The Ephemeral Brent Geopolitical Risk Premium

Hany Abdel-Latif[a,*], Mahmoud El-Gamal[b], and Amy Myers Jaffe[c]

May 2020

[a] *Swansea University, UK*
[b] *Rice University, USA*
[c] *Council on Foreign Relations*

Abstract

We study the changing relationship between Brent oil prices and geopolitical risk, conditional on physical oil market conditions. We conduct the analysis at three frequencies, medium (1-3 years), high (2-3 months), and very high (daily), using three complementary techniques at the different levels (respectively, continuous wavelet partial coherence, VAR and GARCH-MIDAS) over the period April 1993 to the end of 2018. At the annual frequency, we find evidence of a sustained positive relationship between oil prices and geopolitical risk over the past decade – with geopolitical risk leading during the Arab Spring, resulting in a substantial geopolitical risk premium, and lagging thereafter by about two months, as oil markets first reacted to and then anticipated geopolitical events. At the monthly frequency, we find the same positive correlation with oil prices anticipating geopolitical risk in both parts of the sample and find that realized geopolitical strife has not led to higher prices in either subsample. At the daily frequency, we find that geopolitical risk has had a positive effect on oil price volatility in later days during the second half of the sample (2005 to 2018). Our findings suggest that some financial market speculators, such as macro hedge funds and algorithmic traders, may amass long positions in Brent in anticipation of geopolitical threats that might potentially lead to oil disruptions.

Keywords: Oil price cycle, geopolitics, economic activity, oil inventories.

1. Introduction

Understanding oil price movements is vital for oil exporters and importers alike, and the broader effects on the global economy have been well documented for several decades. Persistent and unexpected changes in oil prices can lead to heightened risks and disrupted investment and production activities. Such changes feed uncertainty and economic instability and can thus curtail world economic growth. Since the 1970s, the global oil market has been characterized by periods of heightened fluctuations in

* Corresponding author: Hany Abdel-Latif (E-mail: h.abdel-latif@swansea.ac.uk), School of Management, Swansea University, Bay Campus, Fabian Way, Swansea, SA1 8EN, UK. We are grateful to participants at the AEA/IAEE meetings in San Diego, January 2020, for valuable comments. All remaining errors are our own.

nominal oil prices. This volatility appears to have accelerated in recent years, creating an increased interest in its drivers and influences.

Economists have shown that there is close linkage between economic activity and oil use. There is an extensive economic literature that relates oil price fluctuations to macroeconomic variables (Chen and Chen, 2007; Basher et al., 2016) and stock markets (Basher et al., 2018; Thorbecke, 2019). As economies in Asia expanded at unprecedented levels of economic development and wealth creation, a new specter of demand-driven shocks to oil prices emerged (Kilian, 2009). Studies provide evidence that specific supply-demand disequilibria, as well as market sentiment, can influence oil price movements (Deeney et al., 2015; Caldara et al., 2019). Still, geopolitical factors also offer compelling explanatory power for larger discontinuities. Over the decades, global oil trade has been interrupted by wars, cartels, revolutions, sanctions, and tariffs, which have had varying degrees of influence on oil prices.

An emerging literature is taking these broader considerations of global uncertainty and geopolitical risks into consideration and studying their role in determining the direction and magnitude of oil price changes (Abdel-Latif and El-Gamal, 2019*a*; Cunado et al., 2019). In the authors' own research, El-Gamal and Jaffe (2018) have analyzed the coupled self-perpetuating cycles of oil prices, financial crises, and geopolitical risk. In this regard, El-Gamal and Jaffe (2018) allowed for non-stationarity of oil production series by employing discrete wavelet decomposition of oil output series in various countries to identify the role that war and regime change may have played in altering oil supply patterns. The study found that change of government, including by revolutionary force, is not dispositive to shifting the supply curve of national oil production downward in a lasting manner. However, if coupled with violence against infrastructure, such disruptions can have dramatic longer-term impacts. Abdel-Latif and El-Gamal (2019*a*,*b*) extended this work on the trivariate cycle by investigating the joint dynamics of oil prices, financial liquidity, and geopolitical risk, using global vector autoregression models that presume a certain degree of covariance stationarity.

We now build on this literature to consider whether geopolitical factors could be weighing more heavily on oil price formation in recent years than in past decades. Such information is important to central banks who may seek to ameliorate the negative consequences of gyrating oil prices via monetary policy. It is also instructive to decision makers overseeing policies connected to national strategic oil stockpiles and to senior officials fashioning international diplomacy both in the context of major international fora such as the G-20 and engaging in diplomacy aimed to bring improvement of conditions in conflict prone regions. Understanding the role of geopolitics in oil price formation could be helpful to policy makers who regulate commodity futures markets and must consider appropriate policies for exchange-based trading amidst unusual circumstances of extreme events or in light of rising volume of speculative activity.

There have been many suggestions for why oil prices fluctuations appear to have become more pronounced in recent years. One theory is that the shorter development cycle of unconventional oil production from shale has hastened the supply response to changes in prices created by other market forces. In addition, there have been no shortage of geopolitical forces at play in recent years, including steady deterioration of stable political structures in multiple oil-exporting economies, intensification of conflicts across the Middle East, a rise in the use of economic sanctions by the United States against several very large oil producing states, and a loosening of the ability of the Organization of Petroleum Exporting Countries (OPEC) to defend its market share.

In this study, we use a variety of methodologies to provide new evidence that the structure of correlation patterns between oil prices and geopolitical risk has been changing over time. We use U.K. Brent crude as our proxy for oil prices because it is considered the widely traded benchmark most influenced by global trends. Brent crude is waterborne, meaning that it is sold in the spot, or non-contract, cargo market where oil can be freely moved by ship from one location to another. This makes the benchmark less susceptible to parochial regional inland trends than West Texas Intermediate crude, another highly visible benchmark grade. Our aim is to study the persistence of significant epochs or trends and related causal relationships. We utilize both identification of patterns of correlation and Granger-causation (in the sense of temporal succession) during extended periods and try to strike a balance between the two sets of results. We take this approach to retain some ability to appeal to stationarity, while allowing for changes in those patterns, which requires allowing for substantial and consequential non-stationarity. Our analysis identifies three periods during which we find statistically significant positive correlation between oil prices and a well-established geopolitical risk index: the period around the 2003 Iraq War; the initial phase of the Arab Spring; and finally, an extended period from the end of Arab Spring protests and violence until 2019.

Our starting point in this paper is a continuous wavelet transform analysis that builds on the methods developed and first used in studying the relationship between oil prices and macroeconomic activity in Aguiar-Conraria and Soares (2011*b*). The advantage of this method is that it does not require time-localized correlation (as measured by coherence) and causation patterns and lags (as measured by phase shifts) to persist for any significant epoch. Nonetheless, we may discover such persistence (local stationarity) in some epochs at some frequencies, without imposing them on the data in our statistical methodology, which makes the discovery of such patterns illuminating. In this regard, a number of recent studies have identified significant non-stationarity in oil price regimes. For example, Kaufmann and Connelly (2019) have found nine oil price regimes between 1938 and 2018, including four after 2004. Ansari and Kaufmann (2019); Ansari (2017) emphasize, most recently, the importance of OPEC's change in strategy to accommodate tight oil. A number of earlier studies have used continuous wavelet coherence analysis to examine causal relationships between oil prices and energy stocks, exchange rates and other energy commodities, (Roberdo et al., 2017; Roberdo and Rivera-Castro, 2013; Vacha and Barunik, 2012, respectively). The closest analogue to our continuous wavelet transform analysis, using partial coherence to condition on variables, such as aggregate economic activity and inventories in our study, is that of Dong et al. (2019), although they conditioned on one variable at a time. We were able in this study to calculate partial coherence conditional on two variables without increasing computational time unreasonably.

Our results are consistent with the hypothesis that some financial market speculators amass Brent oil futures contract holdings in anticipation of geopolitical threats that could potentially disrupt oil supplies. We find that in the one to three-year time horizon, oil price movements consistently lead in the direction of changes in geopolitical risk predating actual geopolitical events by roughly two months. Our study finds evidence that a start in the higher correlation between threats of risk and oil prices coincided with the worsening of the political crisis in Venezuela that cut off oil supplies temporarily in 2002. It is possible that the Venezuelan crisis altered perceptions about the importance of geopolitical risk to oil price formation and was sustained by the Iraq war and Arab Spring events. The persistence of a geopolitical risk factor to oil prices amid higher than usual oil price volatility in recent years informs industry and policy makers alike about the importance of policies that ameliorate perceptions of the threat to supplies, including strategic stocks. It also provides additional data for future updated studies on the role of speculation in exchange based oil trading.

We proceed by outlining our methodology and summarizing the results in stages. In Section 2, we outline the medium-term one to three-year frequency analysis via partial wavelet coherence, highlighting the main result of oil prices leading geopolitical events by about two months. We then follow with short-term time domain analysis via vector autoregression to study Granger causality and impulse response functions between oil prices and geopolitical risk (Section 3). In Section 4, the paper then proceeds with a model of very-short-term oil price volatility using a variant of the GARCH-MIDAS model to account for structural breaks in the short-term volatility component. We end with a summary of results and concluding remarks in Section 5.

2. Medium-Term (2–3 Year) Frequency Analysis via Partial Wavelet Coherence

We begin our data analysis in this section by studying the time-changing partial-correlation analogue (partial coherence) between Brent oil prices and geopolitical risk as measured by Caldara and Iacoviello (2018). This index is constructed from the frequencies of geopolitical risk keyword occurrences in eleven leading newspapers. The partial coherence is calculated for different frequencies and over time, conditional on global economic activity, as measured by Kilian's index – c.f. Kilian (2009); Kilian and Zhou (2018); Kilian (2019) – and global oil storage, as retrieved from data from Energy Intelligence Group, publisher of Petroleum Intelligence Weekly. All series in this initial analysis are monthly, extending from March 1993 to end of 2018. The first two series are plotted in Figure 1, and the latter two series are plotted in Figure 2. We present the wavelet approach in subsection 2.1 and the results in subsection 2.2 below.

2.1. Wavelet Analysis

We analyze time- and frequency-localized covariance between Brent oil price returns (measured as first-difference in log prices) and the Geopolitical Risk (GPR) Index of Caldara and Iacoviello (2018), using continuous wavelet partial coherence at different times and frequency bands. Continuous wavelet methods aim to replace Fourier analysis, which relies on approximation of time series by cyclical sine and cosine waves, with

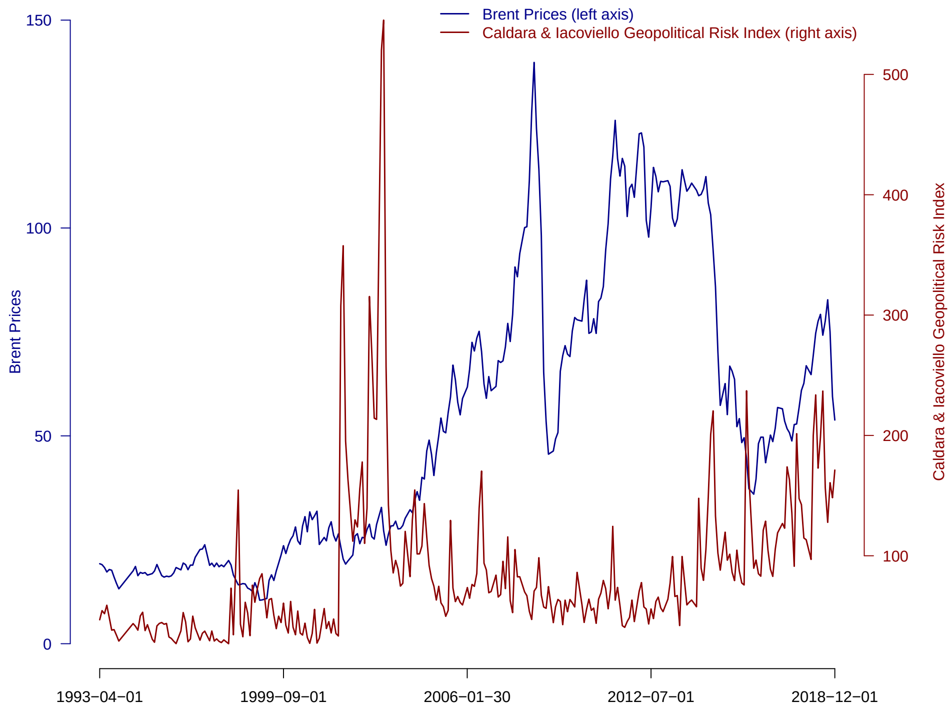

Figure 1: Brent Oil Prices and Caldara & Iacoviello Geopolitical Risk Index

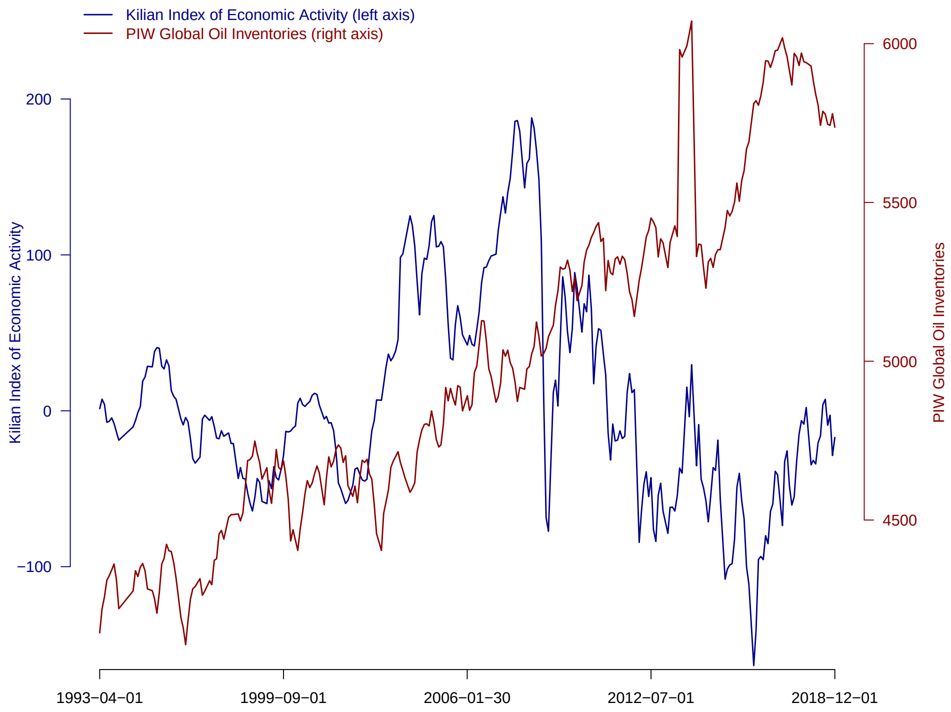

Figure 2: Kilian Index of Global Economic Activity and PIW Global Oil Inventories

local wavelets that allow fluctuations at various frequencies to vary over time. The building block of wavelet analysis is a mother wavelet $\psi(t)$, which is square integrable $\int_{-\infty}^{\infty} \psi^2(t)dt < \infty$, and integrates to zero $\int_{-\infty}^{\infty} \psi(t)dt = 0$. The mother wavelet is used to generate daughters with amplitude (dilation; frequency domain) s and location (time domain) τ

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right)$$

Similar to Fourier transform analysis, these basis functions are used to produce a continuous wavelet transform (CWT) of time series $x(t)$ by convolution, producing the wavelet power function at time τ and frequency s

$$\text{Wavelet Power}(\tau, s) = \frac{1}{s}W_{x;\psi}(\tau, s)^2,$$

where

$$W_{x;\psi}(\tau, s) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{s}}\psi^{\star}\left(\frac{t-\tau}{s}\right)dt \approx \sum_t x_t \frac{1}{\sqrt{s}}\psi^{\star}\left(\frac{t-\tau}{s}\right)$$

In our CWT analysis reported in this section, we used a slightly adapted version of Aguiar-Conraria and Soares's GWPackage, which is an R adaptation of their Matlab ASToolbox.[1] The mother wavelet used in our analysis is the Morlet Wavelet,

$$\psi(t) = \pi^{-1/4}e^{i\omega t}e^{-t^2/2}.$$

This wavelet, which, at $\omega = 6$ reduces to $\psi(t) = e^{-t^2/2}\cos(6t)$, is plotted below.

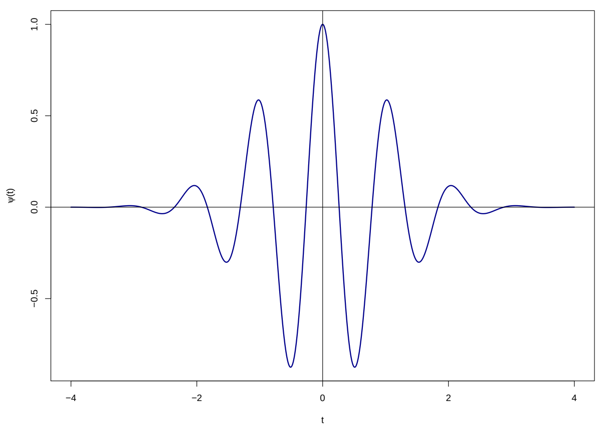

Figure 3: Example Morlet Mother Wavelet with $\omega = 6$

Given two time series $x(t)$ and $y(t)$, the cross wavelet is defined by

$$W_{xy} = W_x W_y^{\star}.$$

The cross-wavelet power, measuring local covariance at each time and frequency is defined as $XWP_{xy} = |W_{xy}|$ Smoothing the CWTs of x and y and the cross-wavelet power,

[1]Both packages are available at `https://sites.google.com/site/aguiarconraria/joanasoares-wavelets/the-astoolbox`. A full summary of the method described in this section is provided in Aguiar-Conraria and Soares (2011*a*, 2014).

we can define the wavelet coherency measure

$$R_{xy} = \frac{|S(W_{xy})|}{\sqrt{S(|W_x|^2)}\sqrt{S(|W_y|^2)}}$$

Phase lead of x over y is measured by phase-difference between $-\pi$ and π. In plots of phase difference (Figures 4 –7 below), we write for each range of *phi* which series is leading and whether the two series are "in phase" (the cross-wavelet version of positively correlated), or "out of phase" (the cross-wavelet version of negatively correlated).

$$\phi_{xy} = \arctan\left(\frac{\Im\mathfrak{m}(S(W_{xy}))}{\Re\mathfrak{e}(S(W_{xy}))}\right)$$

The four regions for ϕ_{xy} are as follows:

- $0 < \phi_{xy} < \pi/2$: the series are in-phase, with x leading
- $-\pi/2 < \phi_{xy} < 0$: the series are in-phase, with y leading
- $\pi/2 < \phi_{xy} < \pi$: the series are out-of-phase, with y leading
- $-\pi < \phi_{xy} < -\pi/2$: the series are out-of-phase, with x leading

When we have p time series $x_1, \ldots, x_p$, we can compute every smoothed pairwise coherency between x_i and x_j, denoted $S_{ij} = S(W_{ij})$. Collect elements in matrix $\mathfrak{S}$, and let $\mathfrak{S}^d_{ij}$ denote the cofactor of the element

$$\mathfrak{S}^d_{ij} = (-1)^{(i+j)} \det \mathfrak{S}^j_i,$$

where $\mathfrak{S}^j_i$ is the sub-matrix without row i and column j Now we can define the partial wavelet coherency, allowing for other series

$$\rho_{1j} = -\frac{\mathfrak{S}^d_{j1}}{\sqrt{\mathfrak{S}^d_{11}\mathfrak{S}^d_{jj}}}, \qquad r_{1j} = \frac{|\mathfrak{S}^d_{j1}|}{\sqrt{\mathfrak{S}^d_{11}\mathfrak{S}^d_{jj}}}, \qquad \phi^p_{1j} = \arctan\left(\frac{\Im\mathfrak{m}(\rho_{1j})}{\Re\mathfrak{e}(\rho_{1j})}\right)$$

The partial phase difference is ϕ^p_{1j}, with the same four-quadrant interpretations for in- or out-of-phase and which series leads as ϕ.

2.2. *Results from Wavelet Analysis*

Using continuous wavelet transform partial coherence and phase-difference estimates, we study the partial coherence between oil prices and geopolitical risk conditional on physical market conditions at a medium frequency corresponding to a period of one to three years, and to a lesser extent at the slightly higher frequency of 6 to 12 months. The partial coherence diagram is shown in Figure 4, with a heat map indicating higher partial coherence (partial correlation at each time and frequency), and with black periphery indicating time-frequency combinations at which the partial coherence was statistically significant at the 5% level, using 500 simulated ARMA(4,4) surrogates. At the medium frequency of one to three years, shown in Figure 7, we find that partial coherence between oil prices and geopolitical risk have been in-phase (positively correlated) for the entire sample, but statistically significant only in three episodes: a brief one around the 2003 Iraq war, another relatively brief one around the period of the Arab Spring, and a prolonged one from the end of the Arab Spring to the end of 2019. With the exception of the Arab Spring period, when geopolitical risk was leading oil price movements, the relationship has been one in which financialized oil prices have led/anticipated geopolitical risk as measured by newspaper coverage in Caldara and Iacoviello (2018).

As we can see in Figures 5 and 6, the partial coherence structure is qualitatively similar at higher frequencies of six to twelve months and three to six months. Of particular interest for the last part of the sample, during the period after the Arab Spring, is the same phase shift behavior. In particular, the phase shifts for one to three year and six to twelve month frequencies both indicate that oil price movement have led same-direction movements in geopolitical risk by about two to three months.[2] Unfortunately, the phase shift and significance of partial coherence oscillate too much once we get to monthly frequency. Therefore, to understand behavior at this higher frequency, we switch to a different method, which imposes stationarity assumptions over different but sufficiently long epochs to uncover patterns that we can interpret in terms of the positive or negative correlation as well as the direction of Granger causality.

Figure 4 shows the partial coherence between Brent prices and the GPR Index of Caldara and Iacoviello (2018), given Kilian's Index of Global Economic Activity and the PIW measure of Global Oil Inventories. It is evident that for all frequency bands, the partial coherence has been in phase, with Brent price leading most of the time, except in the short period of the Arab Spring, when geopolitical risk was leading. There were also two brief episodes after financial crises of 2000 and 2007 when the partial coherence at annual frequency was slightly out-of-phase, again with geopolitical risk leading. The results at medium frequency of one to three years (Figure 7) and six to twelve months (Figure 6) show that following the Arab Spring, oil prices have been leading same-direction movements of geopolitical risk by about two months (see approximate calculation in Footnote 2, with phase shift approximately equal $\pi/6$ in Figure 7, and slightly below $\pi/2$ in Figure 6).

[2]The calculation is rather straight forward. $timelead = phaseshift(deg) \times period/360$). Of course, interpretation of phase-shift is determined by the arbitrary/parsimonious convention of taking the smaller lead/lag ($\pi/6$ is the same angle/phase-shift as $-11\pi/6$), as cosine curves, the building blocks of Fourier analysis for stationary time series, repeat every 2π. In Figure 7, we can see the steady lead of Brent ahead of geopolitical risk by approximately (24 months $\times$ 30 degrees /360 degrees = 2 months). Likewise, the lead for most of the same period in Figure 6 is approximately (9 months $\times$ 80 degrees/360 degrees = 2 months).

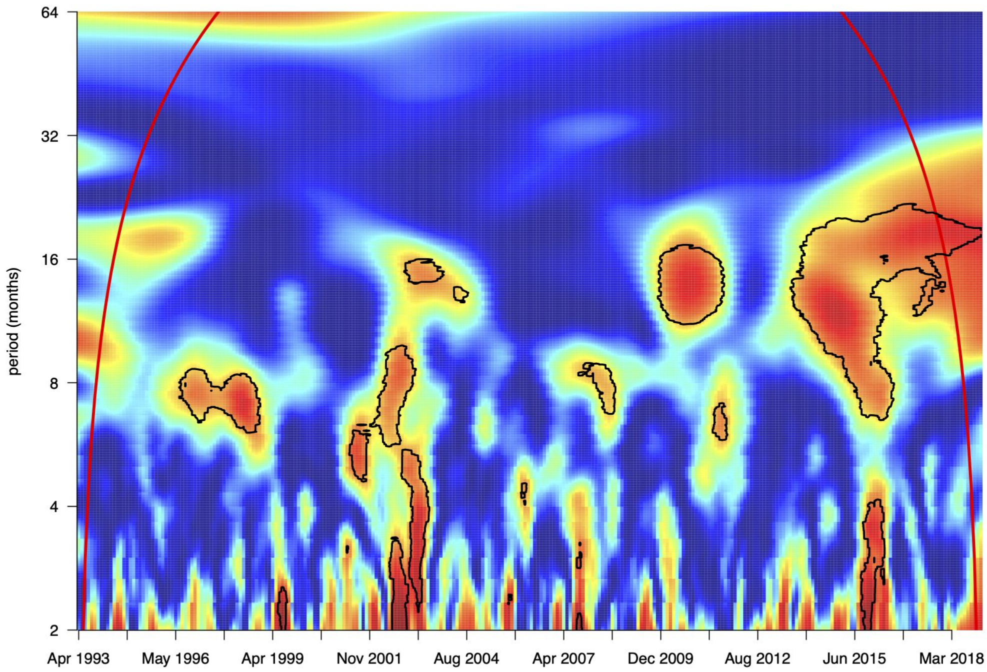

Figure 4: Partial Wavelet Coherence Brent prices and Global Political Risk Index given Kilian Index of Global Economic Activity and PIW Global Oil Inventories (significant at $\alpha = 0.05$ in black)

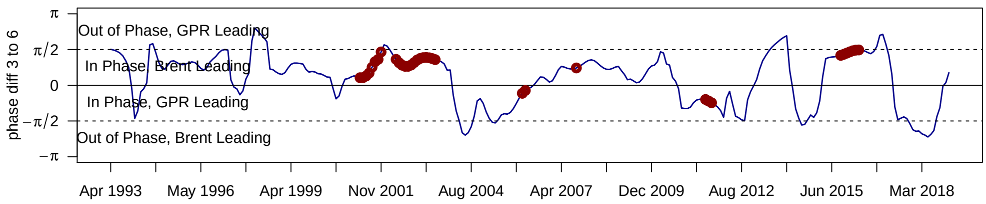

Figure 5: Phase Difference at 3 to 6 month Frequency (significant at $\alpha = 0.05$ in red)

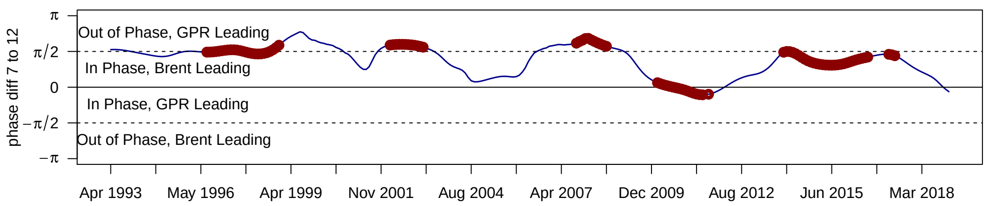

Figure 6: Phase Difference at 7 to 12 month Frequency (significant at $\alpha = 0.05$ in red)

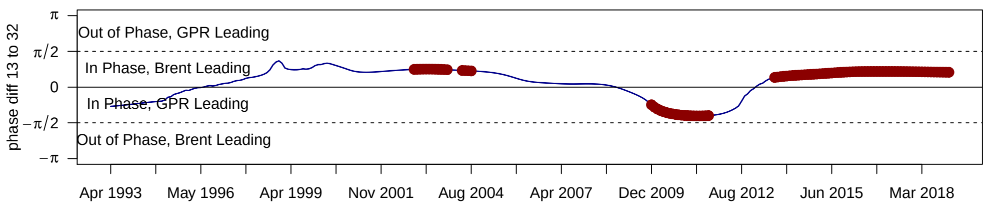

Figure 7: Phase Difference at 13 to 32 month Frequency (significant at $\alpha = 0.05$ in red)

3. Short-Term (2–3 Month) Time-Domain Analysis via Vector Autoregression

3.1. Granger Causality and VAR Modeling Approach

In order to understand the relationship better at higher frequency of two to three month periods, we use traditional vector autoregression (VAR) methods, which we had used in Abdel-Latif and El-Gamal (2019*a*,*b*), but allowing for a structural break around the end of 2004. F-tests suggest a break around August 2004, but we chose to make the two subsamples more balanced by placing the break at the end of 2004. There is also evidence that the Venezuelan crisis of 2002 fundamentally changed market perceptions of the importance of geopolitical risk in oil markets and drove an inventory-based rally in oil prices by late 2004, c.f. Billig (2004). The impulse response functions reported in Section 3 (Figures 9–10) suggest that at this monthly frequency, oil price movements have Granger-caused (led, by about two months) geopolitical risk movements in the same direction. This agrees with our analysis in Section 2, which shows positive partial coherence, with oil prices leading geopolitical risk for most of the sample, especially following the Arab Spring. In the meantime, Granger causality tests fail to reject the null hypothesis that changes in geopolitical risk do not lead to significant changes in oil prices.

3.2. Granger Causality and VAR Model Results

In this section, we report results from Vector Autoregression (VAR) analysis of Brent prices and GPR conditioning on Kilian's Index of Global Economic Activity and PIW's Global Oil Inventories. Tables 1–3 and Figure 8 report, respectively, estimates for the Brent price and GPR VAR equations, Granger tests for both directions of causation, and impulse response functions (IRFs) for the two variables. The results show that oil price changes Granger cause same-direction movements in geopolitical risk, but the latter does not Granger cause oil price movements.

Table 1: VAR Results Brent Eq.- Full Sample

	Estimate	Std. Error	t value	Pr(>|t|)
Brent.l1	1.256	0.056	22.382	0.000
GPR.l1	-0.013	0.007	-1.809	0.071
Kilian.l1	0.022	0.016	1.336	0.183
Inventory.l1	0.002	0.004	0.450	0.653
Brent.l2	-0.293	0.055	-5.287	0.000
GPR.l2	0.005	0.007	0.750	0.454
Kilian.l2	-0.014	0.017	-0.834	0.405
Inventory.l2	0.000	0.004	0.044	0.965
const	-6.809	3.624	-1.879	0.061

Table 2: VAR Results GPR Eq. - Full Sample

	Estimate	Std. Error	t value	Pr(>|t|)
Brent.l1	0.907	0.452	2.007	0.046
GPR.l1	0.875	0.057	15.408	0.000
Kilian.l1	-0.204	0.132	-1.550	0.122
Inventory.l1	-0.012	0.031	-0.388	0.698
Brent.l2	-1.004	0.447	-2.247	0.025
GPR.l2	-0.118	0.057	-2.070	0.039
Kilian.l2	0.187	0.133	1.404	0.161
Inventory.l2	0.024	0.031	0.779	0.436
const	-33.610	29.189	-1.151	0.250

Table 3: Granger Causality Tests - Full Sample

	H0	Statistic	p-value
A	Granger causality H0: Brent do not Granger-cause GPR Kilian Inventory	5.518	0
B	Granger causality H0: GPR do not Granger-cause Brent Kilian Inventory	1.099	0.361

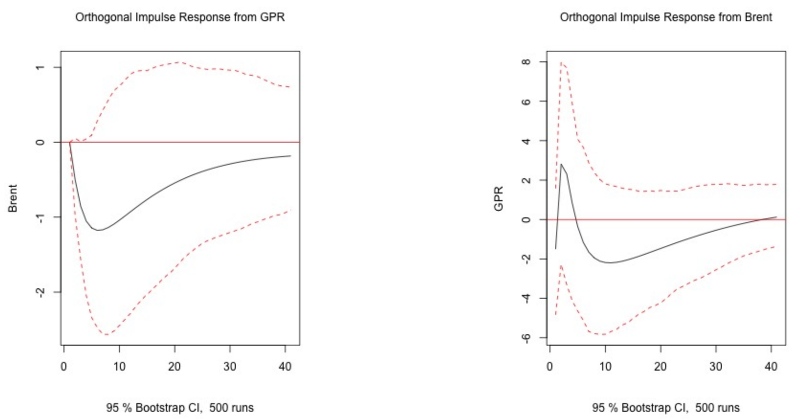

Figure 8: IRF shock = GPR, response = Oil (left) and shock = Oil, response = GPR (right)

Tables 4–6 and Figure 9 show the same estimation results, test results, and IRFs for the subsample to end of 2004. We fail to reject that changes in geopolitical risk granger causes (later) movements in Brent oil prices, but reject strongly the null hypothesis that movements in oil prices do not Granger cause geopolitical risk changes. The right panel of Figure 9 shows that the impact of a standard deviation positive shock in oil prices has a significant positive effect on geopolitical risk two months after the shock.

Table 4: VAR Results Brent Eq.- Sample to End 2004

	Estimate	Std. Error	t value	Pr(>|t|)
Brent.l1	0.929	0.089	10.479	0.000
GPR.l1	-0.009	0.004	-2.388	0.018
Kilian.l1	0.004	0.020	0.196	0.845
Inventory.l1	0.002	0.004	0.409	0.683
Brent.l2	0.003	0.094	0.027	0.978
GPR.l2	0.008	0.004	2.187	0.031
Kilian.l2	0.004	0.020	0.216	0.829
Inventory.l2	0.000	0.004	0.055	0.957
const	-6.393	5.039	-1.269	0.207

Table 5: VAR Results GPR Eq. - Sample to End 2004

	Estimate	Std. Error	t value	Pr(>|t|)
Brent.l1	5.853	1.875	3.122	0.002
GPR.l1	0.959	0.082	11.629	0.000
Kilian.l1	-0.601	0.425	-1.414	0.160
Inventory.l1	-0.167	0.083	-2.023	0.045
Brent.l2	-4.373	1.980	-2.209	0.029
GPR.l2	-0.205	0.081	-2.528	0.013
Kilian.l2	0.426	0.430	0.990	0.324
Inventory.l2	0.179	0.081	2.198	0.030
const	-64.933	106.518	-0.610	0.543

Table 6: Granger Causality Tests - Sample to End 2004

	H0	Statistic	p-value
A	Granger causality H0: Brent do not Granger-cause GPR Kilian Inventory	3.446	0.002
B	Granger causality H0: GPR do not Granger-cause Brent Kilian Inventory	1.369	0.225

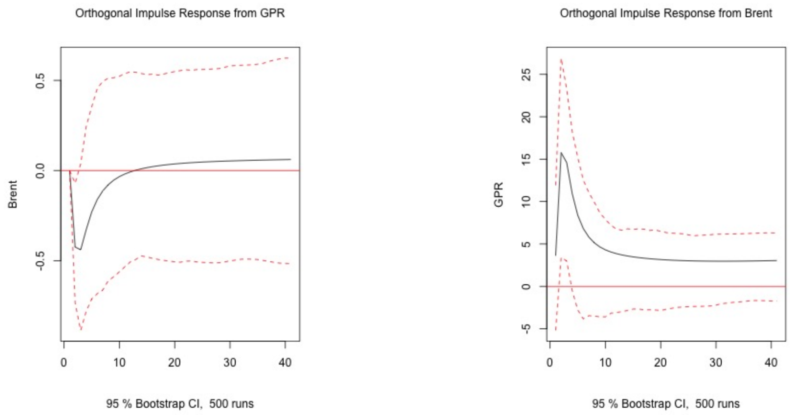

Figure 9: IRF shock = GPR, response = Oil (left) and IRF shock = Oil, response = GPR (right)

Finally, Tables 7–9 and Figure 10 show the same estimation results, test results, and IRFs for the subsample from beginning of 2005. Again, we fail to reject that changes in geopolitical risk granger causes (later) movements in Brent oil prices, but reject strongly the null hypothesis that movements in oil prices do not Granger cause geopolitical risk changes. However, the right panel of Figure 10 shows that the impact of a positive standard deviation shock in oil prices on geopolitical risk two months after the shock is not statistically significant as it was in the first subsample, although the Granger causality test rejects the null of no effect just as strongly.

Table 7: VAR Results Brent Eq.- Sample from 2005

	Estimate	Std. Error	t value	Pr(>|t|)
Brent.l1	1.253	0.077	16.339	0.000
GPR.l1	-0.026	0.016	-1.575	0.117
Kilian.l1	0.025	0.023	1.088	0.278
Inventory.l1	0.000	0.006	0.014	0.989
Brent.l2	-0.315	0.075	-4.181	0.000
GPR.l2	-0.010	0.017	-0.594	0.553
Kilian.l2	-0.022	0.023	-0.937	0.350
Inventory.l2	0.001	0.006	0.237	0.813
const	0.606	10.315	0.059	0.953

Table 8: VAR Results GPR Eq. - Sample from 2005

	Estimate	Std. Error	t value	Pr(>|t|)
Brent.l1	0.417	0.372	1.121	0.264
GPR.l1	0.572	0.079	7.216	0.000
Kilian.l1	-0.166	0.111	-1.501	0.135
Inventory.l1	0.035	0.028	1.264	0.208
Brent.l2	-0.511	0.366	-1.395	0.165
GPR.l2	0.073	0.080	0.905	0.367
Kilian.l2	0.165	0.113	1.461	0.146
Inventory.l2	-0.014	0.027	-0.518	0.605
const	-73.552	50.095	-1.468	0.144

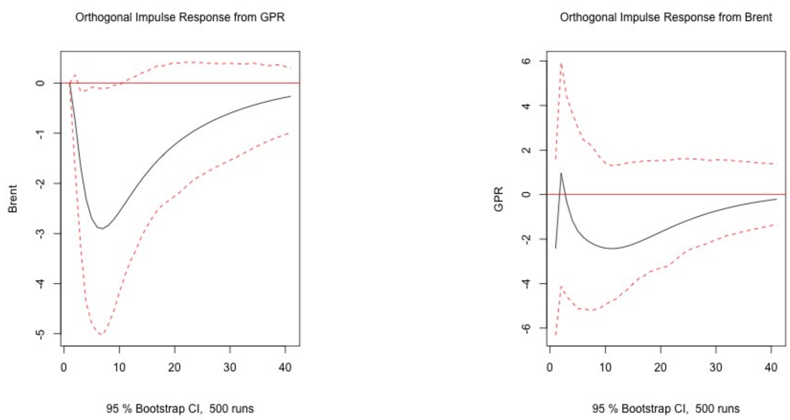

Figure 10: IRF shock = GPR, response = Oil (left) and IRF shock = Oil, response = GPR (right)

4. Very High Frequency (daily) Conditional Heteroscedasticity — GARCH-MIDAS

To complete the picture, and utilize the availability of Brent prices at daily frequency, we follow earlier studies in the literature that have used Mi(xed) Da(ta) Sampling (MIDAS) methods to study the relationship of oil prices with variables measured at lower frequency, c.f. Baumeister et al. (2013); Guérin and Marcellino (2011). At the daily frequency, we are more interested in studying the effect of geopolitical risk on oil price returns volatility, allowing for stochastic volatility as specified in a GARCH models, in the tradition of Antonakakis and Filis (2013); Sadorsky (1999). In particular, following Nguyen and Walther (2018), we use the GARCH-MIDAS model of Engle et al. (2013), in which the generalized autoregressive process for oil price conditional volatility is broken

Table 9: Granger Causality Tests - Sample from 2005

	H0	Statistic	p-value
A	Granger causality H0: Brent do not Granger-cause GPR Kilian Inventory	3.444	0.002
B	Granger causality H0: GPR do not Granger-cause Brent Kilian Inventory	1.095	0.364

into short-term and long-term components. We fall short of following Pan et al. (2017) in using a regime-switching GARCH-MIDAS model, but follow our analysis in Section 3 by breaking the sample into two subsamples at end of 2004. Because the GARCH-MIDAS model is estimated using maximum likelihood, simple likelihood ratio tests of parameter constancy are possible, and they strongly support the hypothesis of regime switching at end 2004. The unconditional analysis shows that geopolitical risk had a positive effect on oil price volatility mainly in the second subsample (see Tables 10–12), and the same result holds when conditioning on inventories (Tables 13–15) and conditioning on global economic activity (Tables 16–18). Not surprisingly, the latter two factors contribute negatively to oil price volatility. Therefore, this GARCH-MIDAS analysis complements the results in Sections 2 and 3, which had shown at lower frequencies that oil prices are positively correlated with and lead geopolitical risk over much of the past decade. In contrast, the results of Section 4 show that realized geopolitical risk contributes positively, while higher inventories and greater resiliency of oil demand contribute negatively, to shorter-term oil price volatility.

4.1. GARCH-MIDAS Model

To utilize the availability of daily price data, we model daily oil price volatility using a variant of the GARCH-MIDAS model, which was initially proposed by Engle et al. (2013) and modified by Pan et al. (2017) to account for structural breaks in the short-term volatility component. Following Engle et al. (2013), the conditional variance of the oil price series is multiplicatively decomposed into two components: The short-term (GARCH) component is estimated primarily based on high frequency data, while the long-term (MIDAS) component integrates both higher and lower frequency series. This strategy is particularly useful because financial data, including crude prices, are available at relatively high (daily) frequency, while macroeconomic and geopolitical data are only available at monthly frequency (for example, we use Kilian (2009) monthly index of aggregate economic activity as our primary measure of oil demand and the Caldara and Iacoviello (2018) index as our main measure of geopolitical risk).

Let $t = 1, \ldots, T$ denote months and $i = 1, \ldots, N_t$ denote the days within month t. The conditional mean of the daily Brent oil price returns (first difference of log prices) series is modeled as follows

$$OilRet_{i,t} = \mu + \zeta_{i,t}, \tag{1}$$

where

$$\zeta_{i,t} = \sqrt{h_{i,t}\tau_t} Z_{i,t} \tag{2}$$

where $Z_{i,t}$ is *i.i.d* with zero mean and variance normalized to one, $h_{i,t}$ denotes the short-term component of the conditional variance of the series and τ_t denotes the long-term component. The short-term component of the conditional variance of oil prices is further modeled as GARCH(1,1):

$$h_{i,t} = (1 - \alpha - \beta) + \alpha \frac{\zeta_{i-1,t}^2}{\tau_t} + \beta h_{i,t} \tag{3}$$

where $\alpha > 0, \beta \geq 0$ and $\alpha + \beta < 1$. The long-term component of the conditional variance depends on explanatory variables at different frequencies:

$$\log \tau_t = m + \theta\, \Sigma_{k=1}^{K} \phi_k(\omega_1, \omega_2) X_{t-k}, \tag{4}$$

where X_t denotes the explanatory variables and $\phi_k(\omega_1, \omega_2)$ a given weighting scheme which can take the following Beta form:

$$\phi_k(\omega_1, \omega_2) = \frac{(k/(K+1))^{\omega_1 - 1} \times (1 - k/(K+1))^{\omega_2 - 1}}{\Sigma_{j=1}^{K} (j/(K+1))^{\omega_1 - 1} \times (1 - j/(K+1))^{\omega_2 - 1}} \tag{5}$$

The weights $\phi_k(\omega_1, \omega_2) \geq 0$, $k = 1, \ldots, K$, sum to one. Following Engle et al. (2013), the GARCH-MIDAS model is estimated in straight forward fashion by quasi-maximum likelihood.

4.2. *GARCH-MIDAS Results*

Estimates for the entire sample are shown in Table 10, while estimates for the two subsamples to end of 2004 and from beginning of 2005 are shown, respectively, in Tables 11 and 12. The estimate of θ, the long-term effect of geopolitical risk on Brent price conditional volatility, is positive and statistically significant for the full sample. Splitting the sample into two halves, before and after Jan 1, 2005, we see that the geopolitical influence on prices is strongly pronounced in the second subsample ($\theta = 0.07$ and statistically very significant), but has the wrong sign and is statistically insignificant in the first. The gain in log likelihood when we split the sample in two yields very significant rejection in the likelihood ratio test of the null of no regime break.

Table 10: GARCH-MIDAS Estimation - Model 0

	Coef.	SE	p-value
mu	0.015	0.026	0.563
alpha	0.036	0.007	0.000
beta	0.938	0.001	0.000
gamma	0.037	0.010	0.000
m	0.709	0.321	0.027
theta	0.008	0.003	0.002
w1	3.158	1.268	0.013
w2	4.749	2.040	0.020
Log Likelihood	-12942.3		

Table 11: GARCH-MIDAS Estimation - Model 0 Before 2005

	Coef.	SE	p-value
mu	0.039	0.057	0.486
alpha	0.040	0.018	0.024
beta	0.949	0.019	0.000
gamma	0.022	0.016	0.175
m	-1.071	0.727	0.141
theta	-0.010	0.012	0.397
w1	2.038	1.010	0.044
w2	6.374	9.532	0.504
Log Likelihood	-6060.227		

Table 12: GARCH-MIDAS Estimation - Model 0 After 2005

	Coef.	SE	p-value
mu	-0.016	0.028	0.569
alpha	0.017	0.000	0.000
beta	0.962	0.000	0.000
gamma	0.042	0.000	0.000
m	-5.781	0.355	0.000
theta	0.071	0.002	0.000
w1	1.157	0.370	0.002
w2	1.343	0.437	0.002
Log Likelihood	-5345.438		

We repeat the analysis for the full sample and two subsamples, adding inventories as a long-term determinant of oil price volatility. The same pattern emerges as before: The geopolitical effect is statistically significant overall in Table 13, but the gain in log likelihood strongly supports the hypothesis of regime change. In the first subsample, until the end of 2004, Table 14 shows that the effects of geopolitical risk and inventory levels are statistically insignificant. However, for the second subsample, starting in 2005, Table 15 shows that geopolitical risk has a very strong positive effect on conditional volatility of oil prices, while inventories have a very strong negative effect on the same.

Table 13: GARCH-MIDAS Estimation - Model 2

	Coef.	SE	p-value
mu	0.016	0.030	0.591
alpha	0.036	0.010	0.000
beta	0.938	0.002	0.000
gamma	0.037	0.010	0.000
m	0.834	2.363	0.724
theta	0.009	0.004	0.047
w2	1.679	1.057	0.112
theta.two	-0.021	0.277	0.941
w2.two	2.349	17.115	0.891
Log Likelihood	-12943.78		

Table 14: GARCH-MIDAS Estimation - Model 2 Before 2005

	Coef.	SE	p-value
mu	0.035	0.038	0.354
alpha	0.075	0.016	0.000
beta	0.876	0.002	0.000
gamma	0.043	0.026	0.091
m	-1.558	33.402	0.963
theta	0.003	0.002	0.174
w2	2.806	1.275	0.028
theta.two	0.355	3.981	0.929
w2.two	1.006	4.877	0.837
Log Likelihood	-6058.663		

Table 15: GARCH-MIDAS Estimation - Model 2 After 2005

	Coef.	SE	p-value
mu	-0.019	0.028	0.500
alpha	0.014	0.000	0.000
beta	0.965	0.000	0.000
gamma	0.041	0.001	0.000
m	-0.160	0.814	0.844
theta	0.065	0.016	0.000
w2	1.194	0.285	0.000
theta.two	-0.597	0.078	0.000
w2.two	4.168	5.594	0.456
Log Likelihood	-5345.82		

Finally, we repeat the analysis adding Kilian's index of global economic activity as a long-term determinant of oil price volatility, instead of inventories. For the full sample, Table 16 shows that neither geopolitical risk nor the Kilian index has a statistically significant effect on oil price volatility. The same insignificance results hold for the first subsample, as shown in Table 17. However, splitting the sample into two halves results in a very significant positive effect of geopolitical risk on oil price volatility in the second subsample (Table 18), as we have seen in earlier specifications, while strong demand, as measured by high values of the Kilian index, results in lower oil price volatility.

Table 16: GARCH-MIDAS Estimation - Model 3

	Coef.	SE	p-value
mu	0.035	0.030	0.239
alpha	0.035	0.011	0.001
beta	0.947	0.012	0.000
gamma	0.036	0.010	0.000
m	-1.318	0.667	0.048
theta	0.001	0.007	0.909
w2	3.261	3.627	0.369
theta.two	-0.000	0.002	0.799
w2.two	5.438	10.719	0.612
Log Likelihood	-12941.39		

Table 17: GARCH-MIDAS Estimation - Model 3 Before 2005

	Coef.	SE	p-value
mu	0.038	0.057	0.502
alpha	0.049	0.029	0.089
beta	0.938	0.033	0.000
gamma	0.024	0.019	0.198
m	-1.161	0.874	0.184
theta	-0.003	0.011	0.798
w2	3.052	2.643	0.248
theta.two	0.007	0.009	0.457
w2.two	1.000	0.618	0.105
Log Likelihood	-6062.596		

Table 18: GARCH-MIDAS Estimation - Model 3 After 2005

	Coef.	SE	p-value
mu	-0.020	0.028	0.468
alpha	0.015	0.000	0.000
beta	0.963	0.000	0.000
gamma	0.043	0.000	0.000
m	-4.478	0.055	0.000
theta	0.063	0.000	0.000
w2	1.154	0.300	0.000
theta.two	-0.004	0.002	0.014
w2.two	20.114	22.023	0.361
Log Likelihood	-5342.215		

5. Conclusion and Directions for Further Research

We have conducted our analysis of the relationship between oil prices and geopolitical risk, conditional on aggregate economic activity and inventory levels at multiple frequencies. The latter corresponds to the time horizons of various investors in oil markets – physical exploration and production companies, refineries, etc. at the lowest frequency, longer term investors at intermediate frequencies, and short-term financial speculators at the highest frequency. Continuous Wavelet Analysis of partial coherence paints a clear picture for lower and intermediate frequencies, respectively, of one to three years and six months to one year. The partial coherence (partial correlation analog at a particular frequency band and a particular time) between oil prices and geopolitical risk given economic activity and inventory levels has been positive throughout the sample, with geopolitical risk leading oil for a short episode during the Arab Spring. At the medium frequency of one to three years, in particular, the pattern post the Arab Spring has been remarkably consistent, with movement in oil prices leading same direction movements in geopolitical risk by approximately two months.

This one-to-three-year result is the strongest and most interesting in our study, especially because it emerges without imposing any additional stationarity assumptions on the data. At higher frequencies, the CWT phase shift changes too quickly for meaningful results to emerge – although the results at the six months to a year frequency agree qualitatively with the one-to-three-year results (of oil leading geopolitics, in phase, by about two months). At monthly frequency and higher, we had to impose some additional stationarity assumptions – estimating VAR models at the monthly frequency, and GARCH-MIDAS models at the daily frequency. At the monthly frequency, we find the same positive correlation with oil prices anticipating geopolitical risk in both parts of the sample and find that realized geopolitical strife has not led to higher prices in either subsample. At the daily frequency, we find that geopolitical risk has had a positive effect on oil price volatility in later days during the second half of the sample. We conclude that while purely financial speculative traders may base their trading reactions on geopolitical events, more sophisticated investors with longer time horizons anticipate geopolitical events successfully, and trade two months in advance of those events – resulting in higher prices two months prior to heightened geopolitical risk, and vice versa.

Our main result – that oil price movements lead same-direction geopolitical risk movements by two months – is consistent with the hypothesis that some financial market speculators, such as macro hedge funds and algorithmic traders, may amass long positions in Brent in anticipation of geopolitical threats that might potentially lead to oil disruptions. Under the hypothesis, such traders would build long positions based on initial news reports regarding a possible geopolitical event, thus contributing to the advance rise in oil futures prices, and would take profits once the events materialize. For example, the Trump administration advised European allies in July 2017, when Brent prices had averaged $48.48 a barrel, to abandon new business plans with Iran as rumors surfaced that the U.S. intended to withdraw from the Iran nuclear deal and reimpose oil sanctions. Through fall 2017, Brent prices rose progressively as additional news made it more apparent that the U.S. was indeed planning to decertify the Iranian deal: In

September, President Trump delivered his speech at the United Nations, and oil prices reached \$52.95 Brent. Official decertification followed in October, driving Brent price to \$54.92 a barrel. When the United States formally withdrew from the Iran accord, in May 2018, Brent prices had reached \$73.43, and the price continued to rise to above \$80 by October 2018. Then, in November, when the final announcement that sanctions were being reinstated but some temporary exceptions would be made, prices receded back to \$64.75.

A similar pattern was observed around the collapse of Libya's government. In August 2009, when the first protests broke out at Zawiya, Brent prices were averaging around \$72 a barrel. By the time violent protests broke at Benghazi, and government troops began firing on protesters in February 15, 2011, oil prices had risen to \$102. Libyan oil production was first shut down on February 23, 2011, pushing oil prices to \$106. Prices continued to rise, reaching \$114 on the day the NATO campaign began on March 19, 2011. However, on the day that Qaddafi fell, Brent prices had fallen to \$108.

Those anecdotal examples suggest that markets have, indeed, moved ahead of some of the most important geopolitical events in our sample, but they also show how the geopolitical risk events have themselves evolved over time, with multiple advance warnings on which speculative investors can trade. In order to study these effects more systematically, we plan to augment the analysis in future research with information about (i) geopolitical risk threats vs realized events, using the subcomponents of the Caldara & Iacoviello Index, and (ii) activity in financial markets, including returns on other asset classes competing for speculative investors' attention, as well as the cost of funding, especially in junk bond markets that helped to fund shale oil investors' ventures in the United States. Including the latter information on financial market behavior has become particularly important as oil market fundamentals have played a smaller role in light of the glut that ensued in 2019 and early 2020.

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