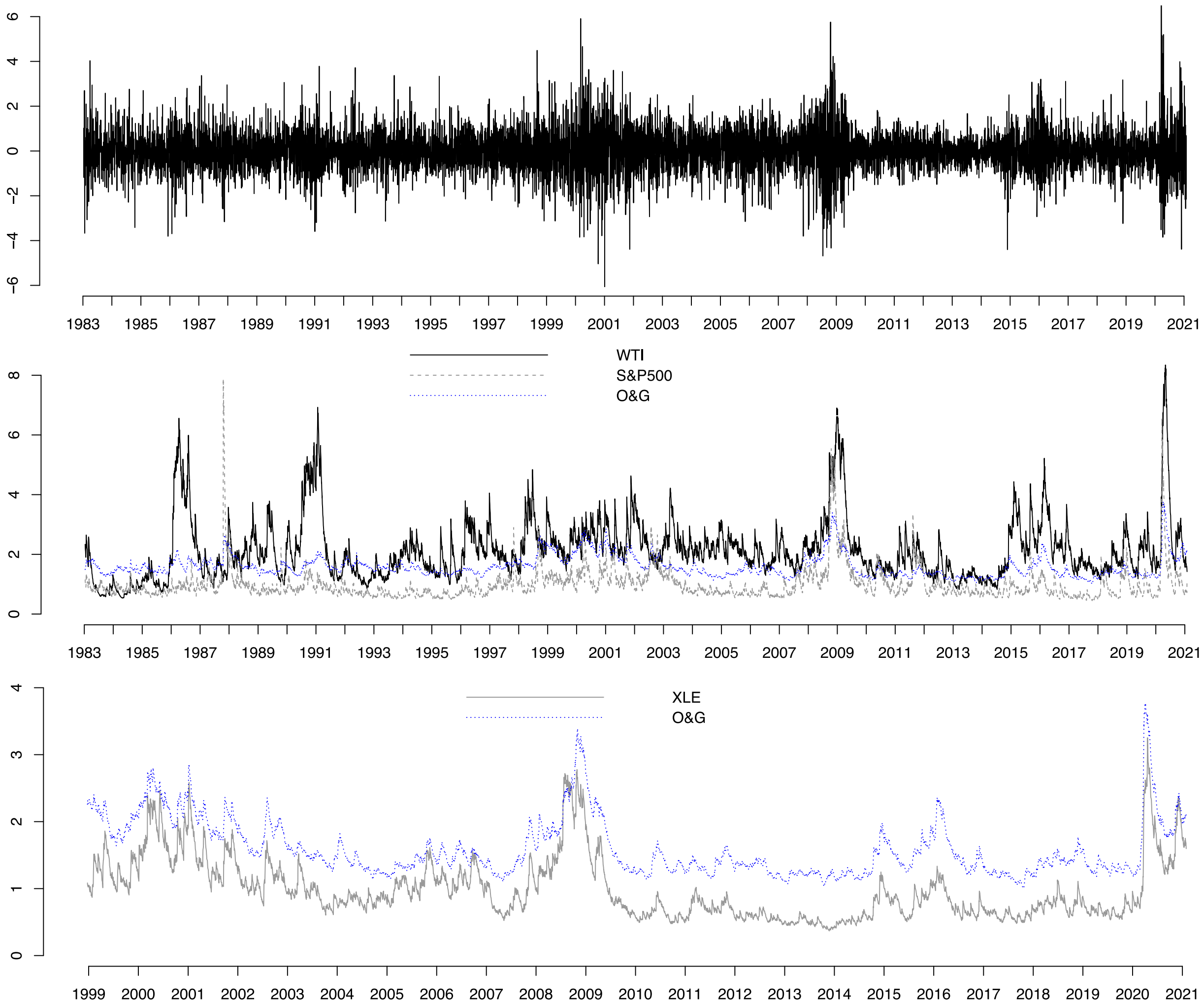

Fig. 1. Cross-sectional mean O&G residuals (top) and estimated conditional volatilities (middle and bottom). For comparison, the volatility of the 1-month WTI crude oil future and of the S&P 500 index are shown in the middle panel, and of the SPDR energy sector fund (XLE, from December 21, 1998) in the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

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 $\hat{f}^{\sigma}_{O\&G,t}$ coincide with large negative returns to the O&G industry. Negative shocks seem to have greater potential than positive ones to have a global effect, but need not be matched by large negative shocks to the WTI, XLE and/or S&P500. This difference suggests some shocks are stock or energy market specific and others commodities exchange specific, reinforcing the view that 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 optimal. As seen below, transition risk seems to materialise only when it has a global impact revealed by common variance shocks to equities of companies operating in different countries and parts of the world.

Table 1 also notes some of the major global economic and financial events, political elections, climate and pandemic policy changes and terrorist attacks likely to influence shocks to global oil demand and supply. Every possible combination of signs of other markets occurs at the same time as an extreme common O&G variance shock.

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 last 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) augmented the model to explicitly include speculative oil demand shocks using data on oil inventories. That 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 been largely and persistently caused by unexpected increases in world oil consumption driven by global business-cycle fluctuations.

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, $r_t^{S\&P500}$ the return of the S&P 500 index, r_t^{WTI} the return of the WTI crude oil 1-month future, and r_t^{XLE} the return of the SPDR energy sector fund.

Date	Event	$\hat{f}^{\sigma}_{O\&G,t}$	$\bar{r}_t^{O\&G}$	$r_t^{S\&P500}$	r_t^{WTI}	r_t^{XLE}
2020-03-20	COVID-19	42.915	1.519	−4.433	−11.724	0.971
2014-11-28	OPEC blocked	35.934	−7.218	−0.255	−10.726	−6.640
1987-10-20	Black Monday	28.158	3.276	5.195	0.101	
1993-09-29	Russian crisis	26.473	3.212	−0.308	−0.167	
1985-12-09	OPEC changes strategy & Plaza Accord?	25.085	−4.301	0.619	−4.338	
2008-07-16	Financial crisis	23.811	−1.402	2.475	−3.029	−2.608
2000-03-07	Dot-Com bubble	23.642	5.492	−2.597	5.883	6.673
1995-04-20	Oklahoma bombing	23.505	2.164	0.073	−6.732	
2020-03-23	COVID-19	22.859	−1.779	−2.973	−9.683	−9.272
1998-09-04	Ruble crisis	22.729	3.645	−0.856	−0.684	
2000-10-13	Middle East turmoil	22.576	−3.320	3.284	−3.096	−3.900
1992-05-26	Katina oil spill?	22.018	4.010	−0.632	4.943	
1993-06-11	Oil fall	21.264	−3.200	0.421	−1.413	
2020-03-17	COVID-19	21.229	−0.167	5.823	−6.291	0.681
1984-10-17	OPEC cut	21.084	−4.416	−0.389	−2.653	
2019-04-12	Quetta bombing & Sudanese coup d'état	21.024	0.241	0.659	0.486	0.267
1985-07-05	Oil shake-up	19.748	−0.379	0.557	0.000	
2020-11-09	US election	19.430	8.913	1.163	8.179	13.344
2010-04-29	Deepwater	18.930	0.322	1.286	2.316	0.115
2001-01-03	Dot-Com crash	18.542	−2.598	4.888	2.896	−3.101
1985-12-10	OPEC threat/cut	17.288	−3.528	0.069	−1.170	
1983-03-31	Oil futures trading	16.997	3.806	−0.281	0.000	
2016-11-30	Oil cut & Post Trump?	16.627	5.538	−0.266	8.900	4.958
2001-09-17	Post 9/11	16.400	−1.637	−5.047	4.251	−2.065
1986-01-27	OPEC cut & Oil collapse	16.370	−2.014	0.464	7.226	

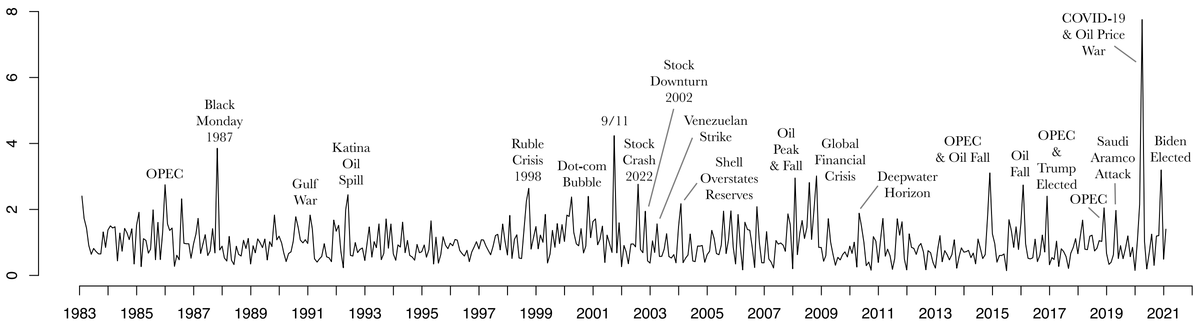

Fig. 2. The monthly averaged O&G global common variance index. 'OPEC' indicates an announcement and 'Peak' or 'Fall' indicates oil price peak or fall, respectively.

All the geopolitical events discussed above caused large absolute 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, $\hat{f}^{\sigma}_{O\&G,m}$, where m indicates the calendar month, is plotted in Fig. 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 not equal across O&G equities as different equities have different loadings on $f^{\sigma}_{O\&G,t}$. The estimated O&G loadings are presented in Table 2 in descending order of magnitude showing the proportion of $\hat{f}^{\sigma}_{O\&G,t}$ that affects each assets' variance. Because the impact of $f^{\sigma}_{O\&G,t}$ is heterogeneous across equities, O&G companies have different exposures to common variance shocks. This heterogeneity partly reflects country-level factors such as climate policy stringency differently impacting companies based in the US, China or Europe as greener policies in the markets or countries where a company operates make it more exposed to climate transition risk (e.g., UK, France or Norway). However, the loadings shown in Table 2 also reflect exposure to other sources of shocks that make all O&G companies move at the same time. It is not surprising that some of the *supermajors*, namely Shell (RDS), BP, Chevron (CVX), and ConocoPhillips (COP), are the companies with the largest exposure to these shocks.

By construction of functions $g(s_i, f^{\sigma}_{O\&G,t}), i = 1, \ldots, N$, the loading s_i measures the exposure of company i to any common volatility shock. Thus, differences in the O&G loadings make it possible to reduce exposure to broad geopolitical

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.

risk: (Engle and Campos-Martins, 2023) examine portfolio optimality facing such common volatility shocks. In the next section, we use regression analysis to disentangle the overall exposure of the O&G industry to climate transition risk.[7]

As an indicator of the goodness of the fit, we compute the test statistic (6) using $\hat{\epsilon}^2_{i,t} = \hat{e}^2_{i,t}/g(\hat{s}_i, \hat{f}^{\sigma}_{O\&G,t})$, $i = 1, \ldots, N$, $t = 1, \ldots, T$. The empirical $\rho_{\hat{\epsilon}^2} = -0.004$ and the test statistic $\xi_{\hat{\epsilon}^2} = -0.522$ ($p-$ value $= 0.699$), which follows a standard normal distribution under $\mathbb{H}_0 : \rho_{\epsilon^2} = 0$. Not rejecting the null indicates the squared standardised residuals become uncorrelated by removing the common volatility which supports the multiplicative decomposition (4)–(5) and the ability of the global common volatility factor to capture the volatility co-movements in the global O&G equity market.

3. Climate-driven shocks to common volatility

Events with large impacts shaking the O&G industry come from different sources, including geopolitical. The 'price war' between Saudi Arabia and Russia in the first quarter of 2020 rapidly spilt over to the global stock market, confirming tail risks can have major implications for the global economy. We now analyse whether tail risk, as measured by large global common volatility, is also driven by climate change media concerns and news. This climate driven global variation in the O&G stock market will be called geoclimatic volatility.

Section 3.1 describes the text-based proxies for climate change news; Section 3.2 presents the evidence for geoclimatic shocks by projecting the O&G global common variance shocks onto climate-related variance shocks; Section 3.3 considers climate risk drivers and Section 3.4 climate sentiment mitigating and amplifying effects.

3.1. Text-based proxies of climate concerns and news

To analyse to what extent climate change is fuelling an additional source of global risk, we use text-based proxies of climate concerns and news as potential drivers of volatility shocks to the O&G industry. The Media Climate Change Concerns (MCCC) index of Ardia et al. (2020) is intended to measure unexpected increases in climate change concerns.[8] MCCC is a daily index constructed by applying text mining to climate change-related news articles from major US newspapers, so captures climate-change concerns portrayed in the news media by combining attention and information. Consider a media sample of $s = 1, \ldots, S$ major US newspapers (e.g., The New York Times) and the $n = 1, \ldots, N_{t,s}$ climate-related articles published by source on a given day t. Using appropriate risk and sentiment lexicons, with textual analysis it is possible to count the number of risk words $w^{risk}_{n,t,s}$, the number of positive words $w^{+}_{n,t,s}$, the number of negative words $w^{-}_{n,t,s}$, and the total number of words $N_{n,t,s}$ in any news article n published on day t by source s. The weighted textual measure of risk perception and consequent negative impact that Ardia et al. (2020) refer to as the *concern* score is computed daily as

$$concern_{n,t,s} = 100 \frac{w^{risk}_{n,t,s}}{N_{n,t,s}} \left\{ \left(\frac{w^{-}_{n,t,s} - w^{+}_{n,t,s}}{w^{-}_{n,t,s} + w^{+}_{n,t,s}} + 1 \right) \Big/ 2 \right\}, \tag{9}$$

where the first ratio measures the percentage of risk words and the second ratio, in braces, the degree of negativity of the article (zero being the most positive and one the most negative). In this setting, a higher weight is attributed to the more negative content. To obtain a daily time-series, the article-level scores (9) are first aggregated to the source-level such that

[7] To analyse individual exposures to climate-related common volatility shocks requires extending the model to a multi-factor level, which is beyond the scope of this paper but a topic for further research.

[8] Different indices using other media outlets are provided by Ardia et al. (2022).

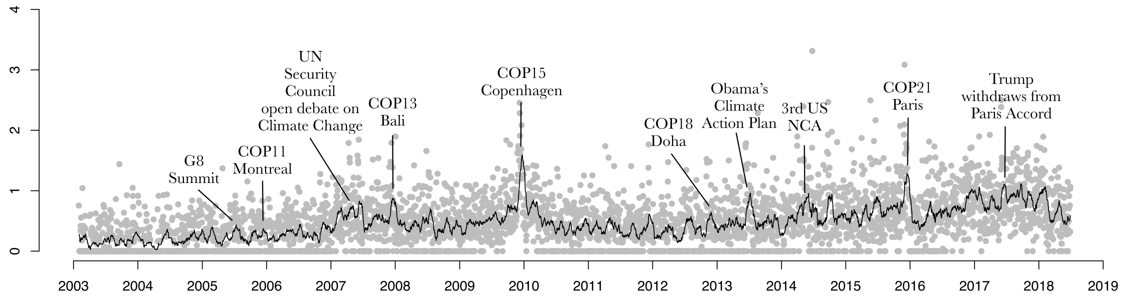

Fig. 3. The daily MCCC index (grey) and its 20-day rolling window average (black). COP stands for the United Nations Climate Change Conference of the Parties and NCA means National Climate Assessment.

$concern_{t,s} = \sum_{n=1}^{N_{t,s}} concern_{n,t,s}$. Normalising by the standard deviation of the source-specific scores, denoted by σ_s, allows to assign more weight to the within source time-series variation than across sources. The resulting normalised score is $concern^{norm}_{t,s} = concern_{t,s}/\sigma_s$. These standardised source-level scores are then averaged across sources and aggregated to get the MCCC index on a given day t. This is done by applying an increasing concave function $h(\cdot)$, to account for the fact that media attention increases concerns at a decreasing rate, as follows:

$$\text{MCCC}_t = h\left(1/S \sum_{s=1}^{S} concern^{norm}_{t,s}\right). \tag{10}$$

The MCCC index is available from January 2, 2003 until June 29, 2018, and is plotted in Fig. 3.[9] Climate concerns peak around 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.

Aggregating news by themes and topics provides a more comprehensive assessment of climate-driven global risks. Ardia et al. (2020) constructed climate change concerns indices for 40 different topics and 8 aggregate themes. The most common words associated to selected topics in our analysis are presented in Table 5. For other topics and further details, we refer to Ardia et al. (2020).

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 organisations. 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, reflecting the less informative WSJ content on that day. A high score 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 computed as the cosine similarity between the scores and each edition of the WSJ. The index ranges between zero, so no words on the WSJ match the climate change vocabulary, and unity if text content of the WSJ shows the same terms in the same proportion as the authoritative texts used to construct the vocabulary. This monthly index is available between 1984/01 and 2017/06.

To distinguish the effect of purely negative climate change news, we also use an index of sentiment. The WSJ-based index assumes that the number of news articles about climate change increases when climate transition risk is high so may spuriously label positive climate news about (say) new mitigation technologies as increases in climate transition risk. Sentiment analysis of the climate-related articles measures 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. To detect negative climate change news, they filter news articles using the search phrase *climate change* then select those with negative content; for more details, see Engle et al.

[9] The data can be found at https://sentometrics-research.com.

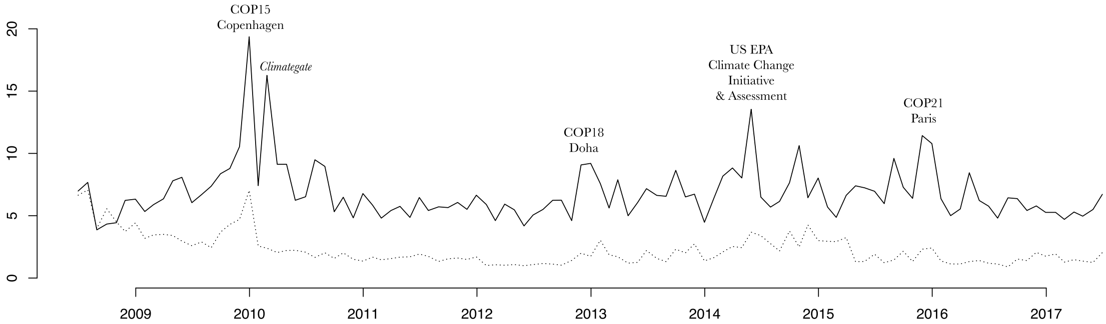

Fig. 4. The monthly generic (solid line) and negative (dashed line) climate change news index (each multiplied by 1000).

(2020). This index thus measures the share of all news articles about climate change in the negative sentiment category, but is only available from 2008/06–2017/06, so restricts our sample to that period. To visualise and compare the two indices (after multiplying each by 1000), Fig. 4 plots their time series.[10]

The two indices tend to move together and both spike around climate summits, with the generic index usually being higher than the negative index. Engle et al. (2020) note a few exceptions when the generic index spikes but the negative index does not. In particular, in early 2010 the WSJ extensively reported on the email controversy at the Climatic Research Unit at the University of East Anglia known as *Climategate*. Hacked emails from a server there were used by climate change deniers to accuse scientists of manipulating data and alleged global warming to be a scientific conspiracy. If investors' beliefs about climate change transition risk have been affected by this news, 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 estimate $\phi^{\sigma}_{\mathrm{MCCC},t}$ as the variance shock to MCCC at time t, and $\phi^{\sigma}_{\mathrm{CC}^+,m}$ to CC^+ and $\phi^{\sigma}_{\mathrm{CC}^-,m}$ to CC^- in a given month m. These are constructed similarly to (3) as the squared standardised innovations from an AR(1)-GARCH(1,1) process. The same modelling approach is applied to each topic and then aggregated by theme, excluding category 'Other' which resulted in 7 themes and 38 topics. We computed the cross-sectional mean of the relevant topics (without repetition) for each theme, so theme 'Research' is the average variance shocks to three topics, and theme 'Financial & Regulation' is the average variance shocks to eleven topics. In the next sections, these will be used as explanatory variables assumed to be observed, so *hats* have been omitted.

3.2. Common volatility driven by the carbon transition

Combining the informational content of climate news with financial asset prices helps capture the materiality of the news. The results in this section provide a systematic assessment of climate-driven global risks, consistent over time, as perceived by not only the press, but also the public, global investors, and policy-makers.

To measure the extent to which climate change news is driving common variance shocks to the O&G industry, we first analyse the centred dependent variable around its mean (no constant is added to the regressions), so in the daily analysis, this is $\tilde{f}^{\sigma}_{\mathrm{O\&G},t} \equiv \hat{f}^{\sigma}_{\mathrm{O\&G},t} - 1$. The regressions shown in Table 3 using climate variance shocks as measured by the MCCC index can be represented as:

$$\tilde{f}^{\sigma}_{\mathrm{O\&G},t} = \alpha\phi^{\sigma}_{\mathrm{MCCC},t} + \boldsymbol{\beta}'\boldsymbol{x}^{\sigma}_{t} + \boldsymbol{\gamma}'\left\{\boldsymbol{x}^{\sigma}_{t} \times \phi^{\sigma}_{\mathrm{MCCC},t}\right\} + \sum_{i=1}^{3}\delta_i\tilde{f}^{\sigma}_{\mathrm{O\&G},t-i} + v_t, \tag{11}$$

where v_t is distributed with zero mean and constant variance, $\boldsymbol{x}^{\sigma}_{t}$ contains control variables and $\boldsymbol{x}^{\sigma}_{t} \times \phi^{\sigma}_{\mathrm{MCCC},t}$ represents interactions terms between the controls and the climate variable. The simplest regression in Table 3 column (1) provides evidence that variance shocks to the MCCC index are systematically associated with increases in O&G global common variance. This is supported by the positive and statistically significant coefficient associated to $\phi^{\sigma}_{\mathrm{MCCC},t}$ i.e., $\hat{\alpha} = 0.042$. Different specifications are obtained by replacing the MCCC by different climate variables and by including or removing controls. The estimated residuals $\hat{v}_t$ show no time dependence in the first or second moment at 5% significance.

Many other shocks are 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 include as covariates the variance shocks to the 1-month future WTI crude oil price, $\phi^{\sigma}_{\mathrm{WTI},t}$, the SPDR S&P 500 exchange traded fund (SPY), $\phi^{\sigma}_{\mathrm{SPY},t}$, and the all country world index (ACWI), $\phi^{\sigma}_{\mathrm{ACWI},t}$, at time t. Each of these 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 Eq. (3).

[10] Both indices can be downloaded from http://pages.stern.nyu.edu/~jstroebe/Data/EGLKS_data.xlsx.

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

	(1)	(2)	(3)	(4)	(5)
$\phi^{\sigma}_{MCCC,t}$	0.042***	0.042***	0.038**	0.037**	0.037**
	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)
$\phi^{\sigma}_{WTI,t}$		0.091***	0.063***	0.090***	0.064***
		(0.013)	(0.013)	(0.013)	(0.013)
$\phi^{\sigma}_{SPY,t}$		0.042**		0.038**	
		(0.018)		(0.018)	
$\phi^{\sigma}_{ACWI,t}$		0.104***	0.102***	0.103***	0.102***
		(0.014)	(0.013)	(0.014)	(0.013)
$\phi^{\sigma}_{XLE,t}$			0.251***		0.251***
			(0.016)		(0.016)
$\phi^{\sigma}_{WTI,t} \times \phi^{\sigma}_{MCCC,t}$				−0.009	−0.007
				(0.009)	(0.008)
$\phi^{\sigma}_{SPY,t} \times \phi^{\sigma}_{MCCC,t}$				−0.020	
				(0.014)	
$\phi^{\sigma}_{ACWI,t} \times \phi^{\sigma}_{MCCC,t}$				−0.007	−0.004
				(0.009)	(0.008)
$\phi^{\sigma}_{XLE,t} \times \phi^{\sigma}_{MCCC,t}$					0.021*
					(0.011)
$\tilde{f}^{\sigma}_{O\&G,t-1}$	0.120***	0.110***	0.107***	0.110***	0.107***
	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)
$\tilde{f}^{\sigma}_{O\&G,t-2}$	0.089***	0.087***	0.081***	0.086***	0.079***
	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)
$\tilde{f}^{\sigma}_{O\&G,t-3}$	0.061***	0.055***	0.051***	0.056***	0.052***
	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)
Obs.	3,898	3,898	3,898	3,898	3,898
Adj. R^2	0.033	0.064	0.116	0.064	0.117
$\hat{\sigma}$	1.630	1.604	1.559	1.603	1.558
F Stat.	34.086***	39.162***	74.195***	27.851***	52.387***

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

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 $\phi^{\sigma}_{WTI,t}$ 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, $\phi^{\sigma}_{SPY,t}$ 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 worldwide equity-market performance, including stocks from developed and emerging markets. Hence, $\phi^{\sigma}_{ACWI,t}$ 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 setting $\boldsymbol{x}^{\sigma}_t = (\phi^{\sigma}_{WTI,t}, \phi^{\sigma}_{SPY,t}, \phi^{\sigma}_{ACWI,t})'$ in (11) (excluding the interaction terms).

All these control variables move O&G equity prices globally. The statistically significantly positive coefficients ($\hat{\boldsymbol{\beta}} \equiv (\hat{\beta}_{\phi^{\sigma}_{WTI}}, \hat{\beta}_{\phi^{\sigma}_{SPY}}, \hat{\beta}_{\phi^{\sigma}_{ACWI}})' = (0.091, 0.042, 0.104)'$) 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: the volatilities of the oil market, the US and global equity markets, and 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 which have 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 $\phi^{\sigma}_{WTI,t}$ tend to drive unexpected changes in O&G share prices, be they demand- or supply-based. The US and global equity markets also affect O&G global common variance. Higher economic uncertainty, locally and globally, is reflected in higher demand-based uncertainty around O&G equities. As volatility is higher and volatility shocks are larger during periods of economic crisis (when output is falling), O&G global common variance tends to be counter-cyclical, a phenomenon also found by Engle and Campos-Martins (2023).

The US-based O&G companies in this study are 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 the importance of the US in the geopolitical panorama, we check whether there is also 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 are denoted by $\phi^{\sigma}_{\mathrm{XLE},t}$ and replace $\phi^{\sigma}_{\mathrm{SPY},t}$ as the US explanatory variable in column (3). Results are robust with climate change concerns driving O&G geoclimatic variance after accounting for shocks arising from the US energy sector.[11]

To account for amplifying and mitigating effects, we 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. When we replace the control variable $\phi^{\sigma}_{\mathrm{SPY},t}$ by $\phi^{\sigma}_{\mathrm{XLE},t}$ 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 ($\hat{\gamma}_{\phi^{\sigma}_{\mathrm{XLE}}\times\phi^{\sigma}_{\mathrm{MCCC}}} = 0.021$). While Russia's invasion of Ukraine has led to record high oil prices, dividends, and O&G share buybacks, creating incentives to continue holding shares in O&G companies, longer-term issues such as climate change and the energy transition may only temporarily have been dominated by geopolitics. Countries in the European Union at least are ramping up renewables investment and increasing energy efficiency to become less dependent on Russian oil and gas.

Regressions similar to those above but for variance shocks to individual equities (rather than $f^{\sigma}_{\mathrm{O\&G},t}$) provide 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 in Section 2.1 but found no evidence that it affects O&G equity returns. Combined, these results suggest that the effects of climate change concerns on financial markets are more intricate and systemic than expected, so more complex volatility or factor models of higher moments, such as the global common volatility model, are needed.

3.3. Climate risk drivers

The two main transmission channels of climate change risk to financial markets in the literature are physical and transition risks (see, among others, TCFD, 2017). Physical risk relates to how climate change can adversely impact capital stock, economic activities and markets directly as more frequent and extreme climate-related disasters occur and are predicted for the future, including floods, droughts, and chronic heat waves as well as slowly rising sea levels. Though physical risk impacts are local, international trade and investment entail companies in countries less vulnerable to climate-related events can be exposed to countries that are vulnerable. Transition risk arises from exposure to sudden carbon pricing policy changes, legislation like the UK's 2008 Climate Change Act, clean-energy technological progress and market sentiment. The systemic implications of climate change for financial markets are thus most likely to come from exposure to transition risk, especially a disorderly transition.

Aggregating news by themes and topics allows us to disentangle the effects of climate change news on financial markets and help understand the mechanisms through which climate change can impact them. Estimation results from the impact of climate change concerns by risk drivers are presented in Table 4 for different themes and in Table 5 for more granular topics.

In addition to the control variables, we start by using the variance shocks to all seven thematic indices from most to least covered theme in columns (6) and (7) of Table 4. The two regressions use different measures 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 Financial & Regulation, Societal Impact or Agricultural Impact. The statistically significant positive coefficient of the variance shocks relating to Financial & Regulation reinforces the results in previous regressions using the MCCC index for common shocks in the global carbon transition.

News about disasters appears to decrease O&G global common volatility so 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 the (International Monetary Fund, 2020) suggested no significant effect of physical risk on equity valuations. This is consistent with Bolton and Kacperczyk (2021a), who found no carbon premium for stocks from countries more exposed to physical risk, only for countries associated with higher transition risk. If only extreme events are considered, then results change. Griffin et al. (2019) find that investors recognise but underprice physical risk by matching climate-related extreme events to the location of a firms' headquarters. Dietz et al. (2016) find much of the climate value at risk of global financial assets to be in the tail. News of a particular disaster seems unlikely to have a global impact on financial markets unless natural disasters become too frequent, costly and widespread, increasing concerns about the energy transition. Physical risk appears to be heavily discounted by investors because of its long-term nature, whereas transition risk tends to materialise 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 terms between the variance shocks by theme and those to the XLE in column (8). This shows that shocks to the US energy sector appear to be amplified by unexpected increases in concerns about Agreement & Summit ($\hat{\gamma}_{\phi^{\sigma}_{\mathrm{XLE}}\times\phi^{\sigma}_{\mathrm{Agreement\ \&\ Summit}}} = 0.029$) such as the Paris Accord. 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 then rejoining when President Joe Biden was elected. Overall, this finding highlights how discussions about climate policies can disrupt global markets.

[11] The effect of climate-related shocks does not change if we keep all four control variables. The gain in terms of the goodness of fit by including $\phi^{\sigma}_{\mathrm{SPY},t}$ in addition to the other three control variables is negligible.

Table 4
Projecting the O&G common variance ($\tilde{f}^{\sigma}_{O\&G,t}$) 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 $\phi^{\sigma}_{XLE,t}$ have been added as regressors.

	(6)	(7)	(8)	
	$\times 1$	$\times 1$	$\times 1$	$\times \phi^{\sigma}_{XLE,t}$
$\phi^{\sigma}_{WTI,t}$	0.091***	0.064***	0.065***	
	(0.013)	(0.013)	(0.013)	
$\phi^{\sigma}_{SPY,t}$	0.043**			
	(0.018)			
$\phi^{\sigma}_{ACWI,t}$	0.104***	0.102***	0.101***	
	(0.014)	(0.013)	(0.013)	
$\phi^{\sigma}_{XLE,t}$		0.251***	0.251***	
		(0.016)	(0.017)	
$\phi^{\sigma}_{Financial\ \&\ Regulation,t} \times$	0.053***	0.056***	0.047***	−0.012
	(0.014)	(0.014)	(0.015)	(0.013)
$\phi^{\sigma}_{Agreement\ \&\ Summit,t} \times$	−0.012	−0.013	−0.005	0.029***
	(0.013)	(0.013)	(0.013)	(0.011)
$\phi^{\sigma}_{Societal\ Impact,t} \times$	0.039**	0.041**	0.045**	0.005
	(0.018)	(0.017)	(0.018)	(0.015)
$\phi^{\sigma}_{Research,t} \times$	−0.003	−0.003	−0.005	−0.002
	(0.003)	(0.003)	(0.005)	(0.05)
$\phi^{\sigma}_{Disaster,t} \times$	−0.034***	−0.035***	−0.034***	−0.006
	(0.012)	(0.011)	(0.012)	(0.009)
$\phi^{\sigma}_{Environmental\ Impact,t} \times$	−0.015	−0.013	−0.017	−0.005
	(0.011)	(0.010)	(0.011)	(0.010)
$\phi^{\sigma}_{Agricultural\ Impact,t} \times$	0.031***	0.025***	0.029***	−0.016***
	(0.009)	(0.009)	(0.009)	(0.006)
$\tilde{f}^{\sigma}_{O\&G,t-1}$	0.109***	0.106***	0.105***	
	(0.016)	(0.015)	(0.015)	
$\tilde{f}^{\sigma}_{O\&G,t-2}$	0.088***	0.082***	0.082***	
	(0.016)	(0.015)	(0.015)	
$\tilde{f}^{\sigma}_{O\&G,t-3}$	0.056***	0.052***	0.052***	
	(0.016)	(0.015)	(0.015)	
Obs.	3,898	3,898	3,899	
Adj. R^2	0.071	0.127	0.126	
$\hat{\sigma}$	1.598	1.552	1.550	
F Stat.	24.068***	43.281***	29.156***	

*p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

To better understand the transmission mechanisms of climate change concerns to the O&G industry, Table 5 summarises the estimation results by the topics that constitute these themes, presenting only those that make O&G stock prices move globally. As a robustness check, we present estimation results for either $\phi^{\sigma}_{SPY,t}$ or $\phi^{\sigma}_{XLE,t}$. The ten words with the highest probability for selected topics are also shown. For more details and other topics, we refer to Ardia et al. (2020).

First consider the transition risk drivers. News with explicit mentions of the fossil fuel industry and carbon pricing (topic 31) or of carbon and technological disruption (topic 40) drive global O&G variance shocks. Topic 6 which relates to legal actions and the closest topic to liability or litigation risk seems to have no impact. Setzer and Higham (2021) show that most cases of climate change litigation were filed before courts and have been brought against governments (and their support for the fossil fuel industry). Only a small, but increasingly significant, number of cases are targeted at companies. It seems litigation may be weakening climate action by challenging the way it is being carried out. Topics 8 and 34 associated with societal impact do seem to affect the O&G industry. As they relate to the consequences of climate action failure, they are likely to alter investors' taste for climate change and create pressure on the O&G industry so can be interpreted as market sentiment risk drivers.

Physical acute events (topic 33) do not seem to directly drive extreme shocks globally and those from chronic risk drivers (e.g., topic 12) have no effect at all. The global impact of physical acute risk drivers can be indirectly adverse through agricultural activities. Agricultural impact has a pronounced two-fold effect, both emitting about 1/3rd of GHG emissions and prone to high costs from climate change. News about acute physical impacts of droughts on agriculture (topic 4) amplifies pressure to cut carbon emissions and accelerate the transition.[12] The increased attention and pressure from climate-damaging agricultural practices appears to cause higher uncertainty around carbon-intensive assets and to

[12] Volatility effects from transition risk drivers similar to those here for the O&G industry are also to be expected for agri-business assets. 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 common variance ($\tilde{f}^{\sigma}_{\mathrm{O\&G},t}$) on the variance shocks to media climate change concerns by statistically relevant topic. The most common words per selected topic (Ardia et al., 2020) are also shown. Climate physical (P.) and transition (T.) risk drivers (TCFD, 2017) in brackets.

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

Most common words

Theme: Financial & Regulation

Topic 6 [T. Legal] rule, administration, agency, regulation, law, court, decision, authority, administrator, action

Topic 31 [T. Policy] oil, tax, fuel, price, carbon_tax, production, taxis, cost, ethanol, revenue

Topic 40 [T. Technology] project, technology, plant, cost, coal, carbon_dioxide, power_plant, facility, scale, carbon

Theme: Societal Impact

Topic 8 [T. Market & Reputation] science, book, story, truth, film, news, movie, medium, reader

Topic 34 [T. Market & Reputation] poll, survey, majority, public, pew, penguin, concern, opinion, result, support

Theme: Disaster

Topic 12 [P. Chronic] island, sea, sea_level, storm, flood, flooding, land, beach, home, village

Topic 33 [P. Acute] fire, wildfire, insurance, risk, home, property, disaster, loss, flood, zone

Theme: Agricultural Impact

Topic 4 [P. Acute + T.] drought, region, river, rain, desert, lake, dam, rainfall, water_supply, mountain

Topic 20 [T.] food, animal, meat, cow, cattle, farm, ski, resort, beef, diet

*p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

spill over to the O&G industry. In particular, topic 20 which relates to meat production is GHG emissions intensive, mainly methane, so bad news there could amplify pressure on cutting other emissions.

Despite the exposure of oil and gas companies to climate concerns, not all geoclimatic shocks are alike. The signs and magnitudes of the impacts differ across climate risk drivers, where carbon transition risk appears to have the most significant adverse global effects.

3.4. Climate sentiment, mitigating and amplifying effects

Negative news about climate change is more likely to cause major changes in the O&G equity returns as it amplifies uncertainty about 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: negative shocks to stock prices produce more volatility than positive shocks. When only generic news is included in the regression, no statistically significant effect is found: positive and negative news affect O&G global common volatility in opposite directions, so partly cancel out. When both indices are included, their effects can be disentangled and show that only negative news has the potential to disrupt the global O&G equity market.

To analyse the impact of climate change news sentiment on the volatility of the global O&G equity market, we use the two climate change monthly indicators, CC^{+}_{m} and CC^{-}_{m}. The dependent variable is the centred $\tilde{f}^{\sigma}_{\mathrm{O\&G},m}$:

$$\tilde{f}^{\sigma}_{\mathrm{O\&G},m} = \alpha^{+}\phi^{\sigma}_{\mathrm{CC}^{+},m} + \alpha^{-}\phi^{\sigma}_{\mathrm{CC}^{-},m} + \boldsymbol{\beta}'\boldsymbol{x}^{\sigma}_{m} + \boldsymbol{\gamma}'\left\{\boldsymbol{x}^{\sigma}_{m} \times \phi^{\sigma}_{\mathrm{CC}^{-},m}\right\} + \delta\tilde{f}^{\sigma}_{\mathrm{O\&G},m-1} + \varepsilon_{m}, \tag{12}$$

where ε_m is distributed with zero mean and constant variance, $\boldsymbol{x}^{\sigma}_{m}$ contains control variables and $\boldsymbol{x}^{\sigma}_{m} \times \phi^{\sigma}_{\mathrm{CC}^{-},t}$ represents interactions terms between the controls and the negative climate variable, including or removing controls and/or interaction terms.

Table 6 presents estimation results for (12). To distinguish the impact of positive and negative climate change news on O&G global common volatility, regressions include variance shocks to both as explanatory variables. Column (1) shows

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

	$\tilde{f}^{\sigma}_{O\&G,m}$			$\phi^{\sigma}_{XLE,m}$
	(1)	(2)	(3)	
$\phi^{\sigma}_{CC^{+},m}$	−0.031**	−0.037**	−0.028**	−0.0005
	(0.016)	(0.017)	(0.012)	(0.009)
$\phi^{\sigma}_{CC^{-},m}$	0.046*	−0.023	0.050***	−0.002
	(0.024)	(0.034)	(0.018)	(0.014)
$\phi^{\sigma}_{WTI,m}$	0.509***	0.409***	0.169*	0.336***
	(0.104)	(0.104)	(0.089)	(0.063)
$\phi^{\sigma}_{SPY,m}$	0.179	0.258*		0.098
	(0.152)	(0.148)		(0.091)
$\phi^{\sigma}_{ACWI,m}$	0.212*	0.216*	0.204**	0.031
	(0.123)	(0.119)	(0.084)	(0.075)
$\phi^{\sigma}_{XLE,m}$			1.062***	
			(0.123)	
$\phi^{\sigma}_{WTI,m} \times \phi^{\sigma}_{CC^{-},m}$		0.111***		
		(0.042)		
$\phi^{\sigma}_{SPY,m} \times \phi^{\sigma}_{CC^{-},m}$		−0.054		
		(0.092)		
$\phi^{\sigma}_{ACWI,m} \times \phi^{\sigma}_{CC^{-},m}$		−0.250***		
		(0.093)		
$\tilde{f}^{\sigma}_{O\&G,m-1}$	0.191**	0.141*	0.221***	
	(0.078)	(0.076)	(0.059)	
Obs.	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 Stat.	9.578***	8.434***	28.570***	7.620***

*p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

that variance shocks to the generic and negative climate change news index indeed have negative ($\hat{\alpha}^{+} = -0.031$) and positive ($\hat{\alpha}^{-} = 0.046$) effects 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. 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. This asymmetry of the O&G geoclimatic variance empirically supports including both indices.

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

To analyse if the impact of climate change news differs when there is simultaneously a shock to the control variables, we include interaction terms between controls and either $\phi^{\sigma}_{CC^{+},m}$ or $\phi^{\sigma}_{CC^{-},m}$. These help account for amplifying and mitigating effects of negative climate news. There is no interaction effect when the news is positive, so these results are omitted. However, in column (2) negative climate change news amplifies the effects of oil variance shocks ($\hat{\gamma}_{\phi^{\sigma}_{WTI} \times \phi^{\sigma}_{CC^{-}}} = 0.111$). For example, the Deepwater Horizon disaster in 2010 had an impact on oil markets at the same time as concerns about its environmental impact possibly increasing uncertainty about the future viability of the O&G industry. Regarding the relative relevance of equity market and climate change sentiments, a variance shock to the global equity market attenuates the effect of simultaneous negative climate change news ($\hat{\gamma}_{\phi^{\sigma}_{ACWI} \times \phi^{\sigma}_{CC^{-}}} = -0.250$) suggesting global equity market shocks are more relevant than the implications of climate change. Global markets (and investors) appear to react more to short-term political and economic news compared to the longer-term problem of climate change so its effect is relatively smaller.

Table 6 column (3) shows the results when the variance shocks to the XLE, $\phi^{\sigma}_{XLE,m}$, are included. 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.

The final column of Table 6 records the regression of the idiosyncratic variance shocks to XLE on the same explanatory variables as in column (1). Here, the univariate XLE series provides the variance shocks, so no cross-sectional or cross-country information is used unlike for the O&G global common variance. Only oil variance shocks explain why the squared returns of XLE are larger than usual in any given month and climate change news is insignificant for this US-based O&G companies index, confirming the need to incorporate cross-country information to capture geoclimatic variance shocks.

Table A.1
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		Company	Country
APC	Anadarko[a]	US	HAL	Halliburton	US
BP	BP	UK	KMI	Kinder Morgan	US
CEO	CNOOC	China	OXY	Occidental	US
CNQ	Canadian Natural	Canada	PBR	Petrobras	Brazil
			PSX	Phillips 66	US
COP	ConocoPhillips	US	PTR	PetroChina	China
CVX	Chevron	US	RDS	Royal Dutch Shell	Netherlands UK
DVN	Devon Energy	US			
E	Eni	Italy	REPYY	Repsol	Spain
EC	Ecopetrol	Colombia	SLB	Schlumberger	US
EOG	EOG Resources	US	SNP	Sinopec	China
EPD	Enterprise Products	US	SU	Suncor Energy	Canada
			TOT	Total	France
EQNR	Equinor	Norway	XOM	ExxonMobil	US

[a]Acquired by Occidental Petroleum in 2019.

This reinforces both how a common climate policy can be important and why negotiations during climate summits can disrupt global markets.

A similar regression using $\phi^{\sigma}_{\mathrm{WTI},m}$ as the dependent variable found 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, possibly reflecting short-term optimism about O&G versus the long-term nature of climate change risks. An alternative explanation may be consumers mis-perception of the carbon footprints of oil producers. Carbon emissions from a company's operations can occur directly (scope 1) and indirectly from the consumption of purchased energy (scope 2), both of which are widely reported. Data on indirect emissions related to products purchased and sold by a company (scope 3) are not widely available. The ability of O&G companies to reduce their scope 3 carbon emissions is obviously limited and major O&G producers have only committed to reduce their (relatively very small) scope 1 and 2 emissions. Presently, oil has a low elasticity of demand as consumers are unable to substitute fossil fuels easily when prices change, but that will change as electric cars replace gasoline.

When accounting for climate sentiment, global turmoil seems to materialise only when climate news is negative. Moreover, the adverse effect is amplified by oil price movements but weakened by stock market shocks.

4. Discussion

The energy transition is underway and the investing world is paying attention. A recent survey by BCG (2021) of 250 institutional investors in the O&G industry confirms both divisions 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 may be optimistic that oil prices will remain high despite short term oil price wars and the COVID-19 pandemic when oil futures trade at negative prices, rapidly followed by the global energy crisis. The uncertainty around future demand for fossil fuels is very high, and our results of the impacts of negative climate news show that uncertainty is already impacting valuations of the O&G industry. The BCG (2021) survey showed that key stakeholders also see value creation in the energy transition and agree that O&G needs to become environmentally sustainable by reducing its carbon emissions and developing low-carbon portfolio alternatives. Activists and hedge funds are already applying pressure on oil majors to do so as the window for an orderly adjustment towards low-carbon economies becomes narrower: fire sales of carbon-intensive assets, liquidity problems and financial instability are all likely in a disorderly transition.

O&G companies disclosure of climate-related information is still scarce, which makes it difficult to assess the risk of holding shares in carbon-intensive assets as the world moves away from fossil fuels. Our approach based on how financial asset prices react to adverse climate change news can help to identify companies and countries that are more exposed to climate risk during decarbonising the global energy system. Measuring the exposure to geoclimatic risk could also 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 in identifying climate risk drivers, assessing risk concentrations and reducing their global economic impacts.

Finally, governments and companies need to assess their climate pledges and rethink the way they publicise 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 transition risks and mobilising capital for low-risk green investments.

Table B.1
Summary statistics of oil and gas stock returns. Results from the tests for serial correlation (Ljung and Box, 1978) in the residuals and squared residuals from a factor model denoted as, respectively, 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
	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

5. Conclusion

Carbon transition risk and O&G markets are by nature geopolitical. Climate-related material news is therefore 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 apply 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. Shocks to the volatilities of major oil and gas stock returns are correlated making them move at the same time. 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 text-based 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 moves O&G equities around the world. 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 climate risk drivers. Climate change news seems to create turmoil in the carbon-intensive industry only when the news is negative, and tends to be amplified by oil price movements. Also geoclimatic news materialises only when it reaches the global scale, supporting the importance of modelling geoclimatic volatility.

Our results shed some light on the exposure of carbon-intensive assets to climate transition risk at the global scale. However, it was difficult to find an association between individual or country stocks and global climate change news. Future research on geoclimatic volatility could include individual or country level climate news as differences in exposures could be related to climate policy stringency, activism, geological events or carbon emissions.

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Appendix A. List of oil and gas stocks

See Table A.1.

Appendix B. Summary statistics

See Table B.1.

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