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OIL PRICE UNCERTAINTY AND CONFLICTS: EVIDENCE FROM THE MIDDLE EAST AND NORTH AFRICA

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Oil Price Uncertainty and Conflicts:

Evidence from the Middle East and North Africa*

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Abstract

We empirically study the relationship between oil price uncertainty and conflict incidence by using different Vector Auto-Regressive (VAR) models, also augmented with Heterogeneous (VHAR) components. We build two measures for oil price uncertainty and investigate the Middle East and North Africa (MENA) interstate conflict, civil conflict and terrorist attacks data. Our results show that uncertainty in the oil market increases the incidence of conflict in the region. By further decomposing the model for OPEC and non-OPEC members of the region, we find that while the OPEC members immunise themselves against conflict, oil price uncertainty affects the conflict in non-OPEC members positively.

Keywords: Conflict, Natural Resources, Oil Prices, SVAR
JEL Classification: D74, E31, F51, Q34, C32, O13

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1 Introduction

Natural resources are very often a primary cause of major wars: no one can deny their key role in the Iran-Iraq war, the Falklands War, or the Iraqi invasion of Kuwait and the subsequent Gulf War.[1] Klare (2002) argues that natural resources became more important after the end of the Cold War, creating more incentives for states to initiate wars. The idea that the abundance of natural resources might be more of an economic curse than a blessing has been investigated in the literature of political economy and referred to the term "resource course" - or "paradox of plenty" - (Basedau & Lay, 2009; Andersen & Aslaksen, 2013). Such abundance often indirectly leads to institutional and economic instability, thus increasing the probability of conflict.

Oil plays a relevant role in the resource course debate and, in particular, in the study of the relationship between natural resource abundance and states' institutional and economic stability. Indeed, since the global distribution of fossil fuels is not uniform and oil is an internationally-traded source of energy, such resource is largely considered a strategic and politically-sensitive commodity that is important to national energy security. Economists have long argued about the effects of oil price shocks on macroeconomic performance and consider oil prices a decisive driver for various macroeconomic outcomes at the national and international level. Higher oil prices have been pinpointed as the cause of recessions, periods of excessive inflation, reduced productivity, and lower economic growth (Barsky & Kilian, 2004). Fossil fuels are a key input for economic growth and industrialisation, and as demand increases so to do concerns about a peak in oil reserves and supply uncertainty (Owen, Inderwildi, & King, 2010). Oil price uncertainty negatively affects aggregate investment, output, and consumption (Pindyck, 1990; Ferderer, 1996) and such uncertainty is one of the determinants of foreign exchange rates, influencing the import and export levels of oil-rich countries. Of course, conflicts also affect the supply of oil and other natural resources. Instability often pushes extractors, whether oil companies or national governments, to cut back on the exploitation of resources.

While the relationship between oil and conflict is bi-directional, the literature has mostly addressed the effect of oil (and, in general, natural resources) on conflict (Besley & Persson, 2011; Collier & Hoeffler, 2004; Rohner, 2011; Mehlum, Moene, & Torvik, 2006). In the aim to reduce the gap, in this paper, we empirically investigate the two-way interaction of conflict and oil market uncertainties. We run our analysis on two main variables: conflict and oil price uncertainty. Analysing them, we are faced with two deeply entwined variables: indeed, oil price uncertainty can be both a

[1] Other relevant examples are well documented by Caselli, Morelli, and Rohner (2015).

factor in the development of conflict and a consequence of such a conflict.

The present paper pays particular attention to the rise of different forms of conflicts in the MENA region, which, in this analysis, includes the following 19 countries: Algeria, Bahrain, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Qatar, Saudi Arabia, Syria, Tunisia, Turkey, United Arab Emirates, and Yemen. The region is the world's richest in oil resources and these resources vary from country to country. According to the British Petroleum Statistical Review of World Energy, 51.4% of world oil reserves are located in the MENA region and 37.6% of world oil is produced there.[2] The MENA states' national economies are heavily dependent on income from energy exports (Cordesman, 1999) and most of them are OPEC (Organization of Petroleum Exporting Countries) members.[3]

There have been multiple military conflicts in the MENA region and in the neighbour area: this evidence suggests a relationship between armed conflict and oil production. The most well known of these conflicts include the Iran-Iraq war, Gulf war, U.S. invasion of Iraq, Russian military intervention in Ukraine, and coalition intervention in Syria. Moreover, there has been a significant increase in the incidence of armed conflict in MENA during the past two decades (1998-2018). This is also confirmed by the data collected by the Uppsala Conflict Data Program (UCDP)[4], as shown in Figure 1 which illustrates share of yearly MENA conflict over all the conflicts recorded by the UCDP dataset in the period 1946-2018. All these facts and figures boost the motivation to investigate the bi-directional association of conflict and oil market uncertainties in this region.

In this paper, we adopt Structural Vector Auto-Regressive methodology and run our empirical strategy on oil price and conflict datasets collecting information on the MENA region in the period 1960 to 2017. Our results indicate that the variables of oil price uncertainty and conflict incidence in the MENA region affect each other; however, the effect of conflict on oil price uncertainty is contemporaneous while only long-term uncertainties in oil prices affect the incidence of conflict in MENA states. Moreover, when we broke down the results by OPEC and non-OPEC members, we found that oil price uncertainty significantly increases the incidence of conflict in non-OPEC MENA states, while the relationship is not statistically significant for OPEC members located in the MENA region. However, long-term uncertainties affect OPEC members' involvement in conflicts as well.

[2] See https://www.bp.com

[3] Specifically, Saudi Arabia, Iraq, Iran, the United Arab Emirates, Kuwait, Qatar, Algeria, Oman, Egypt, and Libya are the oil-producing countries in the region, while the remaining states are producing just relative smaller quantity. Moreover, Qatar, Oman, Egypt, Algeria, Libya, Iraq, Kuwait, United Arab Emirates, Iran, and Saudi Arabia are OPEC members.

[4] (Gleditsch, Wallensteen, Eriksson, Sollenberg, & Strand, 2002; Pettersson, Högbladh, & Öberg, 2019)

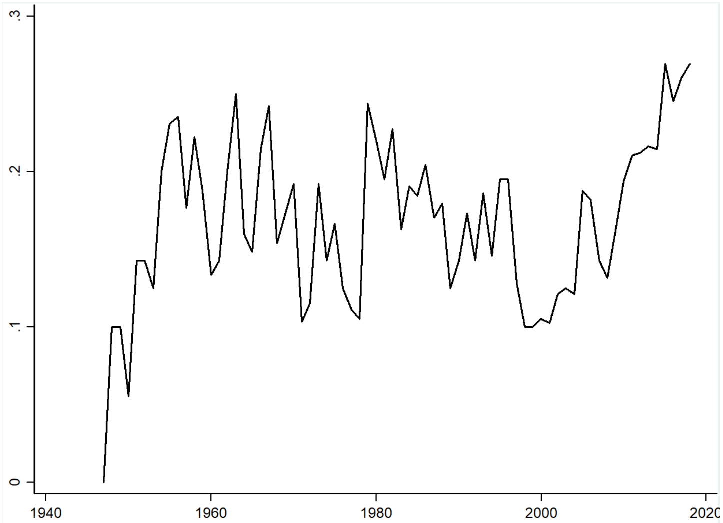

Figure 1: Share of yearly MENA conflicts, 1946-2018
The vertical axis is measures the incidence of conflicts in MENA region as divided by all conflicts recorded in the UCDP dataset.

The rest of the paper is organised as follows. Section 2, presents and discusses related literature this paper contributes to. Section 3, first presents our data and then our methodology. Section 4, describes our results and Section 5, concludes , and also discusses policy implications.

2 Related Literature

Existing literature on the relationship between conflict and oil price uncertainty in the Middle East includes both empirical and theoretical contributions. In what follows, we first discuss how this paper adds to the empirical literature, and then how it refers to the theoretical one.

As discussed in Barsky and Kilian (2004), even though it is widely argued that increases in oil prices are largely driven by "exogenous" political events in the Middle East, recent history shows instability in that area does not necessarily lead to higher oil prices. Some shocks in oil prices bear no apparent relation to events in the Middle East: the oil price shocks of March 1999 and November 2000, for example, were significant but were unrelated to any particular incident in the Middle East. The same authors also highlight that the decline in crude oil prices in 2001 provides a significant counterexample to the prevailing wisdom: the low prices in that period coincided with the terrorist attacks of September 11, 2001, the outbreak of war in Afghanistan, and a build-up in the U.S. Strategic Petroleum Reserve.

Specifically, Kilian (2009) shows that oil price fluctuations have historically been preceded by a combination of aggregate demand shocks and precautionary demand shocks.[5] Disruption in precautionary demand can be a consequence of concerns over unforeseen increased demand, supply declines, or both. He suggests that precautionary demand shocks can be interpreted as a shift in the conditional variance, as opposed to the conditional mean, of oil supply shortfalls. Other authors -Acemoglu and Robinson (2005); Ross (1999); Stern and Kander (2012); Wrigley (1990)- highlight that faster growth and higher income are both associated with higher demand for fossil fuel energy today and in the future. This volatility is depicted in the oil price uncertainty index, while increased uncertainty around oil prices may make conflicts more likely to escalate, due to the lack of information about the future value of resources and economic activities. In general, this literature highlights that the management of natural resources relates to economic power and that the disruption in the supply of these resources can precipitate conflict between states. Any controlling relationship (directly or through an alliance) over natural resources, especially oil, affects straightly the balance of economic power: in such cases, uncertainty in oil prices often reflects changes or shifts in power. Our paper contributes to this strand of literature with an investigation on the co-determination issue of oil price uncertainty variable and of conflict variable, and on their dynamic interdependence. The novelty of our research is to adopt a Structural Vector Auto Regression (SVAR) framework where the dynamics might also take a Heterogeneous AR form (SVHAR). These models account for the contemporaneous and lagged impact across variables, as well as for the associated impact of specific lagged periods (i.e., the previous semester and the previous year).[6] In so doing, we also add to literature focussing - in general - on the economic causes of war (Fearon (1995); Levy and Thompson (2011)) and - in particular - on the analysis of conflict in the MENA region (Colgan, 2013; Devarajan, 2016; Colgan, 2014). As for the latter, we provide an empirical investigation of the occurrence of armed conflict and terrorism in MENA countries over the period 1960-2017. As for the former, the present paper contributes to investigations on conflicts over natural resources at the international and national level (also including the effect of terrorism). Note that the literature have addressed the impact of the presence of natural resources and oil rents only on one type of conflicts, whether civil or interstate conflicts (Collier & Hoeffler, 2005; Fearon, 2005; Ross, 2003a, 2004, 2003b; Arbatli, Ashraf, & Galor, 2015)[7]: indeed, even though the market for oil is

[5] "Precautionary demand shocks" are defined as the response to increased uncertainty about future oil supply shortfalls or fears about future oil supply shortfalls.

[6] Notably, these models are widely used in the area of energy market analysis (Hamilton, 2009; Basher, Haug, & Sadorsky, 2012).

[7] Other studies in this category include: Brunnschweiler and Bulte (2009); Montalvo and Reynal-Querol (2005); Cotet and Tsui (2013); Koubi, Spilker, Böhmelt, and Bernauer (2014)

global, limited research has been done on the relationship between natural resources and conflict at different levels. We add novel empirical results about the impact of the global energy market on the incidence of interstate and civil conflicts. Moreover, we address the association of oil and terrorism as a specific type of conflict in MENA (Shughart, William, et al., 2011; Lee, 2018; Blomberg, Hess, & Jackson, 2009).

Referring to economic theories dealing with conflict, our empirical analysis on oil price uncertainty and conflict mostly relates to frameworks developed by Chassang and Miquel (2010) and Acemoglu, Golosov, Tsyvinski, and Yared (2012). In an incomplete information game where players have different assessments of the environment and fear is a motive for conflict, Chassang and Miquel (2010) highlight that predatory and preemptive incentives are the determinants of cooperation and conflict. In contrast, in a complete information game, only predatory motives result in conflict incidence.[8] Uncertainty in the value of the payoffs creates strategic uncertainty in equilibrium. Accordingly, in such a setting, the presence of uncertainty in the model maintains both the preemptive and predatory motives for conflict. A volatile oil market signals to the oil-poor state that availability of oil is uncertain, and can eventually lead the oil-poor state to take hostile actions to control the future supply of oil. In this setting, the oil-rich state has an incentive to attack preemptively to gain the first-strike advantage and prevent invasion. Thus, uncertainty can push the equilibrium condition towards war, i.e., it is a plausible determinant of conflict. Note that this uncertainty, Chassang and Miquel's theoretical model refers to, is captured in our empirical analysis by measuring the monthly oil price volatility. Specifically, we provide two indicators for it: first, by using GARCH and second, realized volatility.

In a rich theoretical setting, investigating natural resources and conflicts, Acemoglu et al. (2012), show that "a key parameter determining the incentives for war is the elasticity of demand". Referring their analysis to our setting, if the resource is inelastic in demand (i.e., the elasticity is below one[9]), the probability of conflict incidence rises over time. As the source of oil is depleted over time, the value of the oil rises, and the oil-poor agent's incentive to incite conflict with the oil-rich agent increases accordingly. The elasticity of demand identifies whether the price or the quantity effect dominates in determining the overall value of the oil revenue. Thus, if the price effect dominates, the overall value of oil consumption escalates. This implies that armed conflict for a scarce, exhaustible and inelastic resource like oil

[8]In the exit game model, Chassang and Miquel (2010) assigns predatory motives if one player is tempted to attack a peaceful opponent, and preemptive motives if the attack is made to avoid a surprise attack from the opponent.

[9]Findings by Gately and Huntington (2002); Pesaran, Smith, and Akiyama (1998) show an approximation between 0.01 and 0.1 for the elasticity of oil demand which categorises oil fields as inelastic demand resources.

becomes more likely over time. In this respect, our paper provides clean empirical evidence about the effect of uncertainty in the price of oil on the incidence of conflict.

3 Data and Methodology

In this section, we develop a dynamic empirical analysis on the effects of oil market uncertainty on conflict incidence. We also develop different dynamic models to determine whether today's energy market instability causes high oil prices or conflicts in the future. Our focus is on the MENA region's conflicts. States in this region are heterogeneous in terms of their oil market characteristics as well as their attitude toward conflict involvement. To examine the direct effects of oil price uncertainty on the incidence of conflict, we adopt a general empirical model that simultaneously estimates the parameters of interest in a dynamic fashion, allowing for both channels of transmission. In what follows, we first present our dataset and then our empirical strategy.

We develop our empirical analysis based on monthly frequency data for two main variables; first, conflict variable and, second, the uncertainty of oil prices variable. For conflict, we use interstate, civil wars, and terrorism data. Specifically, for inter-state conflict data, we use the Militarized Interstate Disputes (MID) dataset of Palmer, d'Orazio, Kenwick, and Lane (2015), which defines all interstate conflicts in the period 1816-2010. We obtain data on interstate conflicts in 19 countries in the MENA region from the Correlates of War Dataset. For civil conflicts, as in Morelli and Rohner (2015) and Lei and Michaels (2014), we use UCDP/PRIO dataset.[10] Finally, to count for the terrorism in the region, we use the Global Terrorism Database (GTD), which is produced by the National Consortium for the Study of Terrorism and Responses to Terrorism (START).

The second main variable of interest in our empirical analysis concerns oil prices. We use monthly data for the West Texas Intermediate (WTI) price of oil (Dollars per Barrel) from the Macro Trend Dataset.[11] We use also daily price variations in WTI spot prices taken from the U.S. Energy Information Administration dataset. The former covers the entire period 1970-2017, and the latter starts in 1986.

As a proxy for oil demand and a global control variable, we adopt the Kilian's index of economic activity dataset (Kilian, 2009). In our empirical analysis, we also consider the changes in the oil quantity by including different time series of oil production and consumption as control variables. Information on global oil production and oil consumption are taken from the U.S. Energy Information Administration. A weighted average of the

[10] See Pettersson et al. (2019); Gleditsch et al. (2002)

[11] See https://www.macrotrends.net/1369/crude-oil-price-history-chart

foreign exchange value of the U.S. dollar (USD) against the currencies of a broad group of major U.S. trading partners is captured from the Federal Reserve Bank of Saint Louis dataset.[12] Finally, we use rig count data as an exogenous proxy for oil production; we recover this variable from the Baker Hughes dataset.[13] Table 1 shows the descriptive statistics for all the variables used in this analysis.

Table 1: Descriptive Statistics

Variables	Sample	Mean	Std Dev	First year of data	Last year of data
monthly oil price return	684	0.005	0.10	1960	2017
Daily oil price return	10,230	0.003	1.16	1986	2017
Interstate conflict	600	0.298	0.23	1960	2010
Civil war	684	00.198	0.11	1960	2017
terrorism	564	0.129	0.13	1970	2017
Economic activity	588	4.096	26.89	1968	2017
Industrial production	504	1357.352	274.91	1975	2017
World rig count growth	504	1.236	125.83	1975	2017
U.S. Dollar	528	0.144	1.07	1973	2017
Production growth	564	0.008	0.01	1970	2017
Consumption growth	564	0.007	0.03	1970	2017

In the remaining part of this section, we explain our empirical strategies, starting with the definition of the variables we consider. In particular, we explain how we build the conflict variable (Section 3.1) and uncertainty in oil price variable (Sections 3.2). Then, we introduce the dynamic models identifying the parameters of interest.

3.1 Conflict Variable

We build three conflict indicators ("Interstate conflict", "Civil conflict", and "Terrorism") by starting with a dummy variable C_{it} which is defined on a monthly frequency for each of the 19 countries in the MENA region. The dummy variables take a value equal to 1 if there is a conflict in the specific month and 0 otherwise. C_{it} is separately measured for each of conflict indicators. C_{it} is built from January 1973 to December 2010 for interstate conflict indicator (due to other variables time constraint). Civil conflict indicator covers the period January 1970 to December 2017 and as for the terrorism indicator, it is measured from January 1970 to December 2017. Our dummy works on a monthly basis, assigning a value of 1 to the month if there exists at least one day of conflict within the month. The cumulative

[12]See https://fred.stlouisfed.org/series/TWEXBMTH

[13]Baker Hughes dataset provides data on the number of rigs actively exploring for or developing oil. See https://rigcount.bakerhughes.com/rig-count-overview

variable for all countries in the region is presented for each of the conflict indicators as follows:

$$CI_t = \sum_{i=1}^{I} \omega_i c_{it} \tag{1}$$

where ω_i is the share of oil discoveries for country i among the 19 countries under study. We adopt the Lei and Michaels's (2014) oil discovery measure of giant oil fields: ω_i gives higher weight to conflicts that arise in countries with a higher probability of oil discovery and it is not likely to be affected by the conflict. We then proceed to the standardisation of our target variable as follows:

$$SCI_t = \frac{CI_t - min(CI_t)}{max(CI_t) - min(CI_t)} \tag{2}$$

where SCI_t is the standardised measure for each of cumulative conflict indicators in the MENA region.

3.2 Uncertainty of Oil Price Variable

We use two approaches to derive uncertainty measures for oil prices. First, we build the proxy for uncertainty by estimating, on monthly oil price returns, a conditional variance model belonging to the Generalized Autoregressive Conditional Heteroskedasticity(GARCH) family. Our uncertainty measure is:

$$v_t = \sigma_t^2 \tag{3}$$

where v_t is our first proxy for the oil price uncertainty, σ_t^2 is the conditional variance as estimated by fitting GARCH(1,1) to Bollerslev's (1986) model on oil price returns. The model has the following structure:

$$\varepsilon_t = \tau + z_t \sigma_t \tag{4}$$

$$\sigma_t^2 = \kappa + G_1 \sigma_{t-1}^2 + A_1 \varepsilon_{t-1}^2 \tag{5}$$

where ε_t is oil price returns, τ is an intercept which is the average oil price return, σ_t^2 is the conditional variance, z_t is a standardised error term, κ is a constant, G_1 is the GARCH coefficient, and A_1 is the ARCH coefficient with $\kappa > 0$, $G_1 \geq 0$, $A_1 \geq 0$ and $A_1 + G_1 < 1$. Elder and Serletis (2010) adopt this measure for oil price uncertainty and they find that uncertainty surrounding oil prices has a negative and significant effect on the real gross domestic product (GDP), durables consumption, and on several components of fixed investment and industrial production. Note that, by assumption in the GARCH model, σ_t^2 responds symmetrically to both positive and negative deviations from the mean. In reality, a negative deviation from the mean of oil prices likely affects the incidence of conflict by a different magnitude than a positive deviation from the mean. Thus, we also adopt the Exponential GARCH (EGARCH) model of Nelson (1991), which adds a leverage effect and thus varies the impact of shocks depending on their sign. The EGARCH model is as follows:

$$log(\sigma_t^2) = \kappa + \beta_1 z_{t-1} + \beta_2 log(\sigma_{t-1}^2) + \gamma \mid z_{t-1} \mid \tag{6}$$

where z_t is the innovation term which is obtained as the ratio between ε_t and σ_t, the coefficient β_1 captures the asymmetric effect of a negative shock on the conditional variance as opposed to a positive shock, γ monitors the lagged impact of shocks, and β_2 is the GARCH parameter.

Our second uncertainty proxy builds on daily frequency data from January 1, 1986, and we use the Realised Volatility (RV) estimator, corresponding to the summation of higher frequency squared returns (Anderson, Bollerslev, & Meddahi, 2004). To derive an index for monthly oil price uncertainty we average the daily squared returns of oil prices for the whole month. The global oil market is not open all days during the month (it closes on weekends and some holidays) so the number of open days varies between months. Accordingly, we define v_t as follows:

$$v_t = \frac{1}{m} \sum_{j=1}^{m} r_{t,j}^2 \tag{7}$$

where v_t is a measure of oil price uncertainty, $r_{t,j}^2$ the daily squared returns of real oil prices and m the open market days within a given the month t (Guo, Kliesen, et al., 2005).

3.3 Dynamic Modelling of Uncertainty and Conflicts

Our empirical methodology is based on a bivariate monthly Structural Vector Autoregressive model, SVAR, which takes into consideration conflicts occurring in the MENA region as well as the uncertainty of oil's real price. This model enables us to understand the interaction between conflicts and energy markets. The relationship between oil prices and conflict incidence remains a matter of concern in quantitative literature, as it cannot be addressed using a regression model. Hence, a novelty of our analysis is the use of an autoregressive model to allow for endogenous oil price shocks as well as to take into account the dynamics of the variables of interest.

The general SVAR model is:

$$AY_t = M + \sum_{j=1}^{p} \Phi_j Y_{t-j} + \Gamma X_t + \varepsilon_t \tag{8}$$

where A is the $K \times K$ structural matrix; Y_t is the $K \times 1$ vector of responses; M is a $K \times 1$ vector of constants; Φ_j are matrices of coefficients of lagged values; and X_t are control variables that include Kilian's index of economic activity as a measure of oil demand globally, the weighted average of the foreign exchange value of the U.S. Dollar (to capture the effect of changes in exchange rates on oil prices), and industrial production of the OECD countries (as a measure of oil demand in industrial countries). We control for U.S. oil consumption, as the U.S. is the largest global consumer of oil for the period studied. We also control for world crude oil production and the number of oil rigs operating globally as measures of supply in the oil market. Finally, ε_t is the structural shock, which is assumed to be $I.I.D$ with mean zero and variance-covariance matrix of Σ. To determine the order p of the model, a Bayesian Information Criteria (BIC) is used. BIC is a criterion for model selection among a finite set of models. It combines both the fit to the data and a penalization term depending on the model parameters. Selection is based on the minimum value of the BIC. In our model, the minimum values are observed for the SVAR(1) for both measures of uncertainty of oil prices. Thus, we set $p = 1$ for all the following equations and analysis.

As discussed in Hamilton (1994), the structural representation in Equation (8) needs an additional restriction for identification. We consider a short-run identification restriction in which we restrict the contemporaneous effects to only one of the response variables. The identification strategy is a standard one, i.e., put constraints on the contemporaneous coefficients matrix. In this case, the model is bivariate so we fix the diagonal to have only ones, and we must set an off-diagonal coefficient to zero. To choose which off-diagonal coefficient to be zero we must use economic reasoning, i.e., we exclude that conflict depends on the contemporaneous oil volatility index, but we allow that oil volatility depends on conflict (Lütkepohl, 2005). We assume that conflict in MENA affects the oil price uncertainty contemporaneously. However, we assume a lagged effect of oil price uncertainty (v_t) on conflict (SCI_t): this assumption is based on the consideration of both the start of armed coflict and of the time unit in our analysyis (i.e., one month). Accordingly, with high economic, political and human cost of beginning an armed conflict, decision-makers are likely to take such actions slowly and starting a war with observing oil price within a month is not likely. The resulting structural relationship between oil price uncertainty and conflict is identified in Equation 9 as follows:

$$\begin{bmatrix} 1 & 0 \\ \alpha & 1 \end{bmatrix} \begin{bmatrix} SCI_t \\ v_t \end{bmatrix} = \begin{bmatrix} \mu_c \\ \mu_v \end{bmatrix} + \begin{bmatrix} \varphi_{11} & \varphi_{12} \\ \varphi_{21} & \varphi_{22} \end{bmatrix} \begin{bmatrix} SCI_{t-1} \\ v_{t-1} \end{bmatrix} + \Gamma X_t + \begin{bmatrix} \varepsilon_{ct} \\ \varepsilon_{vt} \end{bmatrix} \tag{9}$$

where SCI_t and v_t are, respectively, the conflict and uncertainty of oil prices variables at time t, μ_c and μ_v are two constants and φ_{ij}, for $i, j \in$

$\{1, 2\}$, are elements of the lagged values coefficients matrix.

To estimate the SVAR model in Equation 8, we derive the reduced form model as represented in the following equation:

$$Y_t = A^{-1}M + A^{-1}\Phi Y_{t-1} + A^{-1}\Gamma X_t + A^{-1}\varepsilon_t \tag{10}$$

where A is the structural matrix that contains α. This reduced form can be rewritten as follows:

$$Y_t = \bar{M} + \Pi Y_{t-1} + \Psi X_t + \eta_t \tag{11}$$

where $\bar{M}$ is equal to $A^{-1}M$, Π is $A^{-1}\Phi$, Ψ is $A^{-1}\Gamma$ and η_t is $A^{-1}\varepsilon_t$.

3.4 The Vector Heterogeneous Autoregressive Model (VHAR)

To estimate the reduced form of our structural model, we employ the Vector Heterogeneous Autoregressive (VHAR) model, a flexible method to describe nonlinearities and long-range dependence in time series dynamics. Corsi (2009) suggests the VHAR model to describe asymmetric propagation of volatility between long and short time horizons. Our model specifications are as follows:

$$Y_t = \bar{M} + \Phi^m Y_{t-1m}^{m-1} + \Phi^{semiann} Y_{t-1m}^{semiann} + \Phi^{ann} Y_{t-1m}^{ann} + \Psi X_t + \eta_t \tag{12}$$

where m, *semiann*, and *ann* denote time horizons of one month, six months and one year, respectively.[14] There are also control variables as listed above: index of economic activity, trade-weighted U.S. Dollar index, OECD industrial production, U.S. consumption, world crude oil production, and world rig count, which all work the same way as in the SVAR model.

Once the reduced-form VAR and VHAR are estimated by maximum likelihood, dynamic time profile and the impacts of the shocks on response variables can be examined using Impulse Response Functions (IRFs). We use IRFs up to 20 lags and we also compute bootstrapped confidence intervals. [15]

[14]Basically *semiann* and *ann* response variables refer to the following components:

$$Y_t^{semiann} = \frac{1}{6}\sum_{j=0}^{5} Y_{t-jm}^{(m)} \tag{13}$$

$$Y_t^{ann} = \frac{1}{12}\sum_{j=0}^{11} Y_{t-jm}^{(m)} \tag{14}$$

[15]See Lütkepohl (2005) for details.

4 The Impact of Oil Price Uncertainty on Conflict

First, as required to have a consistent VAR estimation, we check that the time series are stationary (Elliott, Rothenberg, & Stock, 1992). Non-stationary time series lead to spurious regression and biased estimated parameters. The standard unit root tests, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) are used to examine the stationary for all variables and their outcomes are presented in Table 2. Mostly level series are not stationary, hence a stationary test in first differences is conducted. The unit root test indicates that the conflict indicators ("Interstate conflict", "Civil conflict", and "Terrorism") and the uncertainty of oil prices variables ("EGARCH" and "Realized volatility") are stationary at 99% significance level and all the other variables are the first-order stationary. Consequently, we model the level of conflict and oil price uncertainty, and include the first difference of control variables.[16]

Table 2: Unit Root Test Results

Unit root test	ADF		PPERON	
Variables	Level	First diff	Level	First diff
Oil price	-1.86	-18.75***	-2.36	-18.67***
EGARCH	-18.59***		-18.92***	
Realized volatility	-35.48***		-27.32***	
Interstate conflict	-8.75***		-8.78***	
Civil conflict	-14.31***		-15.76***	
Terrorism	-25.48***		-28.49***	
Economic activity	-2.56	-3.73***	-3.04	-14.36***
Industrial production	-0.94	-23.96***	-0.98	-24.06***
World rig count	-1.24	-11.61***	-1.78	-11.17***
U.S. Dollar	-1.35	-14.29***	-1.22	-14.16***
Production	-1.15	-23.25***	-0.77	-23.93***
Consumption	-4.03***	-28.93***	-3.16	-30.97***

The table reports the Z-statistics of the ADF and PP unit root tests. Automatic selection criteria for the specification of the test equation (in terms of deterministic components and lag structure) is used. *** significance according top-values at 1%.

Table 3 shows the SVAR results where α is the structural parameter showing the contemporaneous effect of conflict on oil price uncertainty, $\sigma^2_{CI.t}$ and $\sigma^2_{v.t}$ are the structural shocks of conflict and uncertainty of oil price respectively. The estimates of α are negative. Because the off-diagonal elements of the A matrix contain the negative of the actual contemporaneous

[16] For consumption the two tests are not concordant but we prefer to be conservative and thus take consumption in first-order difference.

effects, the estimated effects are positive, as expected, confirming our intuition that a conflict shock increases oil price uncertainty contemporaneously . The contemporaneous effect of "Civil conflict" is larger in the Realized Volatility model comparing to the EGARCH model while the contemporaneous effect of "Terrorism" is larger in the EGARCH model. Finally, the contemporaneous effect of conflict remains almost the same in both measures of oil price uncertainty, i.e., EGARCH and Realized Volatility.

Table 3: SVAR Estimation for Two Measures of Volatility

Structural Parameter	α	σ^2_{CI}	σ^2_{v}
SVAR for EGARCH			
Interstate conflict	-0.006**	0.241**	0.004**
Civil conflict	-0.005***	0.029*	0.057*
Terrorism	-0.246*	0.058*	0.154*
SVAR for Realized Volatility			
Interstate conflict	-0.008**	0.259**	0.006**
Civil conflict	-0.008*	0.589*	0.082**
Terrorism	-0.268**	0.154**	0.282*

** and * Significant at 5% and 10%.

The VAR coefficients capturing the dynamic interdependence between variables, along with the Z-statistics, are presented in Tables 4, 5, and 6 for three different conflict measures, i.e., "Interstate conflict", "Civil conflict", and "Terrorism" respectively. First, our results confirm that the oil production indexes ("Production", "World rig count ") are statistically significant with the expected sign when the "Oil price uncertainty" is the response variable in the Tables 4, 5, and 6 . This supports our hypothesis that higher oil production makes the market for oil more secure and less concerned about supply disruption, and eventually decreases oil price uncertainty. Positive and significant oil consumption indexes (i.e., "Industrial production" and "Consumption") when "Oil price uncertainty" is the response variable confirm that higher consumption is associated with a more volatile oil market.

Regarding the variables of interest, the coefficient of oil price uncertainty in its first lag is positive and statistically significant in both of our models' estimations when the response variable is "Interstate conflict" (as depicted in the "Oil price uncertainty" in *Panel A* and *Panel B* of Table 4). When the response variable is "Civil conflict" the result is the same although smaller (see *Panel A* and *Panel B* of Table 5), but when "Terrorism" is the response variable the coefficient of oil price uncertainty is not statistically significant in both models (see *Panel A* and *Panel B* of Table 6). Such difference between "Terrorism" and other forms of conflict might be related to the causes of terrorism in the MENA region which is mostly based on ideological motivations, thus, the mechanisms that push “Civil conflict” and “Interstate conflict” to respond to “Oil price uncertainty” neccessarily are not the same for “Terrorism”.

Also, the coefficients of the first lag of conflict indicators are positive and significant when “Oil price uncertainty” is the response variable in both models. Such results is depicted in *Panel A* and *Panel B* of Tables 4, 5, and 6 for “Interstate conflict” of , “Civil conflict”, and “Terrorism”, respectively. The effect of oil price uncertainty on terrorism incidence is not significant, while the opposite - i.e., the effect of the incidence of terrorism on oil price uncertainty - is significant. These results suggest the diverse responses of the different type of conflicts to the uncertanty of oil prices shocks. However, model estimation coefficients suggest that oil price uncertainty and different conflict incidence indicators affect each other, as expected. In the VAR model, as shown in Equation 11, all response variables affect each other, both through the shocks they can generate as well as through dynamic interaction among the variables (i.e., through the lags of the VAR model). To observe such dynamics, the Impulse Response Functions (IRF) for “Interstate conflict” are depicted in Figures 2 and 3 for “EGARCH” and “Realized Volatility” measures respectively. A positive oil price uncertainty shock leads to a positive response from the “Interstate conflict” (i.e., an increase in conflict incidence) in both models (see upper-right panel in Figure 2 and 3). However, conflict shocks do not trigger a clear response from the oil price uncertainty index in the EGARCH model (see lower-left panel in Figure 2 and 3). Figures 4 and 5 show the IRFs for “Civil conflict” and “Terrorism” respectively where in both of them the “Oil price uncertainty” measures are EGARCH. “Civil conflict” respond positively to the shock of “Oil price uncertainty” (see B in Figure 4), while the response by “Terrorism” is not significant (see B in Figure 5).

As observable in the upper-right panels of the IRFs in Figure 2, 3, and 4 the responses are maximised at around month 5 to 6. This is our main motivation to enhance the VAR to VHAR models, as discussed above in Section 3.4. The VHAR model estimation helps us gain an effective understanding of the model’s dynamic by adding 6-month and 12-month average components of the two response variables. These additional components lead to a VAR-type model with the feature of considering uncertainties realised over different time horizons. In Table 7, the semiannual variable of uncertainty (as depicted in “6-month oil price uncertainty” in *Panel A, B,* and *C*) is positive and statistically significant: this shows that oil price uncertainty over a 6-month time horizon has a meaningful effect on conflict incidence. The results of VHAR are illustrated in Table 7.[17]

[17]The main results for all three conflict indicators and the two oil price uncertainty measures are compressed in Table 7. Detailed results (as those presented in Tables 4, 5, 6) are avaiable on request.

Table 4: VAR(1) Interstate conflict and Oil price uncertainty

Response variable	Interstate conflict	Oil price uncertainty
Panel A, EGARCH model for Oil price uncertainty		
Interstate conflict	0.707***	0.114***
	(20.96)	(1.73)
Oil price uncertainty	1.358*	0.087***
	(1.80)	(39.36)
Economic activity	0.001	0.014*
	(0.69)	(-2.28)
U.S. Dollar	0.002	-0.006**
	(0.58)	(1.82)
Industrial production	0.000	0.035***
	(0.40)	(2.64)
World rig count	-0.000	−0.042***
	(-0.56)	(-2.72)
Consumption	0.410	0.004*
	(2.09)	(1.83)
Production	0.545	−0.022*
	(0.96)	(-1.92)
Observations	450	
Panel B, Realized volatility model for Oil price uncertainty		
Interstate conflict	0.736***	0.289*
	(18.82)	(2.62)
Oil price uncertainty	1.516*	0.086***
	(1.91)	(3.61)
Economic activity	0.003	0.011*
	(0.30)	(1.74)
U.S. Dollar	0.007*	-0.006**
	(1.68)	(-0.73)
Industrial production	-0.319	0.012***
	(-0.15)	(3.83)
World rig count	-0.008	-0.021***
	(-0.12)	(-4.60)
Consumption	0.515*	0.161*
	(1.81)	(1.90)
Production	0.084	-0.007*
	(1.00)	(-1.66)
Observations	372	

In round brackets (z-statistics) are reported. *, **, *** are statistically significant at 10%, 5%, and 1% confidence levels, respectively.

Table 5: VAR(1) Civil conflict and Oil price uncertainty

Response variable	Civil conflict	Oil price uncertainty
Panel A, EGARCH model for Oil price uncertainty		
Civil conflict	0.922***	0.013*
	(49.53)	(1.93)
Oil price uncertainty	0.126*	0.842***
	(1.80)	(30.05)
Economic activity	0.002***	0.004***
	(2.66)	(3.24)
U.S. Dollar	0.051	-0.104*
	(1.04)	(1.70)
Industrial production	0.024	0.048***
	(0.84)	(3.21)
World rig count	0.021	-0.085***
	(1.17)	(-3.48)
Consumption	0.001	0.149*
	(1.02)	(1.75)
Production	0.051*	-0.042**
	(0.47)	(-1.96)
Observations	564	
Panel B, Realized volatility model for Oil price uncertainty		
Civil conflict	0.942***	0.001*
	(53.04)	(1.72)
Oil price uncertainty	0.762***	0.083***
	(4.49)	(3.29)
Economic activity	0.000	0.001*
	(1.65)	(3.29)
U.S. Dollar	-0.000***	-0.000**
	(2.49)	(-1.73)
Industrial production	0.017	0.447*
	(0.07)	(1.72)
World rig count	-0.076	-0.051**
	(-0.15)	(-2.54)
Consumption	0.086**	0.091*
	(2.43)	(1.72)
Production	-0.167	-0.008*
	(-1.39)	(-1.82)
Observations	372	

In round brackets (z-statistics) are reported. *, **, *** are statistically significant at 10%, 5%, and 1% confidence levels, respectively.

Table 6: VAR(1) Terrorism and Oil price uncertainty

Response variable	Terrorism	Oil price uncertainty
Panel A, EGARCH model for Oil price uncertainty		
Terrorism	0.563***	0.042**
	(12.88)	(1.98)
Oil price uncertainty	0.335	0.847***
	(1.53)	(31.58)
Economic activity	0.004	0.005***
	(1.01)	(3.29)
U.S. Dollar	0.014	-0.056**
	(1.04)	(-2.02)
Industrial production	0.011	0.007***
	(1.21)	(2.74)
World rig count	0.000	-0.020***
	(0.14)	(-2.78)
Consumption	0.175	0.211*
	(0.12)	(1.82)
Production	0.104*	-0.008*
	(0.38)	(-1.72)
Observations	564	
Panel B, Realized volatility model for Oil price uncertainty		
Terrorism	0.509***	0.036*
	(10.14)	(1.85)
Oil price uncertainty	1.57	0.084***
	(1.54)	(3.36)
Economic activity	0.000	0.001*
	(0.91)	(4.24)
U.S. Dollar	-0.000***	-0.000**
	(0.94)	(-0.17)
Industrial production	0.001	0.026*
	(0.87)	(1.91)
World rig count	0.000	-0.065***
	(0.74)	(-3.34)
Consumption	0.084	0.093*
	(1.01)	(1.85)
Production	0.023	-0.008*
	(0.42)	(-1.88)
Observations	360	

In round brackets (z-statistics) are reported. *, **, *** are statistically significant at 10%, 5%, and 1% confidence levels, respectively.

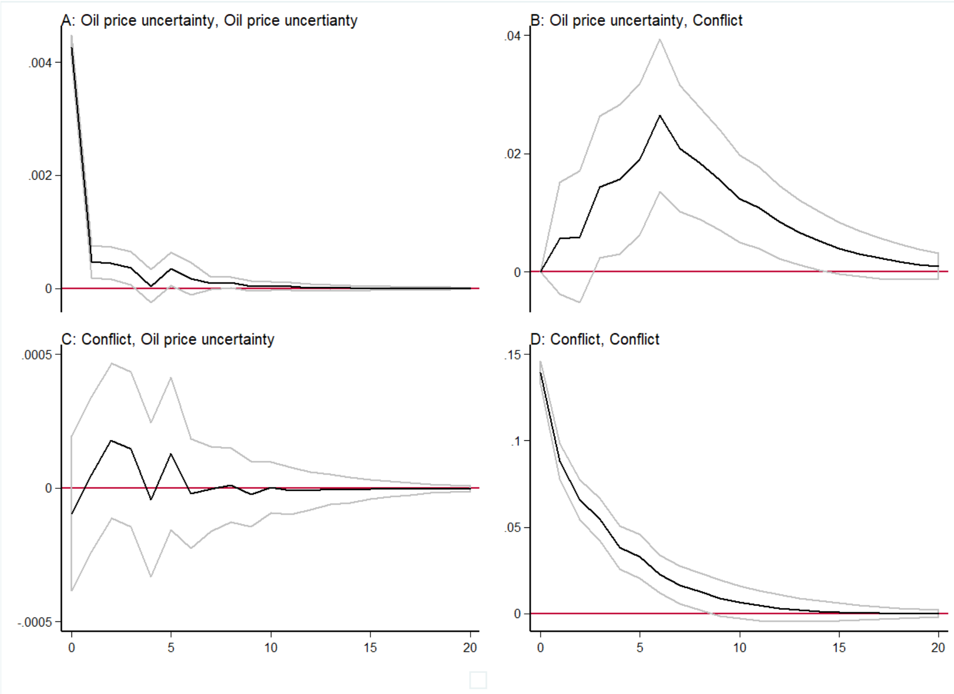

Figure 2: Impulse responses for Interstate conflict and EGARCH
Note that B shows the effect of oil price uncertainty shocks on conflict incidence, while C shows the reverse effect (i.e., that of conflict shocks on oil price uncertainty). The gray lines represents the 90% confidence interval.

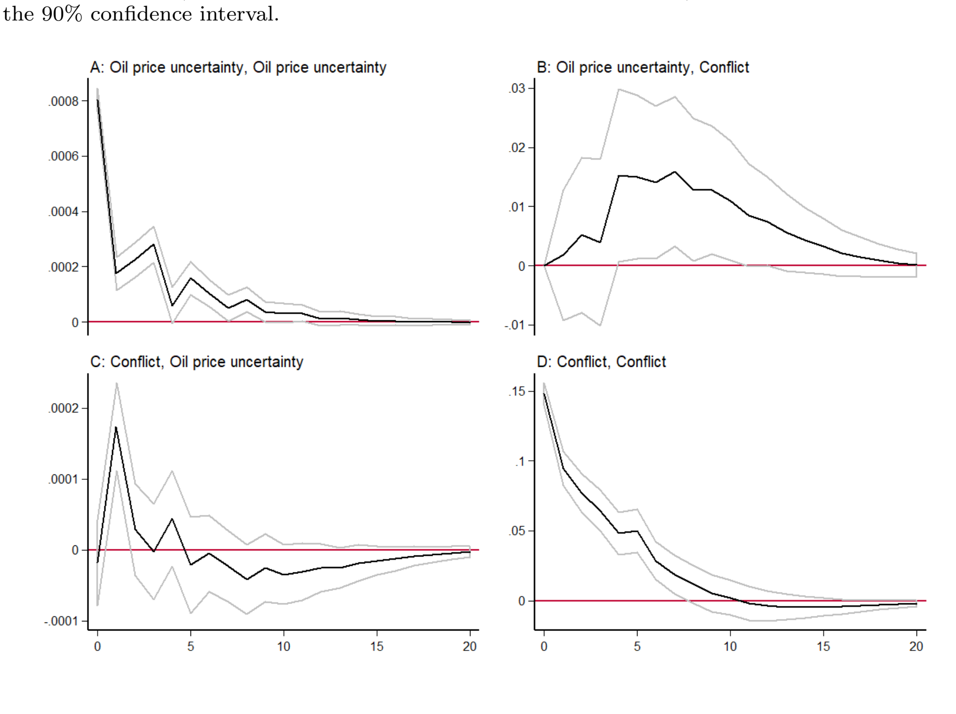

Figure 3: Impulse responses for Interstate conflict and Realized Volatility
Note that B shows the effect of oil price uncertainty shocks on conflict incidence, while C shows the reverse effect (i.e., that of conflict shocks on oil price uncertainty). The gray lines represents the 90% confidence interval.

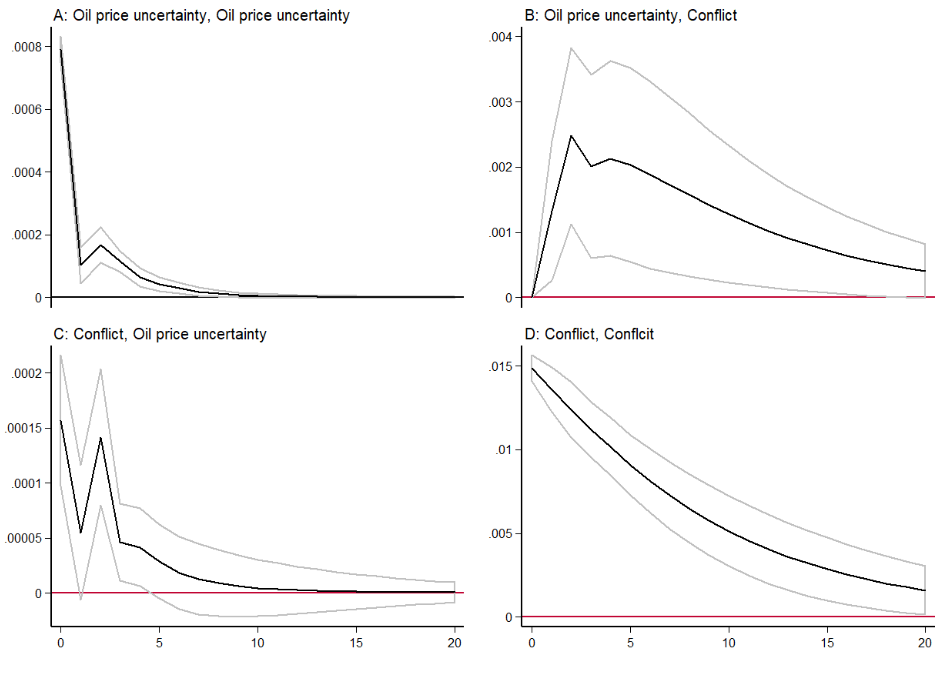

Figure 4: IRFs for Civil conflict

Note that B shows the effect of oil price uncertainty shocks on conflict incidence, while C shows the reverse effect (i.e., that of conflict shocks on oil price uncertainty). The gray lines represents the 90% confidence interval.

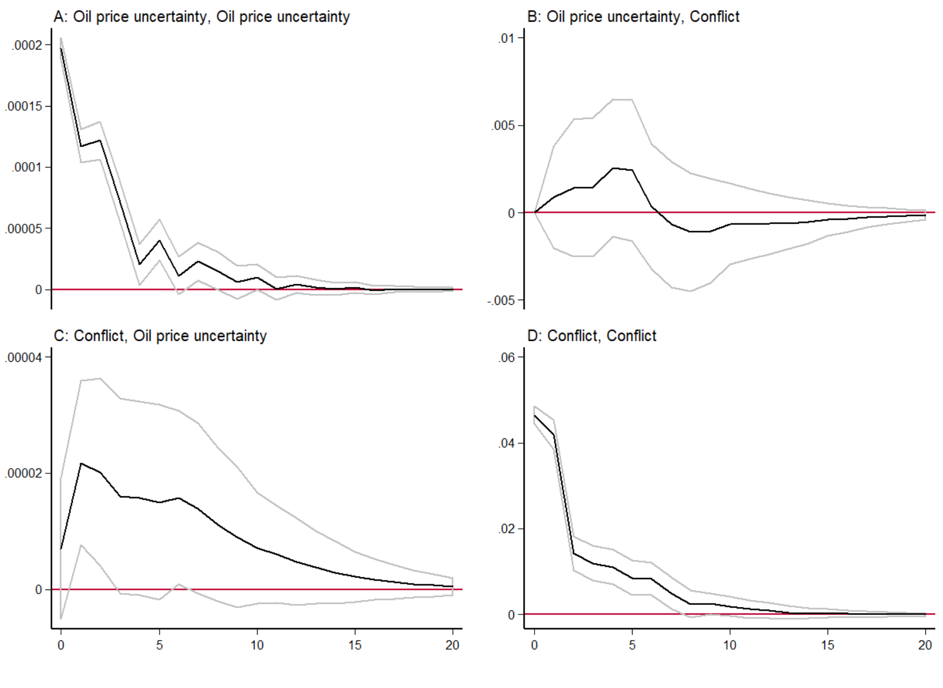

Figure 5: IRFs for Terrorism

Note that B shows the effect of oil price uncertainty shocks on conflict incidence, while C shows the reverse effect (i.e., that of conflict shocks on oil price uncertainty). The gray lines represents the 90% confidence interval.

Table 7: VHAR(1), EGARCH and Realized Volatility

Oil price uncertainty model	EGARCH	Realized volatility
Panel A, Response variable: Interstate conflict		
Oil price uncertainty	0.265	0.157
	(0.33)	(0.65)
6-month oil price uncertainty	0.734**	0.832**
	(2.25)	(2.18)
Annual oil price uncertainty	0.695***	0.191***
	(4.72)	(3.29)
Panel B, Response variable: Civil conflict		
Oil price uncertainty	0.123	0.587
	(1.25)	(1.36)
6-month oil price uncertainty	0.697***	.514***
	(2.86)	(3.57)
Annual oil price uncertainty	0.028***	0.009***
	(3.54)	(4.87)
Panel C, Response variable: Terrorism		
Oil price uncertainty	0.008	0.157
	(1.54)	(1.18)
6-month oil price uncertainty	0.019	0.007
	(0.27)	(0.11)
Annual oil price uncertainty	0.149	0.247
	(0.75)	(1.24)
Panel D, Response variable: Uncertainty of oil price		
Conflict	0.011**	0.001***
	(1.96)	(3.86)
6-month conflict	0.001	0.001
	(0.08)	(0.08)
Annual conflict	0.002	0.004
	(0.24)	(0.67)
Economic activity	0.006***	0.008*
	(3.12)	(1.73)
U.S. Dollar	-0.003**	-0.003*
	(-2.38)	(-1.70)
Industrial production	0.000	0.000
	(1.03)	(0.54)
World countrig	0.000	0.000
	(1.18)	(1.57)
Consumption	0.003	0.000
	(0.43)	(0.96)
Production	0.545*	0.084*
	(1.72)	(1.91)
Panel E, Response variable: Uncertainty of oil price		
Civil conflict	0.024*	0.005***
	(1.89)	(3.45)
Terrorism	0.017*	0.084**
	(1.91)	(2.43)

In round brackets (z-statistics) are reported. *, **, *** are statistically significant at 10%, 5%, and 1% confidence levels respectively.

Interestingly, in Table 7, the effect of all three conflict indicators on oil price uncertainty are almost contemporaneous, as seen in the coefficients of "Interstate conflict" in *Panel D* and "Civil conflict" and "Terrorism" in *Panel E*, while the effect of oil price uncertainty on "Interstate conflict" and "Civil conflict" are significant in the lagged variables (i.e., "6-month oil price uncertainty" and "Annual oil price uncertainty" in *Panel A and B*) and the "Oil price uncertainty" coefficeints are not significant for "Terrorism" (i.e., "Oil price uncertainty", "6-month oil price uncertainty", and "Annual oil price uncertainty" in *Panel C*). Hence, the effect of oil price uncertainty on conflict incidence appears over the long term rather than as a short term lag. This is also confirmed in the IRFs, as shown in Figure 6.

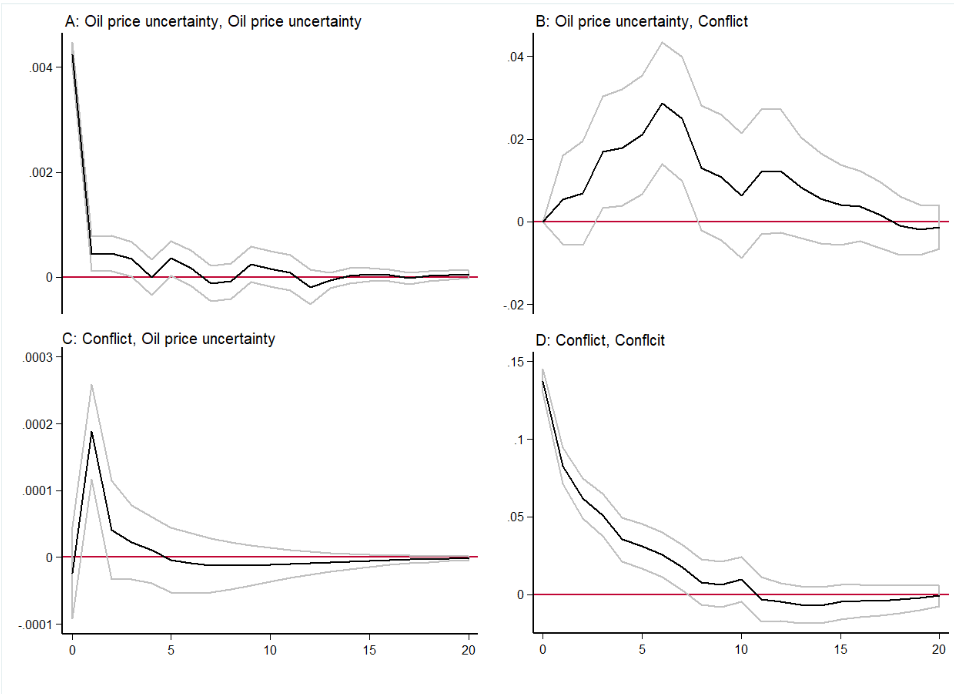

Figure 6: Impulse responses of VHAR

Note that B shows the effect of oil price uncertainty shocks on conflict incidence, while C shows the reverse effect (i.e., that of conflict shocks on oil price uncertainty). The gray lines represents the 90% confidence interval.

Besides, the VHAR results confirm the intuition behind our identification strategy in the structural parameter estimation. We used this logic to identify the structural model. The structural parameter estimation, also confirms the contemporaneous effect of conflict on oil price uncertainty measures.

In the MENA region, Qatar, Oman, Egypt, Algeria, Libya, Iraq, Kuwait, United Arab Emirates, Iran, and Saudi Arabia (corresponding to 10 countries over the total of 19 considered) belong to OPEC. OPEC is a powerful organisation with the ability to affect oil prices as well as to anticipate their direction, and thus membership in OPEC has the potential to modify the relationship between oil prices and political stability. Accordingly, we decompose the VHAR model for OPEC and Non-OPEC member states of the MENA region. Results are shown in Table 8 and 9 and highlight that increasing uncertainty surrounding oil prices has a significant effect on conflict incidence in Non-OPEC countries; differently, its effect in OPEC member states is not significant. To rationalise these findings, we argue that the OPEC cartel is successful at dampening the negative externalities of oil price uncertainty on its members, while their non-member neighbours in the MENA region suffer from the negative effects of oil price fluctuations. However, persistent oil price uncertainty can eventually affect OPEC members as well, as seen in the 6-month and 12-month uncertainty coefficients in the OPEC panel in Tables 8 and 9. Figures 7 and 8 show impulse response functions for these estimations. They confirm that positive conflict shocks in OPEC states affect oil price uncertainty immediately (see lower-left panel of Figure 7), while conflicts starting in non-OPEC countries do not have a significant effect on oil price uncertainty (see lower-left panel of Figure 8). This mirrors oil market concerns about an OPEC supply shock. Conversely, oil price uncertainty shocks significantly affect the incidence of conflict in non-OPEC members (see upper-right panel of Figure 8), but have a negligible effect of conflict incidence in OPEC member states (see upper-right panel of Figure 7).

Additionally, we exploit different available time series to perform some robustness checks of our model, i.e., different interstate conflict measure and oil price index. The Uppsala Conflict Data Program (UCDP) provides another dataset widely used to track the occurrence of interstate conflict. The UCDP/PRIO Armed Conflict Dataset reports on conflicts where at least one of the antagonists is a state. We screened this dataset to find conflicts in the MENA region where both sides are states and re-estimate our models using this dataset. The new results are consistent with those obtained using the Militarized Interstate Disputes (MID) dataset and show a positive relationship between oil price uncertainty shocks and conflict incidence. As for different oil price index, Kilian (2009) uses a real oil price series based on the refiner acquisition cost of imported crude oil, which is provided by the U.S. Department of Energy, deflated by the U.S. Consumer Price Index (CPI). Using this index of oil prices in our model, significance and results are substantially equivalent to those obtained using WTI oil prices.

Table 8: VHAR(1), EGARCH, OPEC and non-OPEC

Conflict in:	OPEC	Non-OPEC
Panel A, Response variable: Interstate conflict		
Oil price uncertainty	0.154	0.215**
	(0.53)	(2.36)
6-month oil price uncertainty	0.083	0.370*
	(0.68)	(1.85)
Annual oil price uncertainty	0.147*	0.017*
	(1.93)	(1.71)
Panel B, Response variable: Civil conflict		
Oil price uncertainty	0.027	0.104
	(1.54)	(2.36)
6-month oil price uncertainty	0.158	0.591*
	(1.21)	(1.91)
Annual oil price uncertainty	0.673**	0.980**
	(1.98)	(2.17)
Panel C, Response variable: Terrorism		
Oil price uncertainty	0.015	0.721*
	(0.81)	(1.67)
6-month oil price uncertainty	0.145	0.468*
	(0.15)	(1.91)
Annual oil price uncertainty	0.207	0.147*
	(1.01)	(1.75)
Panel D, Response variable: Uncertainty of oil price		
Conflict lag(1)	0.011***	0.001
	(3.87)	(1.23)
6-month conflict	-0.012	0.022
	(0.29)	(-0.13)
Annual conflict	0.008	0.011
	(0.39)	(0.32)
Economic activity	0.005*	0.000
	(1.77)	(1.59)
U.S. Dollar	0.004**	0.004**
	(2.78)	(2.42)
Industrial Production	0.003**	0.003**
	(2.80)	(2.59)
World rig count	-0.003***	-0.003***
	(-2.58)	(-2.62)
Consumption	0.302	0.259
	(0.56)	(0.70)
Production	-0.004**	-0.004**
	(-1.98)	(-2.39)
Panel E, Response variable: Uncertainty of oil price		
Civil conflict	0.159*	0.005
	(1.73)	(0.54)
Terrorism	0.011*	0.124
	(1.73)	(0.57)

In round brackets (z-statistics) are reported. *, **, *** are statistically significant at 10%, 5%, and 1% confidence levels respectively.

Table 9: VHAR(1), Realized Volatility, OPEC and Non-OPEC

Conflict in:	OPEC	Non-OPEC
Panel A, Response variable: Interstate conflict		
Oil price uncertainty	4.599	-2.268^{*}
	(0.71)	(0.65)
6-month oil price uncertainty	0.072	0.326^{*}
	(0.73)	(1.68)
Annual oil price uncertainty	0.167^{*}	0.029^{*}
	(1.72)	(1.85)
Panel B, Response variable: Civil conflict		
Oil price uncertainty	0.249	0.841^{***}
	(1.41)	(4.28)
6-month oil price uncertainty	0.183	0.237^{*}
	(0.17)	(1.85)
Annual oil price uncertainty	0.462	0.012^{*}
	(1.10)	(1.91)
Panel C, Response variable: Terrorism		
Oil price uncertainty lag(1)	0.007	0.215^{**}
	(0.14)	(2.36)
6-month oil price uncertainty	0.179	0.370^{*}
	(0.17)	(1.85)
Annual oil price uncertainty	0.207	0.517^{*}
	(0.93)	(1.71)
Panel D, Response variable: Uncertainty of oil price		
Conflict	0.006^{**}	0.002
	(2.45)	(0.97)
6-month conflict	0.001	0.007
	(0.25)	(0.58)
Annual conflict	0.001	0.032
	(0.56)	(0.35)
Economic activity	-0.007^{*}	-0.005^{*}
	(1.74)	(1.91)
U.S. Dollar	0.004^{***}	0.005^{***}
	(2.82)	(2.54)
Industrial Production	0.001^{**}	0.003^{***}
	(2.23)	(2.84)
World rig count	-0.006^{**}	-0.009^{*}
	(-2.47)	(-1.67)
Consumption	0.659	0.249
	(0.54)	(0.74)
Production	-0.047^{*}	-0.024^{*}
	(-1.67)	(-1.79)
Panel E, Response variable: Uncertainty of oil price		
Civil conflict	0.524^{***}	0.127
	(2.88)	(1.28)
Terrorism	0.042^{***}	0.357
	(2.63)	(0.16)

In round brackets (z-statistics) are reported. *, **, *** are statistically significant at 10%, 5%, and 1% confidence levels respectively.

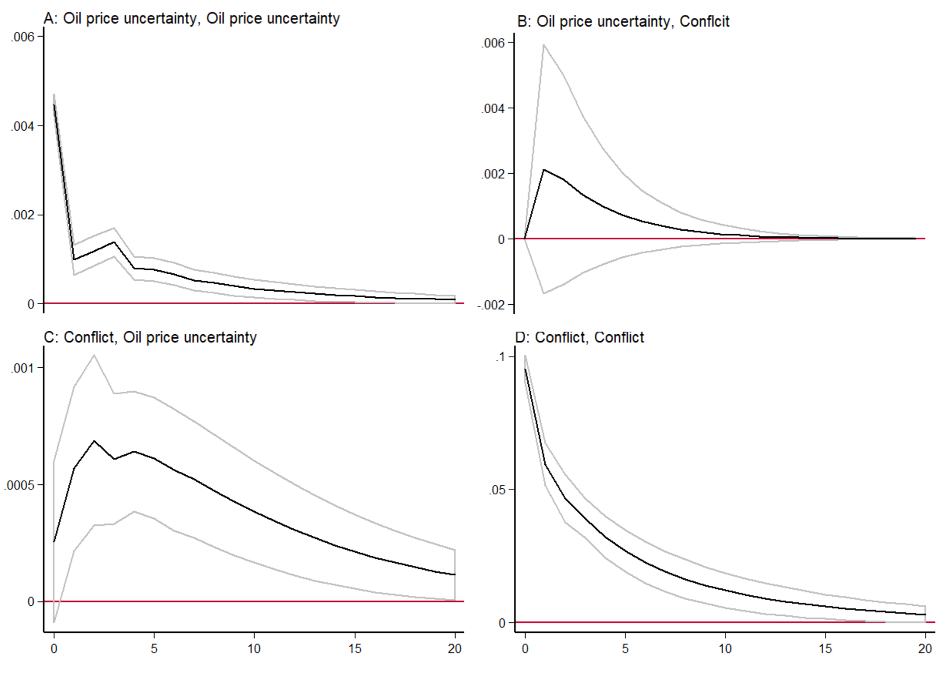

Figure 7: IRFs of VHAR, OPEC members

Note that B shows the effect of oil price uncertainty shocks on conflict incidence in OPEC member states, while C shows the impact of conflict shocks on oil price uncertainty. The gray lines represent the 90% confidence interval.

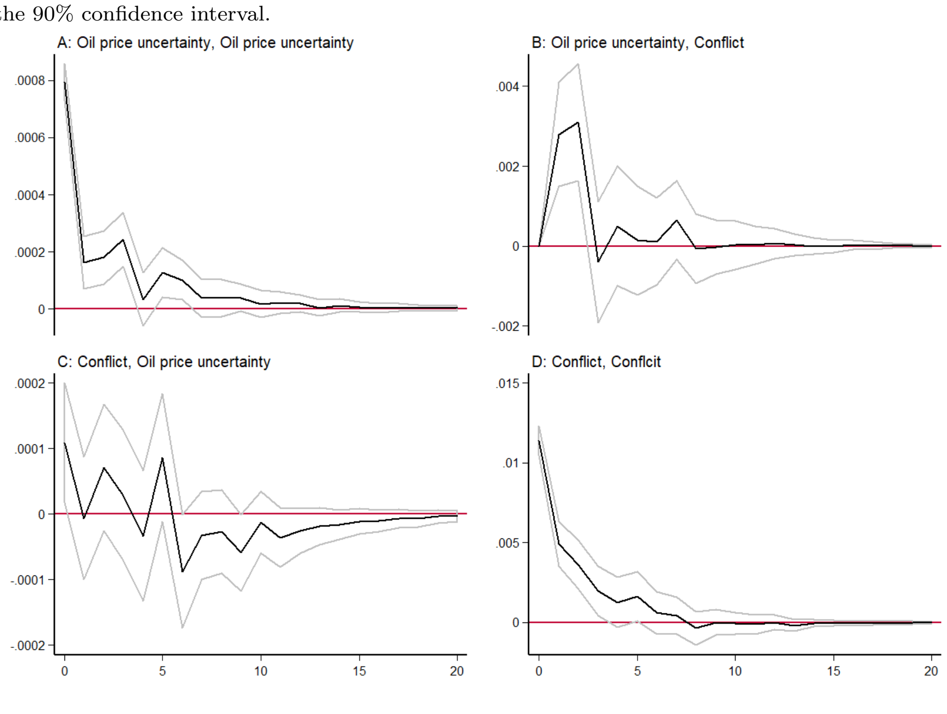

Figure 8: IRFs of VHAR, non-OPEC members

Note that B shows the effect of oil price uncertainty shocks on conflict incidence in non-OPEC states, while C shows the impact of conflict shocks on oil price uncertainty. The gray lines represent the 90% confidence interval.

5 Conclusion

The economic literature recognises natural resources as an important factor in the occurrence of war and militarized conflicts. Oil resources can be particularly contentious due to their uneven distribution, their strategic characteristics, and their status as a globally traded commodity. At the same time, conflicts are more common in some areas of the world (i.e., in the Middle East and North Africa), than in others, and they have potential to cause supply shocks that affect the oil market and oil prices. Given the existence of these complex connections between oil and conflicts, this paper investigates the bi-diretional relationship between oil price uncertainty and interstate conflict in the MENA region. Although this relationship needs to be investigated in a two-directional and dynamic fashion, the literature has mostly studied the two effects separately.

We build two indexes representing oil price uncertainty, using EGARCH and Realized Volatility specifications differently from the existing literature on the topic; we then adopt several Structural Vector Auto Regression and Vector Heterogeneous Auto Regression models as empirical methodologies to capture the bi-directional relationship between conflict and oil price uncertainty. These methods can account for the time lag in the relationship and we consider specific lagged periods including 6 months and 1 year. Our estimation is run for the period from January 1973 to December 2010, by using different datasets.

Our results can be summarised as follows. For both measures of oil price uncertainty, conflicts in the MENA region increases uncertainty surrounding oil prices almost contemporaneously. However, only longer-term increases in oil price uncertainty, i.e., elevated 6-month or one-year periods, have a positive influence on the incidence of interstate conflicts in the MENA region. This result is obtained by using different control variables including measures of global economic activity, oil demand and production.

Oil price uncertainty shocks do not affect the incidence of conflict involving OPEC members states, while they significantly increase the incidence of conflict in non-OPEC member states. Both of our models confirm this result. Intuitive reasoning suggests that OPEC is successful in mitigating or even eliminating the negative effects of oil price uncertainty on its member states, while non-OPEC members suffer from instability caused by oil price uncertainty. However, longer-lasting oil price uncertainty can increase conflict incidence in OPEC members as well. Furthermore, the conflict involving of OPEC member states leads to oil price uncertainty immediately, but conflict in non-OPEC member states does not lead to oil price uncertainty.

Our empirical results lead to two interesting and novel policy implications. First, when tackling the problem of instability in the MENA region, which has and continues to have a negative global impact, policymakers should consider the impact of oil market volatility. It is impossible to address instability in the MENA region without considering the dynamic economic relationships linking oil-producing states, oil-importing states and their neighbours. Increased volatility in the oil market contributes to greater instability in the region and may eventually lead to another armed conflict, and oil market volatility is thus an important topic of consideration for the international community. Second, energy markets would benefit from diversification, but some new dynamics deserve attention. In particular, on the one hand, policymakers considering alternative energy projects (like renewable sources which are famous for high initiation costs) should also consider their potential to reduce armed conflict and its associated costs in their cost-benefit analysis. On the other hand, the reduction in international dependence on oil producers can determine new internal instability for these oil producers, and the related consequences would call for a renewal of relationships at local and global levels.

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