Geoclimate, Geopolitics, and the Geovolatility of Carbon-Intensive Equity Returns

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Abstract

The systemic implications on carbon-intensive equity prices of the disruptive technological progress from decarbonising the global energy system are compounded by the geopolitical nature of both the global oil market and transition risk. We show empirically that climate change news affects oil and gas stock return volatilities at the global scale. But not all geoclimatic shocks are alike. Climate change news increases global uncertainty around carbon-intensive equities and it amplifies the effects of oil volatility shocks when the news is bad. The geoclimatic impact on the global oil and gas equity market has changed over time and is reflected by increasing geoclimatic volatility. Moreover, the impact of climate change news differs across topics and themes.

1 Introduction

In chemistry, patina is defined as a thin greenish layer that naturally forms on the surface of brownish metals such as copper or bronze by oxidation when exposed to air. Patina can also be produced artificially as by acids for protection. Is the 'financial patina' from decarbonising the global energy system to greening the global economy likely to be forced by climate policies, carbon prices and litigation, or by market forces as investors price in climate change risks? There is growing pressure to divest from so-called brown assets and activities, which are carbon-intensive, and make green investments. Pledges to build a green economy are surging in the climate agenda of not

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only governments but also large companies and hedge fund firms everywhere. Countries with net zero targets now represent 61% of the global greenhouse gas emissions, 68% of the global gross domestic product and 56% of the world's population (Black et al., 2021).

Human influence is unequivocal in causing climate change (IPCC, 2021). Anthropogenic climate change is due to burning fossil fuels and the consequent release of greenhouse gases. Excessive emissions of carbon dioxide, the most tracked carbon compound, have caused a greenhouse effect which has been accelerating global warming. Brown assets are carbon-intensive and primarily associated with fossil fuels such as coal, oil and natural gas, which are intrinsically high in carbon. Green assets are associated with cleaner energy and so are low in carbon. To reduce the carbon footprint and mitigate the global effects of climate change, the transition process for greening the global economic system is under way. Given current technology, a shift away from fossil fuels is however going to take decades.

Global carbon dioxide emissions have increased dramatically around the world during the last few decades and are projected to increase in the coming years. Countries such as China, the US, the EU member countries, India and Russia together account for 2/3 of the global carbon dioxide emissions. Given current technology, a transition towards low-carbon economies requires a shift away from fossil-fuel energy. However, countries are still highly dependent on fossil fuels to produce energy. According to the Statistical Review of World Energy (BP, 2020), the distribution of the primary energy consumption by fuel type around the world indicates that, on average, 84% of primary energy is produced by means of fossil fuels (oil, coal and natural gas) and only 16% by non-fossil fuels (hydroelectricity, renewable energy, and nuclear energy). Coal is by far the worst polluter among fossil fuels and yet, in countries such as China and India, more than 50% of their primary energy consumption comes from coal. The effectiveness of changes in investment decisions also depends on expectations about climate policies around the world. The systemic implications of disruptive technological progress on the prices of carbon-intensive assets are thus compounded by the geopolitical nature of not only the global oil market, but also transition risk.

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

The literature on climate change and finance focuses on the pricing of climate change risks, in particular, on how stock returns reflect investor concerns about climate change. Bolton and Kacperczyk (forthcoming) provide a cross-country analysis of the effects of corporate carbon emissions and a country's transition risk on stock returns. A company's carbon premium seems to be related to not only its level of emissions (long-run exposure to transition risk) but also changes in its level of emissions (short-run exposure to transition risk). Moreover, the carbon premium tends to be higher (lower) in countries with a higher share of brown (green) sectors (even though it does not seem to reflect physical risk). Studies of the impact of climate change on financial markets also include the analysis of value at risk associated with climate shocks (Dietz et al., 2016) in which financial losses are aggregated and derived top-down from estimated output losses due to climate change. Climate stress-tests of the financial system show the inter-linkages among financial institutions may amplify both positive and negative shocks (Battiston et al., 2017).

From a cross-country analysis of the impact of climate-related disasters on aggregate stock market indexes from 68 developed and emerging countries since 1980, International Monetary Fund (2020) found no significant effect of climate change physical risk on equity valuations. Even though financial losses can be massive and vary widely, they conclude that the reaction of equity prices to large climatic disasters is relatively modest. Other country characteristics, such as a higher rate of insurance penetration and a greater sovereign financial strength, seem to explain this low impact and so improve financial stability. Yet, the authors argued that equity investors may not be paying sufficient attention to climate variables. Interestingly, the same study shows that investors in long-term sovereign bonds demanded a premium from countries with high climate risk meaning that investors do appear to be pricing climate change physical risks when making long-term investment decisions.

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

If media-aware and sophisticated investors are pricing transition risk, one should expect all the prices of carbon-intensive assets to be responsive to geoclimatic news. If climate change news is geopolitical, it should affect a very wide range of carbon-intensive asset prices at the same time. To measure the co-movements of volatilities of carbon-intensive asset returns at the global scale, we apply the geopolitical volatility model introduced by Engle and Campos-Martins (2020). When innovations to volatilities are correlated across assets, common volatility shocks to the idiosyncratic volatilities can be identified. Economic, political or epidemiological events impact volatilities and move financial markets globally. Geopolitical volatility is thus interpreted as a measure of the magnitude of global volatility shocks and is intended to capture geopolitical risk due to its broad impact on many assets, asset classes and countries. Volatility shocks arising from climate change are identified as an additional determinant of the volatility of the global carbon-intensive equity market. The variation driven by climate change news of the oil and gas geopolitical volatility is called geoclimatic volatility.

The geopolitical volatility model is applied to the daily share prices of oil and gas companies from different countries but all traded on the New York Stock Exchange (NYSE) to assure synchronicity of observations. Oil and gas geopolitical volatility peaks during the COVID-19 pandemic, after the 9/11 terrorist attack, Black Monday in 1987, and during the global financial crisis in 2008. But many announcements by the Organization of the Petroleum Exporting Countries (OPEC) or the drone attack to the Saudi Aramco production facilities in 2019 show up as extreme geopolitical events driving changes in the global oil and gas equity market as well. Whereas the first set of geopolitical events are more likely to come from the oil demand side, the second are categorized as being driven by oil supply shocks.

As a proxy for climate change risk, we use the monthly climate change news index of Engle et al. (2020) and the daily media climate change concerns index of Ardia et al. (2020). Each index is a time-series that captures news about climate risk, constructed by applying text mining to the content of United States newspapers. The innovations to each of these indexes reveal that not all geoclimatic shocks are alike. Climate change geopolitical news is inducing global volatility co-movements of a wide range of carbon-intensive equities. Overall, climate change generic news drives geoclimatic volatility as it seems to affect oil and gas stock return volatilities at the global scale. However, the effect on the oil and gas geopolitical volatility is adverse only when the news is bad, an effect which has become stronger over time. Bad news about climate change seems to increasingly create global uncertainty around carbon-intensive asset returns and to amplify the effects of oil price shocks. Moreover, the impact on geoclimatic volatility differs across climate change topics.

The paper is organized as follows. In section 2, the geopolitical volatility model is presented and the estimation procedure is briefly described. The results from the empirical application of the geopolitical volatility model to oil and gas stocks, including a detailed analysis of the major geopolitical events affecting this global market over time, are shown in this section as well. Subsequently, in section 3, we develop the strategy addressed to identify the volatility shocks driven by climate change news which can affect the oil and gas geopolitical volatility. Section 4 links the geopolitical volatility shocks to oil and gas stock returns with the volatility shocks to climate change innovations using regression analysis. In section 5, the policy implications are discussed. Finally, section 6 concludes the paper.

2 Modeling carbon-intensive geopolitical volatility

It is a stylized 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) associate these volatility shocks to geopolitical events due to their very wide impact. To measure geopolitical volatility, they propose a new model of idiosyncratic volatility co-movements based on a multiplicative volatility factor decomposition of the volatility standardized residuals.

Consider the $(N \times 1)$ vector of carbon-intensive equity returns $\boldsymbol{r}_t = (r_{1t}, \ldots, r_{Nt})'$ given by

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

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

Assuming factors are sufficient to reduce the contemporaneous correlations to zero, this implies

$$\mathbb{E}_{t-1}(\boldsymbol{e}_t \boldsymbol{e}_t') = \mathbb{I}. \tag{2}$$

Assumption (2) does not mean that residuals are independent in the cross-section, it simply means they are uncorrelated. The fundamental observation in this model is that, even though the standardized residuals are orthogonal with unit variance, their squares (or absolute values) may 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 correlation between shocks to those volatilities (which are unpredictable). Engle and Campos-Martins (2020) provide strong evidence that the squared standardized returns net of factors are positively correlated. Define a volatility shock as the proportional difference between the squared idiosyncrasy and its expectation,

$$\phi_{i,t} \equiv e(_{i,t})^2 - 1 = \frac{(r_{i,t} - r^f - \boldsymbol{\beta}_i' \boldsymbol{f}_t)^2 - h_{i,t}}{h_{i,t}}, \tag{3}$$

For each asset, the realized squared e is on some days bigger than one and on other days smaller than one. If many carbon-intensive equities around the world have squared e bigger than one at the same time, this can be interpreted as a global volatility shock which we will associate to volatility shocks arising from geoclimatic news.

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

$$e_{it} = \sqrt{g_{it}(s_i, x_t)}\epsilon_{it}, \tag{4}$$

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

$$g_{it}(s_i, x_t) \equiv s_i x_t + 1 - s_i, \tag{5}$$

$x_t > 0, t = 1, \ldots, T$, and $0 \leq s_i \leq 1, i = 1, \ldots, N$. Recall that $\mathbb{E}_{t-1}[\boldsymbol{e}_t \boldsymbol{e}_t'] = \mathbb{I}$.

But (4) implies the variance-covariance matrix of the squared standardized residuals $\mathbb{E}_{t-1}[\boldsymbol{e}_t^2(\boldsymbol{e}_t^2)'] = \Psi$. Testing for geopolitical volatility is carried out using the empirical counterpart of Ψ and by checking whether it is diagonal or not. For further details, we refer to Engle and Campos-Martins (2020).

Because the data generating process is multiplicative between two sets of unknowns $x_t, t = 1, \ldots, T$ and $s_i, i = 1, \ldots, N$, we estimate each conditional on the other. The first order conditions for both s and x give the following heteroskedasticity relationships:

$$\begin{aligned} \text{Time-Series: } e_{i,t} &= \sqrt{s_i(\hat{x}_t - 1) + 1}\epsilon_{it} \text{ for } i = 1, \ldots, N, \\ \text{Cross-Section: } e_{i,t} &= \sqrt{\hat{s}_i(x_t - 1) + 1}\epsilon_{it} \text{ for } t = 1, \ldots, T, \end{aligned} \tag{6}$$

where the cross-sectional regression allows us to estimate the unobserved value of $x_t, t = 1, \ldots, T$ (using some initial values for the factor loadings) and then the time-series regression maximizes the likelihood function conditional on the estimated latent variable to obtain estimates for $s_i, i = 1, \ldots, N$. There is thus an estimator for each $s_i, i = 1, \ldots, N$ given $\hat{x}_t, t = 1, \ldots, T$ using time-series and another estimator for each $x_t, t = 1, \ldots, T$ 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-section regressions until convergence. At that point, both first order conditions are satisfied and a joint maximum can be achieved.

2.1 The oil and gas global volatility shocks

Carbon-intensive volatility co-movements at the global scale can be driven by shocks arising from fossil fuel demand (e.g. global financial crises, China slowdown, COVID-19 pandemic, carbon prices) or supply (e.g. OPEC announcements, crude oil price shocks). To analyze to what extent climate change news affects the global carbon-intensive equity market[1], we first model the geopolitical shocks to the volatilities of global oil and gas stocks returns from which we disentangle the geoclimatic volatility shocks constructed from climate change news indexes.

The daily closing prices of shares from 25 major oil and gas companies around the world are extracted from the data platform Datastream. They are all traded in the NYSE so we are guaranteed to have synchronous observations when measuring the 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

[1]For a discussion on the climate-policy relevant sectors in the economy we refer to Battiston et al. (2017).

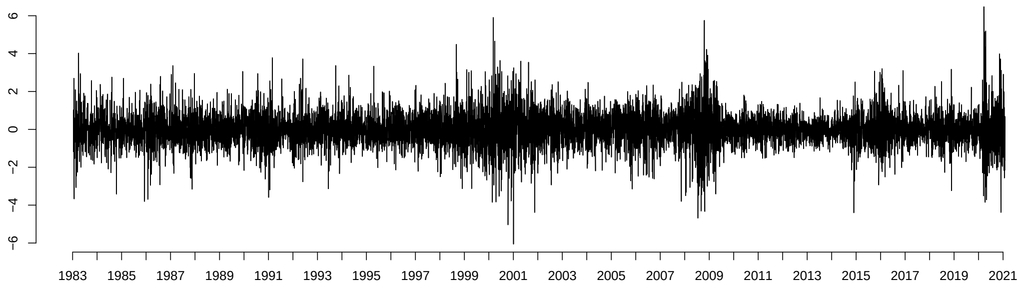
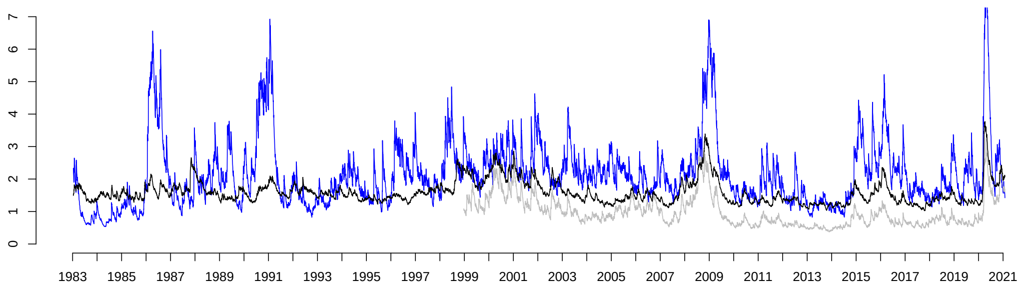


Figure 1: Cross-sectional mean of oil and gas residuals from factor models.

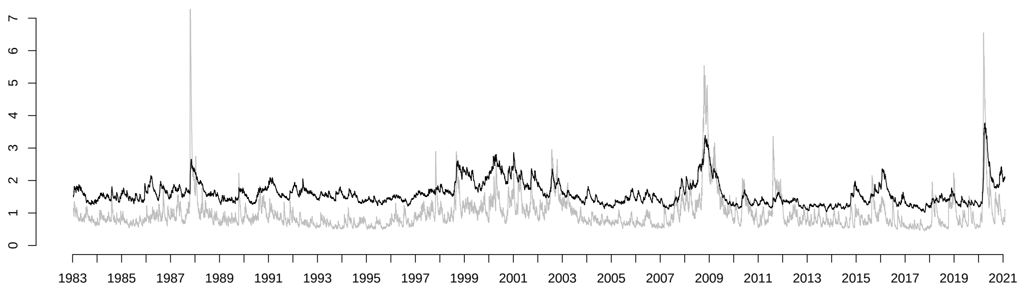
dates) with a minimum of eight observations per day. To remove any stochastic trend, we convert prices into log-returns. Our modeling framework starts by estimating a factor model with GARCH errors for each carbon-intensive asset. Extreme positive (negative) returns are truncated to $\pm 10\%$ to avoid problems in the estimation of the GARCH models. For modeling the time dependence observed in the first moment of the data, a first-order autoregressive (AR) component is added to the pricing factor models. The choice of the order of the AR model is supported by Ljung-Box AR(1) tests. To account for common factors affecting the series of returns, we assume a Fama and French three factor model. We also include the excess returns on the West Texas Intermediate (WTI) 1-month future price as a covariate. To model the heteroskedasticity 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, which seems sufficient to capture the heteroskedastic behavior of each series.

The oil and gas cross-sectional mean excess returns is depicted in Figure 1 and the estimated oil and gas cross-sectional mean volatility in black in Figure 2. For comparison, the estimated volatility of the excess returns of the WTI crude oil future and the Energy Select Sector Fund (XLE) are also shown in (2a) and of the S&P 500 index in (2b). The XLE reflects the exposure to mostly oil, gas and consumable fuel companies in the US. The global oil and gas geopolitical shocks will be compared to those affecting this XLE because, even though they share some constituents, they are not the same. The WTI crude oil future is much more volatile than the oil & gas cross-sectional mean volatility, which in turn is more volatile than the other two. Nevertheless, all volatilities depicted tend to co-move over time, especially in periods of higher uncertainty, namely the global financial crisis, the oil price plunge of 2014-2016 and the COVID-19 pandemic.

Even after extracting the pricing factors (Fama and French and the WTI excess returns), idiosyncratic volatilities are still correlated. Their cross-sectional mean cor-



(a) WTI (blue) and XLE (gray)



(b) S&P 500 (gray)

Figure 2: Cross-sectional mean of oil and gas idiosyncratic volatilities (black). For comparison, the volatility of the 1-month WTI crude oil future and of the SPDR energy sector ETF are also shown in the upper panel and of the S&P 500 index in the bottom panel.

relation is 0.583 and their first principal component accounts around 65% of their total variance. The correlation between the oil and gas cross-sectional mean volatility and that of the WTI oil future is 0.554, of the energy sector XLE is 0.913, and of the S&P 500 index is 0.643. Even though highly correlated, they do not perfectly match the variation captured in the global oil and gas equity market. The correlation between the cross-sectional mean of the oil and gas volatility shocks and those to the WTI future is only 0.188, to the energy sector XLE is 0.648, and to the S&P 500 index is 0.099.

Having estimated the series of residuals and volatilities, we compute the vector of standardized residuals $\hat{\boldsymbol{e}}_t, t = 1, \ldots, T$. To help estimate the carbon-intensive geopolitical volatility, we add the oil and gas cross-sectional mean standardized residuals to the sample such that $N = 26$. We will denote this series by O&G. It is straightforward to test for geovolatility using the sample covariance matrix of $\hat{\boldsymbol{e}}^2$. We assume an equicorrelated alternative (all factor loadings are equal to one) and use the test statistic proposed by Engle and Campos-Martins (2020) under the null hypothesis that the cross-sectional mean correlation of $\hat{\boldsymbol{e}}^2$ is zero against the one sided alternative that it is positive. The test statistic follows in distribution a standard normal under the null. In practice, we test $\mathbb{H}_0 : \bar{\rho}_{e^2} = 0$ against the one-sided $\mathbb{H}_0 : \bar{\rho}_{e^2} > 0$. The empirical average correlation $\bar{\rho}_{e^2} = 0.096$. For this sample, the test statistic is $\xi = 141.3$ and $p-$value $= 0.000$. The hypothesis that the cross-sectional mean correlation of the squared standardized residuals is zero is thus strongly rejected. This result provides evidence that the squared standardized residuals are correlated and so we proceed to the estimation of the oil and gas geopolitical volatility factor in order to capture global shocks driving co-movements of their volatilities.

We shall briefly describe the iterative estimation of the oil and gas volatility factor and corresponding factor loadings. As the starting values for the estimation of $x_t, t = 1, \ldots, T$, record the factor loadings on the first principal component of $\boldsymbol{e}^2$. This is not necessary as the algorithm converges to the same optimal solution when we choose other initial values. Take the estimated standardized residuals as observable and iterate the estimation of the cross-sectional and time-series regressions (6) until convergence. In each iteration, impose the normalization $x_t/(1/T)\sum_{t=1}^{T} x_t$ and $\sum_{i=1}^{N} s_i^2 = 1$ after estimating, respectively, the cross-section and the time-series regression. For this empirical sample, 15 iterations were performed until the algorithm converged. The oil and gas geopolitical volatility denoted by $\sqrt{x}$, will for the remaining of the paper, be denoted by O&G GEOVOL to make the interpretation of results more intuitive.

The most extreme common oil and gas volatility shocks captured by the estimated squared GEOVOL and denoted by O&G $\hat{\text{GEOVOL}}_t^2$ are summarized in Table 1. For comparison, the returns on the same day are shown for the cross-section average of oil and gas stocks ($\bar{r}_t^{\text{O\&G}}$), the S&P 500 index (r_t^{SPX}), the crude oil 1-month future (r_t^{WTI}), and the energy sector fund (r_t^{XLE}). Several dates are easily recognized as being the days when major events happened affecting global financial markets, including oil and gas. Many extreme shocks coincide with large negative returns but we also observe large volatility shocks for some positive returns. The extreme values observed in the global oil and gas geopolitical volatility are strongly correlated with large WTI or XLE returns (or both) and also with the SPX returns.

Geopolitical events 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; or even attacks to oil facilities like the one on September 16, 2019 when the drone attack to the Saudi Aramco production facilities caused its biggest disruption ever. These are different from other geopolitical shocks, such as economic or financial, political elections, climate policy changes or terrorist attacks that are rather likely to reflect changes in 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 indexes, namely Dow, S&P 500 and Nasdaq Composite, since October 2008), financial crashes and crises (such as the global financial crisis of 2008-2009), 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 trade wars). All these events appear to have caused large returns across all the indexes showing up in the geopolitical volatility as some of the biggest common shocks affecting the global oil and gas equity market. The monthly means of the estimated global oil and gas volatility (averaged oil and gas geovolatility) are plotted in Figure 3, where some of these major events are labeled.

The empirical variances and covariances of the squared standardized residuals are not equal across oil and gas equities. This reflects the fact that different equities have different loadings on the geopolitical volatility factor. The loading captures the proportion of O&G GEOVOL that affects an asset's volatility. The estimated O&G GEOVOL loadings are presented in Table 2 in descending order. The impact of O&G

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

t	O&G $\hat{\mathrm{GEOVOL}}_t^2$	$\bar{r}_t^{\mathrm{O\&G}}$	r_t^{SPX}	r_t^{WTI}	r_t^{XLE}
2020-03-20	42.915	1.525	−4.433	−11.724	0.971
2014-11-28	35.934	−7.705	−0.255	−10.726	−6.640
1987-10-20	28.158	4.216	5.195	0.101	
1993-09-29	26.473	3.333	−0.308	−0.167	
1985-12-09	25.085	−4.270	0.619	−4.338	
2008-07-16	23.811	−1.395	2.475	−3.029	−2.608
2000-03-07	23.642	5.584	−2.597	5.883	6.673
1995-04-20	23.505	2.187	0.073	−6.732	
2020-03-23	22.859	−1.910	−2.973	−9.683	−9.272
1998-09-04	22.729	3.667	−0.856	−0.684	
2000-10-13	22.576	−3.295	3.284	−3.096	−3.900
1992-05-26	22.018	4.024	−0.632	4.943	
1993-06-11	21.264	−3.188	0.421	−1.413	
2020-03-17	21.229	−0.486	5.823	−6.291	0.681
1984-10-17	21.084	−4.373	−0.389	−2.653	
2019-04-12	21.024	0.962	0.659	0.486	0.267
1985-07-05	19.748	−0.351	0.557	0.000	
2020-11-09	19.430	12.616	1.163	8.179	13.344
2010-04-29	18.930	0.323	1.286	2.316	0.115
2001-01-03	18.542	−2.572	4.888	2.896	−3.101
1985-12-10	17.288	−3.497	0.069	−1.170	
1983-03-31	16.997	3.833	−0.281	0.000	
2016-11-30	16.627	5.877	−0.266	8.900	4.958
2001-09-17	16.400	−1.619	−5.047	4.251	−2.065
1986-01-27	16.370	1.989	0.464	7.226	

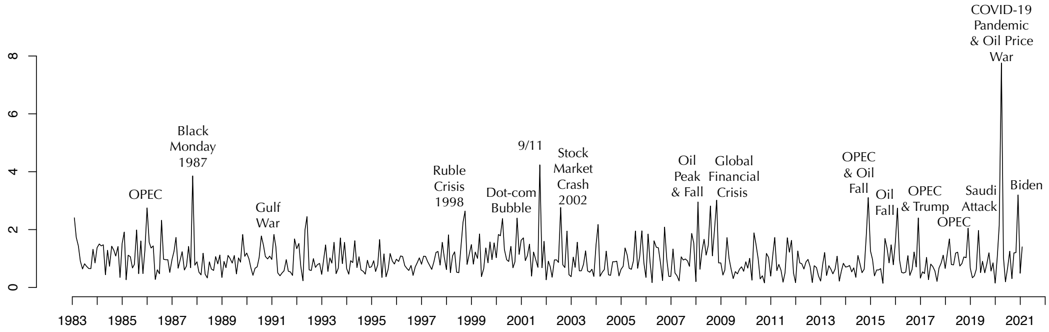


Figure 3: The (monthly averaged) oil and gas geopolitical volatility index.

GEOVOL is heterogeneous across equities. These companies have different exposures to climate change risks and, more importantly, have shown different sustainability strategies in their budget plans. An important implication of this difference is that it makes possible to hedge against geopolitical risk by buying equities with largest loadings and selling the ones with smaller loadings. For more details on portfolio optimality in the presence of geopolitical volatility, we refer to Engle and Campos-Martins (2020).

Table 2: The estimated oil and gas geopolitical volatility 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

As a measure of the goodness of the fit, we re-run the test for common volatility shocks on the standardized residuals, now standardized by O&G GEOVOL. The null hypothesis is re-defined to $\mathbb{H}_{02} : \bar{\rho}_{\boldsymbol{e}^2/\hat{\boldsymbol{g}}} = 0$, where $\boldsymbol{g}$ contains the heterogeneous volatility factors $g_{it} \equiv g_{it}(s_i, x_t)$ defined in (5), $i = 1, \ldots, N$. The empirical $\bar{\rho}_{e^2/\hat{x}} = -0.004$, the test statistic is -0.522 and the $p-$value $= 0.699$. This failure to reject the null of no correlation in the square standardized residuals $\boldsymbol{e}^2/\hat{\boldsymbol{g}}$, supports the multiplicative decomposition of the standardized residuals and the ability of O&G GEOVOL to capture the common shocks driving changes in the global oil and gas equity market.

3 Measuring climate change volatility shocks

Two main transmission channels of climate change risk to financial markets are usually pointed out in the literature. These are referred to as physical and transition risks. Climate change can adversely impact capital stock, economic activities and markets directly as more frequent and severe climate-related disasters occur and are predicted for the upcoming years. The social, economic and political impact of physical risk is mostly country-specific, but it has potential systemic implications. A country that is less vulnerable to climate-related events can still have a great indirect exposure to physical risk through international relations with countries that are particularly vulnerable. Financial stability is however most likely to be affected by climate change indirectly through increasing transition risk. As the uncertainty about the timing and the speed of adjustment towards green economies increases, so does transition risk. The systemic implications that climate change poses to financial markets are thus most likely to come from transition risk and carbon-intensive sectors. Transition risk includes the impact on carbon-intensive asset prices of policy changes towards carbon pricing, legislation like the UK's Climate Change Act of 2008 and disruptive technological progress.

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

In assessing the economic impact of climate change, research has relied on rising mean temperature levels. Diebold and Rudebusch (2019) go a step further and propose a novel range-based measure of daily temperature volatility. The new measure of temperature volatility is called the diurnal temperature range and is defined as the difference between the daily maximum and minimum temperatures at a given location.

However, when assessing how climate change is affecting financial markets through transitional risk, it is difficult to think that shocks to temperature volatility will impact the volatilities of many asset returns around the world.

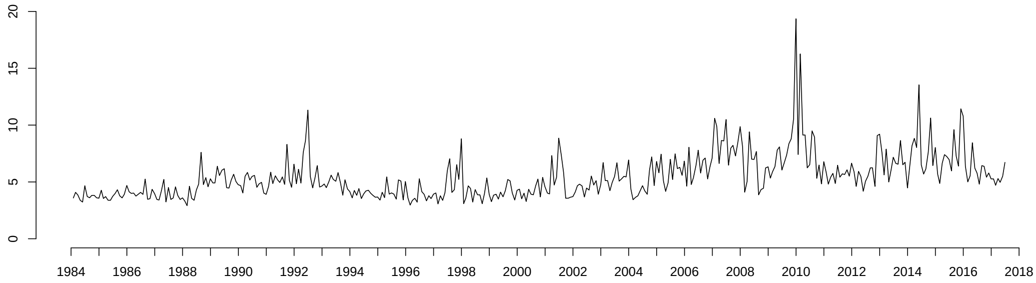
To measure the impact of climate change empirically, we start by using the monthly climate change news index of Engle et al. (2020). By applying textual analysis to the daily Wall Street Journal (WSJ), the climate change news generic index measures the fraction of its text content dedicated to the topic of climate change. The climate change vocabulary is defined as a set of representative words from relevant texts published by governments and research organizations. To construct the index, a score is assigned to each edition of the WSJ based on the relevance of its climate change content. For instance, a low score is attributed to a particular edition if it has terms that appear in most editions on other days as well. The low score is thus intended to reflect the less informative WSJ content on that particular day. A high score, on the other hand, reflects a text content on a given day with representative terms that appear infrequently overall but frequently in that day's newspaper edition. The index is then computed as the cosine similarity between the scores and each edition of the WSJ. The index ranges between zero - no words on the WSJ match the climate change vocabulary - and unity - if text content of the WSJ shows the same terms in the same proportion as the authoritative texts used to construct the vocabulary. This monthly index is available between 1984/01 and 2017/06. To distinguish between positive news and bad news, a different version of the index is provided. Using sentiment analysis, bad (or negative) news about climate change can be identified and a climate change bad news index is constructed for the period between 2008/06 and 2017/06. Both indexes, general and bad news, are plotted in Figure 4.

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

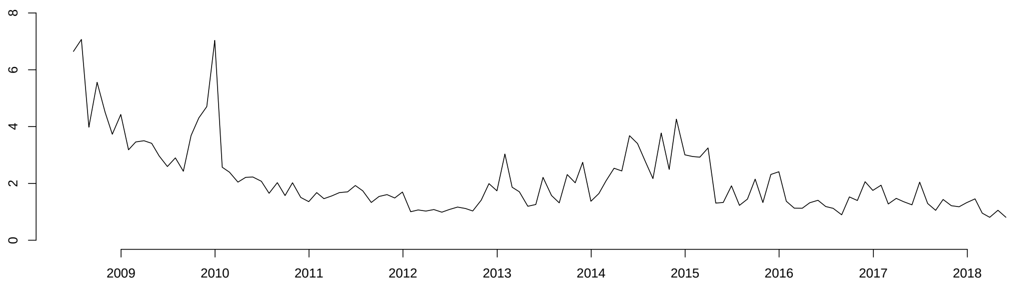
To compute the climate change volatility shocks, we start by modeling the climate change news index, generally denoted by $CC_t, t = 1, \ldots, T$, as an AR(1) process. A climate change volatility shock is then defined as

$$e^2_{CC,t} - 1 = \frac{(CC_t - \mu_{CC} - \beta_{CC} CC_{t-1})^2 - h_{CC,t}}{h_{CC,t}}, \tag{7}$$

where μ_{CC} is the intercept in the mean equation, β_{CC} is the coefficient of the first-order autoregressive term, and $h_{CC,t}$ is the variance of the residuals from the mean equation of the climate change news index. The climate change volatility shock represents the

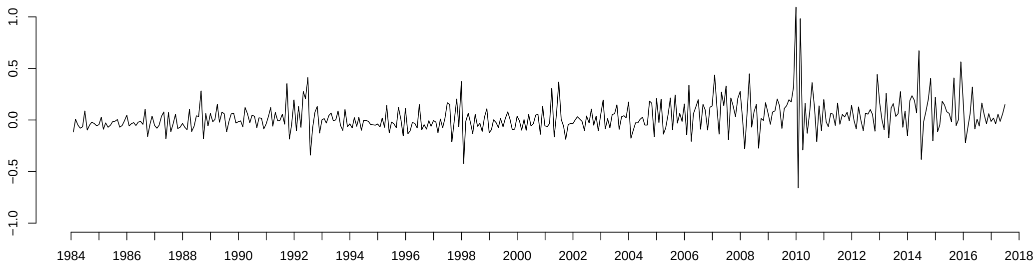


(a) Generic news index

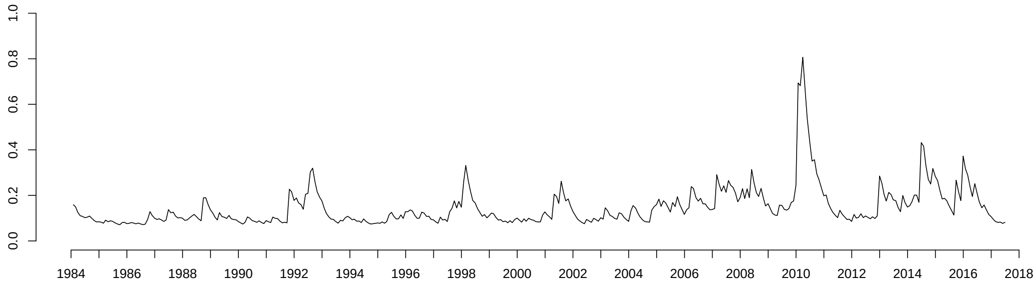


(b) Bad news index

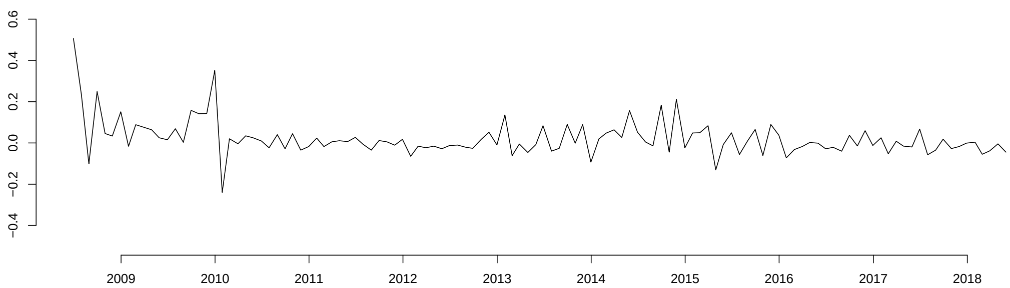
Figure 4: The monthly climate change generic and bad news index (multiplied by 1000) of Engle et al. (2020). Both indexes are available at http://pages.stern.nyu.edu/~jstroebe/Data/EGLKS_data.xlsx.



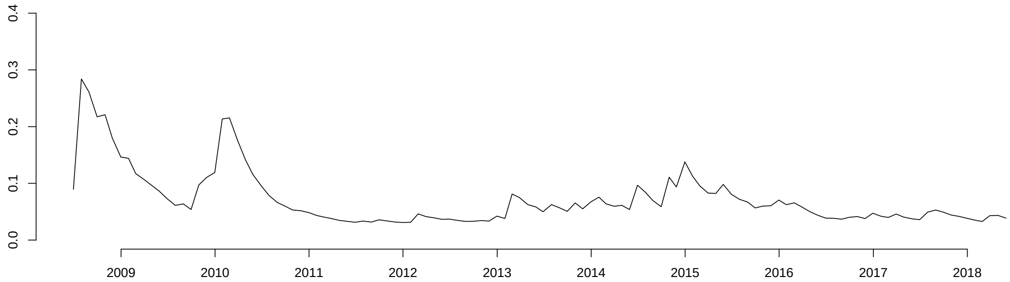
(a) CC: Innovations



(b) CC: Volatility



(c) CC^{-}: Innovations



(d) CC^{-}: Volatility

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

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

The same strategy to identify volatility shocks is applied to the other determinants of O&G GEOVOL considered below.

4 Disentangling geoclimatic volatility

Common volatility shocks to the global oil and gas equity market come from different sources. 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. This is an important result to assessing the systemic nature of geopolitical risk. However, the direction of these effects is not clear. As a proxy for geopolitical risk, Smales (2021) uses the geopolitical risk index of Caldara and Iacoviello (2019). This index measures the monthly ratio of the number of articles related to geopolitical tensions to the total number of articles in eleven newspapers published in the US, the United Kingdom and Canada. By applying text mining, the index seems biased towards the words selected, which include explicit mentions of geopolitical risk, military-related and nuclear tensions, war and terrorist threats. This makes the index presumably a better indicator of military risk. It might be the case that by using a broader measure of geopolitical risk, such as geopolitical volatility, results are reversed. Shocks to the global oil market such as those arising from price or trade wars drive geopolitical risk (rather than the other way round) as this market is by nature geopolitical.

To control for other relevant shocks affecting the oil and gas geopolitical volatility, we consider volatility shocks to the 1) 1-month future West Texas Intermediate crude oil price (denoted by WTI), 2) Standard & Poor's Depositary Receipts (SPDR) S&P 500 exchange traded fund (SPY), and 3) all country world index (ACWI). The WTI is a global benchmark index likely to reflect three types of volatility shocks, namely supply shocks, shocks to the global demand for all industrial commodities, and demand shocks specific to the global crude oil market (Kilian, 2009). The latter is interpreted as the precautionary demand that arises almost instantaneously with market concerns regarding future oil supplies. In practice, expectations about future oil supply change in response to exogenous political shocks reflected in shifts in the conditional variance - rather than the conditional mean - of oil supply shortfalls and consequent increase in the real price of oil. Kilian (2009) shows that demand shocks, in particular precautionary demand shocks, are the main drivers of the global oil market price as opposed to the common wisdom favoring oil supply shocks. The volatility shocks arising from the global oil market are interpreted as either oil supply volatility shocks as they are likely to reflect OPEC decisions regarding oil production as found in section 3 or oil precautionary demand volatility shocks. 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 all carbon-intensive equities are traded in the NYSE and the relevance of the US in the global financial system, the SPY is used here to capture US equity market shocks as well as indicate 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. This index is indented to capture global equity market shocks. Even though they both measure global volatility shocks, the ACWI and the geopolitical volatility of country equity ETFs, the reason why we choose to use the ACWI rather than the country GEOVOL index of Engle and Campos-Martins (2020) has to do with reverse causality. Some of the geopolitical shocks affecting the oil and gas global equity market are the same as the ones affecting the global country equity market, as measured by GEOVOL. We find however no evidence for reverse causality between O&G GEOVOL and the ACWI volatility shocks. It may also be argued that oil price shocks are likely to affect the US and the global equity markets as well. Finally, precautionary demand volatility shocks may also reflect concerns about future oil shortfalls due to tighter climate policies regarding carbon-intensive activities. Disentangling the source of common shocks to the global oil and gas equity market may thus be challenging.

To analyze to what extent climate change news affects the volatility of the global oil and gas equity market, we define and compute climate change volatility shocks as in (3). In Table 3, we present the estimation results for the multiple linear regressions of the oil and gas geopolitical volatility (O&G GEOVOL) on two climate change indicators, namely the volatility shocks arising from climate change generic news (CC_m^+) and climate change bad news (CC_m^-), and the three other variables controlling for volatility shocks arising from the global oil market (WTI), the US equity market (SPY), and the global equity market (ACWI). Because the climate change news indexes are monthly, we compute monthly averages for all other variables. The sample size for the bad news index is limited to the period between 2008/06 until 2017/06 so the sample is shortened accordingly. The good news is that from 2008/06 the oil and gas panel is balanced (with no missing values).

Table 3: Geoclimatic volatility: the effects of volatility shocks to the climate change generic (CC_m^+) and bad (CC_m^-) news index on oil and gas geopolitical volatility, O&G GEOVOL. Volatility shocks to the SPDR S&P 500 ETF (SPY_m), the 1-month WTI crude oil future (WTI_m) and the all country world index ETF ($ACWI_m$) are included as control variables. For comparison, results are also shown for the energy sector fund (XLE_m).

	O&G GEOVOL$_m$			
	(1)	(2)	(3)	XLE$_m$
CC_m^+	-0.031^{**}	-0.039	-0.037^{**}	-0.005
	(0.016)	(0.024)	(0.017)	(0.010)
CC_m^-	0.046^{*}	0.041	-0.023	-0.002
	(0.024)	(0.025)	(0.034)	(0.014)
WTI_m	0.509^{***}	0.485^{***}	0.409^{***}	0.329^{***}
	(0.104)	(0.124)	(0.104)	(0.064)
SPY_m	0.179	0.219	0.258^{*}	0.234^{**}
	(0.152)	(0.156)	(0.148)	(0.093)
$ACWI_m$	0.212^{*}	0.207	0.216^{*}	-0.025
	(0.123)	(0.137)	(0.119)	(0.076)
$WTI_m \times CC_m^+$		-0.054		
		(0.124)		
$SPY_m \times CC_m^+$		0.089		
		(0.094)		
$ACWI_m \times CC_m^+$		-0.019		
		(0.092)		
$WTI_m \times CC_m^-$			0.111^{***}	
			(0.042)	
$SPY_m \times CC_m^-$			-0.054	
			(0.092)	
$ACWI_m \times CC_m^-$			-0.250^{***}	
			(0.093)	
O&G GEOVOL$_{m-1}$	0.191^{**}	0.195^{**}	0.141^{*}	
	(0.078)	(0.079)	(0.076)	
Observations	107	107	107	108
Adj. R^2	0.325	0.316	0.385	0.250
$\hat{\sigma}$	0.467	0.470	0.445	0.289
F Statistic	9.578^{***}	6.500^{***}	8.434^{***}	8.212^{***}

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

The Ljung-Box AR(1) test statistic for the model without the lagged dependent variable is 5.769 (0.016). Thus, to model the time dependence in the data we add a first-order auto-regressive component to every regression.

According to the estimation results for the baseline regression (1), volatility shocks to the climate change generic and bad index have, respectively, negative and positive effects on the global oil and gas equity market volatility. By including both indexes in the analysis, we aim to distinguish the effects of each on O&G GEOVOL. Notwithstanding the evidence that climate change generic news affects O&G GEOVOL, bad news tends to rather create adverse and larger (in magnitude) effects. Interestingly, when only the generic news index is included in the regression, no statistically significant effect is found. This may be due to the fact that good and bad news affect O&G GEOVOL in opposite directions, which presumably cancel out. Only when both indexes are included, are we able to disentangle the significant effects of good and bad news.

The positive coefficient associated with the bad news index (0.046) indicates that unexpected volatility shocks driven by bad news about climate change are associated with relativity large oil and gas geopolitical volatility. When arising from a climate change generic news, a relatively smaller decrease in the global oil and gas equity market volatility is estimated (-0.031). The negative sign does not mean oil and gas equity return volatilities are decreasing, it means they are changing less in either direction. By including the bad news index, we hope that the generic news index is able to mostly capture the effect of positive news about climate change. This seems to be supported by the negative sign of the estimated coefficient for CC^{+}. Good news about climate change makes investors feel more confident about the future of oil and gas leading to less uncertainty and smaller oil and gas unexpected volatility shocks. Bad news about climate change is more likely to cause major changes in the oil and gas equity returns as it creates more uncertainty regarding the viability of investments in carbon-intensive assets and activities. This follows the literature on the asymmetric effects of good and bad news on volatility. It is well known that negative shocks to stock prices produce more volatility than positive shocks. Similarly, the magnitude of the effect of climate change volatility shocks on the volatilities of oil and gas stock returns is greater when the news is bad compared to a generic news.

Overall, shocks to any of the control determinants seem to make the global oil and gas equity market move. In other words, the volatility of global oil market, the US equity market, and the global equity market and that of the global oil and gas equity market all move together. We find however robust evidence that shocks to the global oil market are also affecting the global oil and gas equity market, as measure by O&G GEOVOL. Some of the largest oil and gas geopolitical volatility shocks coincide with days when OPEC announced its decisions regarding oil production, decisions that have frequently been different from what markets were expecting or hoping for. Hence, supply-based oil volatility shocks tend to drive large unexpected changes in the global oil and gas equity market volatility. The US and the global equity markets also affect O&G GEOVOL meaning that higher economic uncertainty, locally and globally, is reflected in higher demand-based uncertainty around oil an gas equities. Considering that 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 GEOVOL is, in general, counter-cyclical.

In order to analyze if the impact of these control determinants changes when there is simultaneously climate change news, we also include interaction terms between them and CC^+ in (2) and CC^- in (3). It is interesting to observe that climate change bad news amplifies the effects of oil volatility shocks. As an example, take the drone attack to the Saudi Aramco oil facilities in Saudi Arabia on November 30, 2016. The disruption in oil production had an immediate impact on oil prices around the world and the effects on the stock prices of major oil companies followed suit. Now suppose that on the same day devastating wildfires hit Australia raising concerns about climate change both in terms of physical and transition risks, and about the future of oil and gas. This climate change bad news thus amplifies the positive effect of the oil volatility shock on O&G GEOVOL. Regarding the equity markets, it seems that a volatility shock to the global equity market attenuates (-0.250) the effect of simultaneous climate change bad news. This may be due to the fact that global equity market shocks are still relatively more relevant than 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 on climate change, it is not surprising that the effect is relatively smaller.

Given the similarities between the companies included in the energy sector fund XLE and those used to estimate O&G GEOVOL, we regress the volatility shocks to the XLE on the same determinants as in (1). The results are shown in the last column of table 3. We find no evidence that climate change news affects the energy sector, where only the WTI seems to explain XLE volatility movements. Climate change news seems to have an impact and be material (rather than fake) only when it affects oil and gas companies around the world (and not just those in the US). From the historical denial and skepticism about climate change to the withdrawal from the Paris agreement during the administration of President Donald Trump, this result is hardly surprising.

There is no evidence that global oil market volatility is driven by climate change news. A linear regression of the WTI volatility shocks on CC^+ and CC^- shows no statistically significant effects, even when controlling for the other determinants. Investors appear to be pricing climate change risks in oil and gas companies rather than the commodities themselves. This is also likely to be reflecting the fact that demand for oil is quite inelastic. Climate change generic news does seem to affect both US and global equity markets. These results are not shown to save space.

To check the robustness of results to the presence of outliers and shifts, we allow for richer structures of O&G GEOVOL. By applying the indicator saturation approach introduced by Hendry (1999), we are able to detect structural changes and outliers in O&G GEOVOL. Time-varying coefficients will later be allowed such that the geo-climatic volatility is also allowed to be more flexible over time. Impulse and step indicators are dummy variables which assume value 1 from time t (inclusive) and zero otherwise. By applying both impulse and step indicator saturation (Hendry et al., 2008), we are able to detect, respectively, outliers and shifts in the mean of O&G GEOVOL. All regressions with indicator saturation have been estimated using the R package *gets* (Pretis et al., 2018). The monthly impulse and step indicators introduced as regressors are not reported to save space. On average, oil and gas geopolitical volatility appears to have increased over time. The statistically significant indicators, for instance, in regression (4) are $\text{IIS}_{m=10/2008}$, $\text{IIS}_{m=04/2010}$ and $\text{SIS}_{m=10/2008}$. But others impulse indicators have also been selected in other regressions such as $\text{IIS}_{m=10/2014}$, $\text{IIS}_{m=01/2016}$ or $\text{IIS}_{m=11/2016}$. Notice that some of the biggest oil and gas geopolitical events are identified as outliers, meaning IIS captures what determinants do not. Hence, including impulse and step indicator saturation seems to improve the empirical results as shown in table 4. Oil and gas geopolitical volatility spikes and shifts appear to be only introducing noise in the geoclimatic volatility. It is now revealed that climate change generic news can have an adverse effect on O&G GEOVOL if at the same time markets face an unexpected volatility shock arising from the US equity market. The coefficient capturing this effect is positive, statistically significant and equal to 0.130.

Table 4: Estimation results when impulse (IIS) and step (SIS) indicator saturation is applied (not shown).

	(4)	(5)	(6)
CC_m^+	-0.020	-0.041^{**}	-0.038^{***}
	(0.013)	(0.018)	(0.014)
CC_m^-	0.036^{*}	0.035^{*}	-0.034
	(0.019)	(0.019)	(0.027)
WTI_m	0.406^{***}	0.336^{***}	0.324^{***}
	(0.085)	(0.095)	(0.085)
SPY_m	0.047	0.179	0.068
	(0.159)	(0.159)	(0.155)
ACWI_m	0.245^{**}	0.245^{**}	0.249^{**}
	(0.104)	(0.109)	(0.100)
$\text{WTI}_m \times \text{CC}_m^+$		-0.116	
		(0.097)	
$\text{SPY}_m \times \text{CC}_m^+$		0.130^{*}	
		(0.072)	
$\text{ACWI}_m \times \text{CC}_m^+$		-0.010	
		(0.071)	
$\text{WTI}_m \times \text{CC}_m^-$			0.118^{***}
			(0.033)
$\text{SPY}_m \times \text{CC}_m^-$			-0.003
			(0.073)
$\text{ACWI}_m \times \text{CC}_m^-$			-0.316^{***}
			(0.076)
O&G GEOVOL_{m-1}	0.098	0.120^{*}	0.062
	(0.062)	(0.060)	(0.062)
Observations	107	107	107
Adj. R^2	0.601	0.625	0.620
$\hat{\sigma}$	0.360	0.349	0.352
F Statistic	15.518^{***}	12.790^{***}	13.353^{***}

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

Finally, results are also consistent when neither the WTI 1-month oil future is included as an additional regressor in the Fama and French three factor models nor the cross-sectional mean of oil and gas standardized residuals is included in the estimation of O&G GEOVOL. These results are not shown to save space.

It is commonly thought that climate change is inducing structural changes in the financial system (Network for Greening the Financial System, 2019). To allow for time-varying effects on the global oil and gas equity market volatility meaning, for instance, a more flexible geoclimatic volatility structure over time, we apply the multiplicative saturation approach of Ericsson (2012). The idea is to interact CC^{+} and CC^{-} with impulse and step indicators. To keep the model parsimonious and given structural changes due to climate change are unlikely to occur at a high frequency, we construct yearly step indicators. These are dummy variables which assume value 1 at or after year y and zero otherwise. To select the relevant dummies, a general to specific approach is applied such that we start with a fairly general unrestricted model with all indicators included and then narrowed down until we get to the final restricted model where only the statistical significant indicators are included. These results are presented in table 5. Notice that the selected monthly IIS and SIS are not reported to save space.

The most important result from this multiplicative indicator saturation approach to geoclimatic volatility is that its time-varying structure is revealed not only for the global oil and gas equity market but also for the US energy sector XLE, which previously showed no impact of climate change news. Results using impulses or steps tell a similar story as steps can be interpreted as combinations of impulses. Hence we opt for only reporting results when yearly steps and their interactions with CC^{-} are included. The results support the existence of an adverse effect of climate change bad news on O&G GEOVOL. Moreover, they provide evidence that this effect has changed in magnitude over time. In particular, the year 2016 is marked by a large increase in the geoclimatic volatility of the global oil and gas equity market. Interestingly, this increase is also observed for the US energy sector (there is no evidence for an adverse effect of climate change bad news on the XLE volatility only until 2016). The year 2016 was a remarkable year in terms of political and climate policy events. The Paris Agreement was signed on April 22, 2016 and became effective on November 4, 2016. The same year, the UK European Union membership referendum surprisingly was in favor of *Brexit* on June 23 raised widespread concerns about their future climate and environmental policy, and Donald Trump was unexpectedly elected as US President on November 9, who regarded climate change as fake news and promised to withdraw the US from the international climate accord.

The effect of climate change generic news appears to be very stable over time as neither the yearly IIS nor the SIS indicators are statistically significant. For that reason, the results are not reported.

Table 5: Estimation results when step indicator saturation (SIS) is applied (not shown), and $\text{SIS}_m^{y \geqslant x}$, taking value 1 for month m in year x and following years, interacted with the climate change bad news CC_m^- are included (only the statistically significant are shown).

	O&G GEOVOL_m	XLE_m
WTI_m	0.312***	0.210***
	(0.083)	(0.054)
SPY_m	0.069	0.055
	(0.149)	(0.094)
ACWI_m	0.265***	0.079
	(0.098)	(0.064)
CC_m^+	−0.024**	0.003
	(0.012)	(0.008)
CC_m^-	0.033*	−0.012
	(0.018)	(0.011)
$\text{CC}_m^- \times \text{SIS}_m^{y \geqslant 2016}$	0.496***	0.377***
	(0.138)	(0.086)
$\text{CC}_m^- \times \text{SIS}_m^{y \geqslant 2017}$	−0.478***	−0.267**
	(0.179)	(0.114)
O&G GEOVOL_{m-1}	0.143**	
	(0.060)	
Observations	107	108
Adj. R^2	0.652	0.539
$\hat{\sigma}$	0.336	0.223
F Statistic	15.180***	12.374***

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

Investors in carbon-intensive activities seem to be pricing climate change risks. Using world's major oil and gas stock prices, our empirical evidence shows that the global oil and gas equity market is reacting to climate change news, especially when the news is bad. The impact has become larger over time and is amplified by oil shocks. In order to analyze if the impact of climate change news on oil and gas geopolitical volatility changes across different climate change frequencies and topics, we use another index to construct the climate change volatility shocks. The Media Climate Change Concerns (MCCC) index of Ardia et al. (2020) and intended to measure unexpected increases in climate change concerns. It is a daily index constructed by applying text mining to climate change-related news published by major US newspapers. The selected high-reaching (daily circulation of more than 500,000) newspapers are (i) The Wall Street Journal, (ii) The New York Times, (iii) The Washington Post, (iv) The Los Angeles Times, (v) The Chicago Tribune, (vi) USA Today, (vii) New York Daily

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

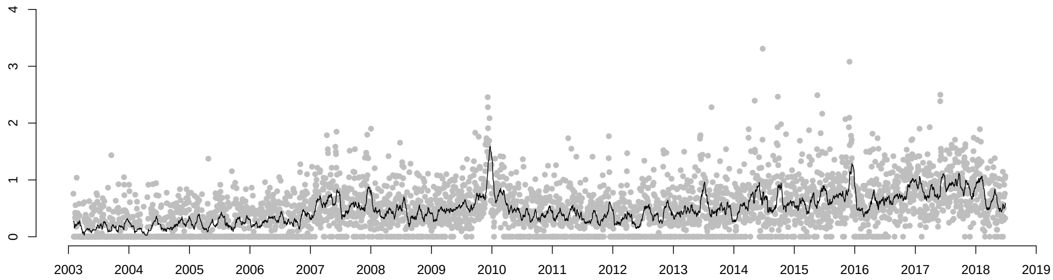


Figure 6: The daily MCCC index (gray) and 20-day rolling window average (black). The index is available at https://www.dropbox.com/s/way43an9xntvqwn/Sentometrics_US_Media_Climate_Change_Index.csv?dl=1.

In order to compare the climate change daily volatility shocks to the oil and gas geopolitical volatility over time, we compute a 20-day rolling window average from the daily point estimates. This averaged series is plotted in figure 7.

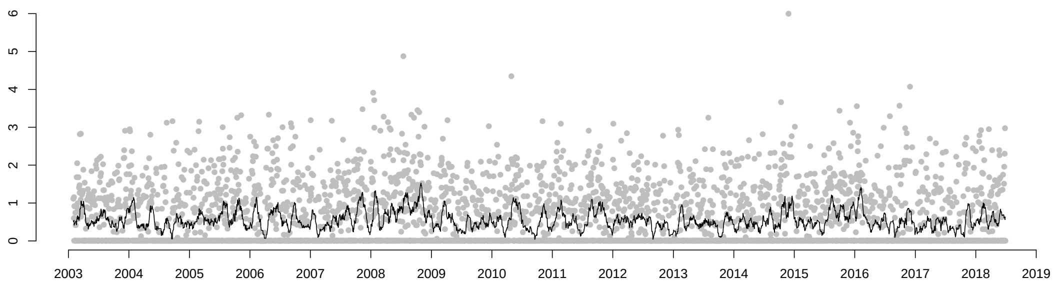


Figure 7: The daily oil and gas geopolitical volatility points (gray) and its 20-day rolling window average (black).

We start by computing the first difference of the MCCC index to remove stochastic trends. There is strong evidence for time dependence in both first and second moments according to, respectively, the AR and ARCH tests results. Similarly to Ardia et al. (2020), using this index as an additional factor in the oil and gas pricing factor models, we find no evidence that it affects the global oil and gas equity returns.

Volatility shocks to the MCCC index do affect the oil and gas volatilities around the world and ultimately the oil and gas geopolitical volatility as shown in table 6. Daily geoclimatic volatility has important implications in terms of the term structure of climate change risk, as transition risk seems to materialize in relatively shorter horizons (Bolton and Kacperczyk, forthcoming). Evidence for daily geoclimatic volatility is supported by the positive and statistically significant coefficient associate to MCCC_t. Interestingly, climate change risk seems to materialize only when there is no volatility shock to the global oil market. Even though climate change bad news seemed to amplify the adverse effect of oil shocks, in shorter horizons climate change concerns appear to be relatively irrelevant to risk managers compared to the global oil market risk. This result is consistent with common wisdom that investors still incorrectly view the implications of climate change to be relevant only in the long run and so are more focused on returns than sustainability.

There is no evidence of time dependence in the first or second moment of the residuals from all regressions. To save space, the results from the AR(2) and ARCH(2) tests are not reported.

Table 6: Geoclimatic volatility: the effects of volatility shocks to the media climate change concerns index MCCC_t on oil and gas geopolitical volatility, O&G GEOVOL.

	(1)	(2)	(3)	(4)	(5)
MCCC_t	0.042**	0.048***	0.039**	0.042**	0.048***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
WTI_t	0.189***	0.184***	0.190***	0.190***	0.184***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
SPY_t	0.054***	0.055***	0.052**	0.054***	0.055***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
ACWI_t	0.086***	0.086***	0.086***	0.084***	0.084***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
$\text{WTI}_t \times \text{MCCC}_t$		−0.030***			−0.031***
		(0.010)			(0.010)
$\text{SPY}_t \times \text{MCCC}_t$			−0.011		0.0001
			(0.016)		(0.016)
$\text{ACWI}_t \times \text{MCCC}_t$				−0.015	−0.016
				(0.010)	(0.010)
O&G GEOVOL_{t-1}	0.062***	0.062***	0.062***	0.061***	0.061***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
O&G GEOVOL_{t-2}	0.058***	0.057***	0.057***	0.058***	0.057***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Observations	3,899	3,899	3,899	3,899	3,899
Adj. R^2	0.061	0.063	0.061	0.061	0.063
$\hat{\sigma}$	1.868	1.866	1.868	1.867	1.866
F Statistic	43.291***	38.506***	37.163***	37.414***	30.214***

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

Our evidence showed that investors have become more concerned over time about oil and gas companies exposing them to climate-related financial losses. By applying yearly impulse and step indicator to the MCCC index, in Table 7 we observe again an increase in the impact of the MCCC index on O&G GEOVOL over time. In particular, it increases in 2004 and then it further increases in 2010. Geoclimatic volatility seems to be gaining more importance as climate change concerns and awareness drive the global oil and gas equity market volatility over time. Our empirical results thus support both monthly and daily geoclimatic volatility.

Table 7: Estimation results when impulse (IIS) and step (SIS) indicator saturation is applied, and $\text{IIS}_t^{y=x}$, taking value 1 for month m in year x, interacted with MCCC_t are included (only the statistically significant are shown).

	(6)	(7)
WTI_t	0.189***	0.187***
	(0.015)	(0.015)
SPY_t	0.050**	0.050**
	(0.021)	(0.021)
ACWI_t	0.086***	0.086***
	(0.016)	(0.016)
MCCC_t		0.042**
		(0.017)
$\text{MCCC}_t \times \text{IIS}_{2004}$	0.167***	
	(0.057)	
$\text{MCCC}_t \times \text{IIS}_{2010}$	0.211**	
	(0.087)	
IIS_{2008}	0.603***	
	(0.118)	
SIS_{2008}		0.606***
		(0.118)
SIS_{2009}		−0.741***
		(0.130)
SIS_{2014}		0.162**
		(0.077)
O&G GEOVOL_{t-1}	0.055***	0.053***
	(0.016)	(0.016)
O&G GEOVOL_{t-2}	0.050***	0.049***
	(0.016)	(0.016)
Observations	3,899	3,899
Adj. R^2	0.069	0.068
$\hat{\sigma}$	1.860	1.861
F Statistic	37.093***	32.738***

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

Aggregating news by topics and themes provides a more comprehensive analysis of the impact of different news on the global oil and gas equity market. In particular, stock prices of oil and gas companies around the world seem to be more volatile following news on the agricultural impact of climate change as shown by regression (8) in table 8. The effect of news involving livestock, topic 20 shown in table 9, on the oil and gas geopolitical volatility is particularly pronounced. Similar effects are thus to be expected if the geoclimatic volatility approach is applied to agri-business assets as increased attention and pressure have been raised due to climate-damaging agricultural practices[2]. Climate change news relating to financial and regulation or public impact has a positive effect on oil and gas geopolitical volatility as well. News on disasters appears to rather decrease oil and gas geopolitical volatility. This may be due to the fact that news on a particular disaster has mostly local effects (International Monetary Fund, 2020) and so unlikely to have a global impact (unless they become too frequent, widespread and increase transition risk).

Finally, the ten words with the highest probability for the statistically significant topics shown in table 8 are the following:

Financial & Regulation

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

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

Environmental Impact

topic1 ship, drilling, oil, sea, fishing, shipping, coast, boat, shell, exploration.

Agricultural Impact

topic4 drought, region, river, rain, desert, lake, dam, rainfall, water_supply, mountain.

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

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

5 Discussion of policy implications

As time for an orderly transition to low-carbon economies runs out, the likelihood of extreme and global climate-related shocks to carbon-intensive asset prices rises and so does the likelihood of massive unexpected losses. It is well known that oil global shocks impact the real economy with effects across all sectors of activity and countries around the world. Financial markets are however not prepared to cope with such

[2]Using stock prices of the largest US meat processing company, the American Tyson Foods, climate change bad news has an adverse effect on the volatility of the Tyson Foods stock returns, and climate change generic news appears to exacerbate the effects of volatility shocks to the US stock market.

Table 8: The effects of MCCC on GEOVOL by theme. MCCC themes were computed as the average of the topics included in each theme following the classification proposed by Ardia et al. (2020).

	(8)	$\times$ WTI	$\times$ SPY	$\times$ ACWI
WTI_t	0.190***	0.189***	0.190***	0.193***
	(0.016)	(0.016)	(0.016)	(0.016)
SPY_t	0.055***	0.057***	0.047**	0.055***
	(0.021)	(0.021)	(0.021)	(0.021)
ACWI_t	0.086***	0.086***	0.088***	0.086***
	(0.016)	(0.016)	(0.016)	(0.016)
Financial & $\text{Regulation}_t \times$	0.032*	−0.011	−0.028	−0.008
	(0.016)	(0.012)	(0.020)	(0.010)
Agreement & $\text{Summit}_t \times$	−0.008	−0.008	−0.002	0.011
	(0.015)	(0.012)	(0.017)	(0.009)
Public $\text{Impact}_t \times$	0.014	0.003	−0.018	−0.030**
	(0.021)	(0.014)	(0.023)	(0.014)
$\text{Research}_t \times$	−0.0003	−0.020*	0.015*	0.006
	(0.007)	(0.011)	(0.008)	(0.008)
$\text{Disaster}_t \times$	−0.025*	−0.015	0.0002	0.005
	(0.014)	(0.010)	(0.015)	(0.011)
Environmental $\text{Impact}_t \times$	−0.014	0.014*	0.006	0.004
	(0.013)	(0.008)	(0.011)	(0.005)
Agricultural $\text{Impact}_t \times$	0.038***	−0.003	−0.003	−0.001
	(0.011)	(0.009)	(0.013)	(0.008)
O&G GEOVOL_{t-1}	0.061***	0.060***	0.062***	0.061***
	(0.016)	(0.016)	(0.016)	(0.016)
O&G GEOVOL_{t-2}	0.059***	0.059***	0.058***	0.059***
	(0.016)	(0.016)	(0.016)	(0.016)
Observations	3,899	3,899	3,899	3,899
Adjusted R^2	0.064	0.067	0.064	0.063
$\hat{\sigma}$	1.865	1.862	1.865	1.865
F Statistic	23.058***	15.730***	15.030***	14.914***

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

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

WTI_t	0.192^{***}
	(0.016)
SPY_t	0.055^{***}
	(0.021)
ACWI_t	0.089^{***}
	(0.016)
Topic1_t	-0.014^{*}
	(0.008)
Topic4_t	0.018^{*}
	(0.010)
Topic20_t	0.017^{***}
	(0.006)
Topic31_t	0.015^{**}
	(0.006)
Topic40_t	0.018^{*}
	(0.010)
O&G GEOVOL_{t-1}	0.061^{***}
	(0.016)
O&G GEOVOL_{t-2}	0.058^{***}
	(0.016)
Observations	3,899
Adjusted R^2	0.064
$\hat{\sigma}$	1.865
F Statistic	6.919^{***}

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

shocks where both carbon-intensive and low-carbon assets are affected by aggregate demand shocks. The uncertainty around future demand for fossil fuels due to climate change and, more recently, exacerbated by 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) is extremely high. Uncertain is also the future oil supply given the recent price wars (e.g., between Saudi Arabia and Russia). By their political power, wealth, and expertise, fossil fuel companies should be proactive in the transition process towards low-carbon economies. Because the current incentives (mostly moral) to shareholders are not enough, governments in countries highly dependent on fossil fuels must pressure them to produce greener and better by applying carbon taxes, taking legal action and financing green activities in order to make them more competitive while greening their financial systems.

Some challenges may hinder the transition process and once again policy action will be crucial. Country data shows that it is possible to reduce CO2 emissions and experience economic growth. But history has also shown that CO2 emissions tend to rise after economic or financial crises. Moreover, oil prices have been remarkably low and oil companies are among the highest dividend payers meaning transition to clean energies will be even more challenging as non-fossil fuels become relatively less competitive. As demand for oil starts showing signs of stagnation in some developed countries, there is a need to regulate oil companies from shifting to developing countries such as India and China and investing in oil exploration and production capacity. Because emissions are likely to grow elsewhere, especially in developing countries, it may be desirable to identify international relations, trade and financial contracts between firms in low and high carbon economies.

Virtually all assets are exposed to transition risk with different magnitudes meaning some assets are more responsive than others. Thus, assets with bigger volatility factor loadings are expected to be the more exposed to climate change risk because the more uncertain investors are regarding the profitability of their investments, and the more volatility shocks can be attributed to climate-related common innovations. Because volatilities are correlated, a common shock will sharply increase the volatility of a portfolio. Although it is not possible in this framework to predict when such a shock will occur (even though we can evaluate future climate scenarios), it is possible to form portfolios with reduced impact. This important feature of the geopolitical volatility model leads to a new criterion for portfolio optimality, intended to reduce the exposure to this type of risk; see Engle and Campos-Martins (2020). Hence, if the loadings on assets differ, it is possible to reduce (but not eliminate) this risk. A stable portfolio should be relatively insensitive to geoclimatic volatility and would prevent market turmoil during the transition process. As the probability of a disordered transition increases, uncertainty is likely to drive global carbon-intensive equity market volatility and pose increased risks to financial stability. Investors are already pricing climate change risks but to what extent are companies or firms reacting and changing accordingly? Information about the exposure of companies to common, global or geoclimate related risks is scarce. To promote more informed investing, lending, and insurance underwriting decisions, organizations across all sectors are recommended to disclose climate-related financial information (Task Force on Climate-related Financial Disclosures, 2017). But interpreting and drawing comparisons out of such non-harmonized information is difficult. The geoclimate volatility approach gives insight on which companies matter and how policymakers should pressure them and take action. As a policy instrument, governments and central banks can take positions on the geoclimate volatility index and help investors to diversify their portfolios during the transition process. At the global scale, it improves responses to tackle climate change as agreed by the Paris agreement. The role of the financial system in managing climate-related risks and mobilizing capital for low-risk investments is crucial (Network for Greening the Financial System, 2019). Our contribution to identifying the high and low risk assets, designing financial regulations and guiding capital flows can help.

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

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

6 Conclusion

Climate change risk, in particular transition risk, is as a source of geopolitical risk. Geoclimatic news is expected to impact the volatilities of a wide range of carbon-intensive equities. From a sample of stock prices from the world's major oil and gas companies, we apply a model of geopolitical volatility to capture global shocks to those volatilities arising from climate change, the global oil market, the US and the global equity markets.

Climate change geopolitical news is inducing global oil and gas equity market volatility. But not all geoclimatic shocks are alike. Overall, geoclimatic volatility has increased over time and differs across time frequencies, climate change sentiment (negative news has an adverse effect compared to positive news) and concerns (by topics and themes). Climate change news drives shocks to the global carbon-intensive equity volatility but not to the global oil market. It seems investors are pricing climate change risk in oil companies rather than the commodity.

Major funds are reluctant to divest from fossil fuels, arguing that by holding those shares they are in a better position to influence managers, to pressure companies to improve and to make sure they stay on track. The empirical evidence seems clear that investors are pricing in climate change risks. However, as long as climate-related financial information is not properly disclosed, it will be difficult to assess the risk of holding those shares. The approach we propose here can help to identify and target companies with debt or equity more exposed to climate risk during the process of decarbonising the global energy system.

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A List of carbon-intensive equities

Table 10: The world's major fossil fuel companies included in the estimation of carbon-intensive geopolitical volatility. These stocks are all traded in the NYSE.

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

*Acquired by Occidental Petroleum in 2019.

B Summary statistics

Table 11: 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)).

	CVX	DVN	E	EC	EOG
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
	EPD	**EQNR**	**HAL**	**KMI**	**OXY**
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
	PBR	**PSX**	**PTR**	**RDS**	**REPYY**
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 10: 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