

COMMODITY SPECIAL FEATURE: ONLINE ANNEX 1.1

Pricing Geopolitical Risk: Real-Time Evidence from Oil and Gas Markets

Part I. Data, Sources, and Transformations

The high-frequency SVAR models use daily data, US working days only for oil and Dutch working days only for TTF, as the TTF is traded in the Netherlands. The variables are the following:

- One-month oil price calculated as the weighted average of front-month Brent settlement price from Refinitiv (LCOc1) and North Sea Dated Brent from Argus. Front-month Brent refers to the most liquid Brent futures contract. It is the nearest maturity available and for most of a given month, its reference period corresponds to the month after next, until it expires towards the end of the month, and it then becomes the subsequent month. For example, in September, the front-month is the November contract until it expires at the end of September and then the front-month becomes December. Dated Brent refers to the price of a barrel of oil in the market for physical oil (spot market for actual delivery of oil, which takes place 10 to 30 days afterward). The transformation ensures that the maturity of the contract is always one month ahead. It is as follows:

$price_t^{1-month} = \alpha_t * price_t^{Front-month} + (1 - \alpha_t) * price_t^{Dated}$, where weights α_t are solutions of the following equation:

$$\alpha_t * Delivery_t^{Front-month} + (1 - \alpha_t) * Delivery_t^{Dated} = 1.$$

Depending on the day within a month, the expected delivery date of the Front-month Brent varies from 1 to 2 months, while that of the dated Brent is about 20 days. The above transformation increases price comparability across time. Indeed, Front-month Brent experiences recurring changes as the reference period changes each month, which could be sizable in periods of extreme backwardation¹. Further, on January 29, 2016, a change was introduced in the expiry calendar of Brent contracts. As a result, prices after this date refer to deliveries roughly one month further ahead compared to prices until then. Finally, for results to be expressed in percent changes, we use the following logarithm transformation:

$100 * \log(price_t^{1-month})$, where t denotes days.

- Seasonally adjusted TTF prices. TTF prices are sourced from Bloomberg (T'ZT1 Comdty, T'ZT2 Comdty, T'ZT13 Comdty, T'ZT14 Comdty). TTF prices present both continuous seasonality fluctuations and discrete seasonal jumps associated with futures calendar changes, a common issue in financial markets that occurs around specific dates. The futures price series is adjusted for discrete jumps using the back-adjustment approach as in Ma and others. (1992). First, TTF prices are transformed in logarithms and multiplied by 100. Second, roll gaps are computed as the discrete price jumps associated with each calendar change date, i.e. the difference between

¹ Front-month dropped by about \$17 on April 1st 2026, as the reference period moved from May to June, as market expected a rapid resolution of the Middle East crisis.

the time t log-price from the 2-month ahead futures (T'ZT2) and the 1-month ahead (front-month, T'ZT1) futures contract in logarithms. Third, the adjusted log-price series sums the observed log-price with the cumulation of future roll gaps. Fourth, the difference of the adjusted log-price series determines the percentage price change of the continuous TTF price series. Fifth, the (log)-back-adjusted price series is computed forward as the sum of the natural logarithm of the original price series at time t and the continuous percentage price change of the adjusted price series associated with the specific date. The resulting (log)-back-adjusted TTF price series in levels is seasonally adjusted with the Seasonal-Trend decomposition using LOESS (STL) technique. The same procedure is repeated for both front-month prices and 13-month ahead futures, as all future prices display roll jumps around calendar change dates.²

- 13-month oil futures price sourced from Refinitiv (LCOc13) and transformed as $100 * \log(price_t)$.
- Cumulated equity daily returns are calculated using a 1-year rolling window on the daily returns of MSCI stock market indices. For oil, we use the MSCI All country World Index (ACWI) sourced from Refinitiv, and which covers large and mid-cap equities across 23 developed markets and 24 emerging markets countries. For gas, we use the MSCI Europe index sourced from Bloomberg (MXEU Index).
- 7-day moving average of the GPRT index: obtained from <https://www.matteoiacoviello.com/gpr.htm>. Only US working days are selected from the data for the oil SVAR and only Dutch working days for the gas SVAR.
- Oil Forward Demand proxy IV selects the days on which there is a large change in stock market volatility, oil price volatility—measured by VIX and OVX, respectively—and the price of gold (New York COMEX price), all from Bloomberg with tickers VIX Index, OVX Index, and GC1, and simultaneously a large change in front-month oil prices of the opposite direction. By large changes, we mean that, on the selected date, the change in the VIX, OVX, the price of gold, and the front-month oil price is below the sample's 10th percentile or above the 90th percentile. Using this method, we identify 25 events during our sample period listed in [Table 1.1.1] below, with a brief description of the event. The Forward Demand IV takes the value of the VIX on the day when this large change occurs and 0 otherwise. This procedure comes from Gazzani and others (2024).
- TTF Current Demand proxy IV is derived based on the daily mean temperature forecast data from the “CFSV2: NCEP Climate Forecast System Version 2” database (Saha and others 2014), aggregated to the country-level using population weights from the “LandScan Global Population Dataset” (Sims and others (2023)).³ Total degree days (TDD), which measure heating and cooling demand as the deviation of daily temperatures from a threshold of 18°C (65°F), are first calculated for each country. The resulting country-level TDD series are then aggregated into a single European series using one-year lagged annual gas consumption data from the “2025

² See Gomez-Gonzalez and others (2026) for further technical details.

³ The calculations were performed by the IMF Statistics Department using Google Earth Engine.

Energy Institute Statistical Review of World Energy” database (Energy Institute 2025). Temperature anomalies are subsequently calculated for each day by taking the aggregated European TDD series and subtracting from it the average TDD for the same calendar day over the previous five years.⁴

Online Annex Table 1.1.1 List of events where oil proxy IV takes a value different from zero

Date	Event	VIX	OVX	Gold
September 30, 2008	Rescue package hopes	-7.3	-4.6	-1.6
October 6, 2008	Global growth fears	6.9	8.6	4.0
October 24, 2008	Global growth fears	11.3	2.7	2.2
November 20, 2008	Global growth fears	6.6	7.5	1.7
January 20, 2009	Banking solvency fears	10.5	7.4	1.8
January 28, 2009	Bank bailout expectations	-2.6	-2.2	-1.3
February 17, 2009	Global growth fears	5.7	10.1	2.7
February 24, 2009	Banking health optimism	-7.1	-3.9	-2.6
March 3, 2009	Banking health optimism	-1.7	-3.5	-2.8
April 20, 2009	Global growth fears	5.2	4.7	2.2
May 6, 2010	Greek sovereign debt crisis	7.9	4.1	1.9
August 8, 2011	U.S. sovereign downgrade	16.0	13.8	3.7
August 18, 2011	Euro sovereign crisis	11.1	14.8	1.5
September 7, 2011	Global growth rebound	-3.6	-2.5	-3.0
June 1, 2012	Global growth fears	2.6	6.8	3.6
January 5, 2015	Political uncertainty in Greece	2.1	3.4	1.5
January 12, 2015	Global growth fears	2.1	3.1	1.4
January 15, 2016	Global growth fears	3.1	4.5	1.6
February 11, 2016	Global growth fears	1.9	5.3	4.4
June 24, 2016	Brexit	8.5	3.2	4.6
April 2, 2018	Trade tensions	3.7	2.5	1.4
February 24, 2020	Coronavirus pandemic	8.0	3.7	1.7
May 5, 2023	Stronger than expected U.S. labor market	-2.9	-6.4	-1.5
April 10, 2025	Trade tensions	7.1	6.1	3.2
August 1, 2025	Trade tensions	3.7	2.6	1.6

Source: Gazzani and others (2024) and Google News

Data for LP

The second-stage local projection analysis focuses on two macroeconomic indicators, both measured at the monthly frequency:

- Consumer prices: seasonally adjusted Consumer Price Index (CPI) from Haver Analytics.
- Labor market conditions: seasonally adjusted unemployment rate from Haver Analytics.

The estimation samples differ across the oil and liquified natural gas (LNG) analyses. For the oil shock analysis, the sample is restricted to advanced-economy net oil importers. Countries are classified as net oil importers or exporters using the most recent annual information on crude oil trade from the US Energy Information Administration (EIA), with net oil importers defined as

⁴ TDD are computed as the sum of heating degree days (HDD) and cooling degree days (CDD), a standard approach used in the literature. HDD are computed as $\max\{18^\circ\text{C} - \text{temperature}_t, 0^\circ\text{C}\}$ during the cold period, while CDD are computed as $\max\{\text{temperature}_t - 18^\circ\text{C}, 0^\circ\text{C}\}$ during the warm period.

economies whose crude oil imports exceed crude oil exports in the latest available year. The resulting sample comprises Germany, Spain, France, Italy, Japan, Korea, and the United States.

For the LNG shock analysis, the sample is restricted to five major European economies: Germany, Spain, France, Italy, and the United Kingdom.

The exogenous disturbances are identified in a first-stage structural vector autoregression (SVAR). For both oil and LNG markets, four structural shocks are analyzed separately: demand shocks, forward-looking demand shocks, supply shocks, and geopolitical supply-risk shocks. These identified innovations enter the local projections as the shock variables.

Part II. Structural Vector Autoregression

Model and Identification Strategy

The Structural Vector Autoregression (SVAR) models for oil and gas can each be written in structural form as:

$$A_0 y_t = c\mathbb{I} + A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + e_t, \quad e_t \sim i.i.d N(0,1) \quad (1)$$

Where y_t is a vector of four variables (adjusted front-month, futures, equity index returns, and GPRT) for each model, $\mathbb{I}$ is a vector 4×1 of 1s, and $p = 4$ is the number of lags. A_0 is a 4×4 matrix of contemporaneous interactions and, for each k , A_{t-k} is a 4×4 matrix.

It can be written in compact form as:

$$A_0 y_t = A_+ x_t + e_t, \quad (2)$$

where $A_+ = [A_1, \dots, A_p, c]$ and $x_t = [y'_{t-1}, \dots, y'_{t-p}, 1]$.

The accompanying reduced-form representation can be written as:

$$y_t = A_0^{-1} c + B_1 y_{t-1} + \dots + B_p y_{t-p} + u_t, \quad u_t \sim i.i.d N(0, \Sigma) \quad (3)$$

where $B_k = A_0^{-1} A_k$, for $k = 1, \dots, p$; $u_t = A_0^{-1} e_t = D e_t$ and $\Sigma = (A_0' A_0)^{-1}$.

$y_t = A_+ x_t + e_t$ Matrix D is the key object in structural identification of the model's four shocks: (i) forward-looking demand, (ii) current demand, (iii) current supply, and (iv) geopolitical supply risk (GSR) or forward-looking supply. The identifying assumptions for each shock are summarized in Table 1.1.2 below.

For oil, the forward-looking demand shock captures shifts in expectations about future demand or changes in global risk appetite, such as the global financial crisis of 2008-2009. It is identified using the IV described above in a proxy-SVAR framework. Conditional on this shock, the remaining three shocks are identified using sign and relative magnitude restrictions, whose economic rationale is as follows:

(ii) *Current demand* reflects an unexpected change in current economic activity (e.g., an unexpected slowdown in manufacturing) and is identified by imposing that the shock has a positive impact on front-month and futures, and a stronger impact on the former relative to the latter (backwardation), as an increase in current demand tightens relatively more oil markets today. It also imposes a

positive correlation with equities, as higher oil prices due to strong economic activity tend to increase firms' cash flows (Kilian and Park, 2009; Ready, 2018).

(iii) *Current supply* includes events that tighten global oil supply such as the closing of the Strait of Hormuz (SoH) during the 2026 Middle East War or OPEC+ surprise cuts in production. Identification imposes a negative correlation between front-month oil and equities, as higher oil prices due to a supply shock hurt consumers' purchasing power, firms' revenues, and consequently equity returns (Kilian and Park, 2009; Ready, 2018).

(iv) *Geopolitical supply risk* refers to unanticipated increases in the probability of a future oil production shortfall related to geopolitical tensions (Kilian and others 2026), excluding other geopolitical risk events that would depress aggregate demand such as trade or financial fragmentation.⁵ Stockpiling is included here as it is indicative of geopolitical supply risk. Some notable examples of geopolitical tensions affecting oil markets include the Ukraine-Russia War during 2022 and the Iran-Israel Twelve-Day War in 2025, and the latter for gas. In both cases, oil supply disruptions were minimal or non-existent, but fears of future supply disruptions rose. The same happened during the Twelve-Day War in 2025 for gas. The possibility of a SoH closure increased the risk of Qatari LNG being shut in the region, but this risk never materialized. Its identification imposes a positive correlation between the 7-day moving average of the daily GPRT index and front-month prices, while leaving the response of futures prices and equities unrestricted.

Online Annex Table 1.1.2: Identification Restrictions for Oil and Gas SVARs

Oil SVAR	Forward demand	Current demand	Current supply	GSR
Front-month	Proxy IV	+	(S)	+
12-month futures	Proxy IV	+	(W)	
World equity index returns	Proxy IV	+	-	
GPRT	Proxy IV			+
Gas SVAR	Forward demand	Current demand	Current supply	GSR
Front-month		Proxy IV	+	+
12-month futures	+	Proxy IV		
European equity index returns	+	Proxy IV	-	
GPRT		Proxy IV		+

Notes: the proxy IVs for oil and gas are described in the previous section of the Annex. (S) denotes stronger and (W) denotes weaker response (relative magnitude restriction).

⁵ In Pinchetti (2026)'s classification, our shock (iv) is GPR energy and not GPR macro.

The identification for natural gas (European TTF prices) changes to adjust to the fact that gas markets are less financialized than oil markets, and weather is a key driver of gas price fluctuations. For this reason, we use a weather-based proxy IV (described above) to identify *current demand*. *Current supply* and *GSR* are identified with the same sign restrictions as oil, reflecting the same economic channels. However, the key difference is that the equity index is the European one, reflecting the regional importance of TTF. Finally, *forward-looking demand* for gas is identified through its positive impact on futures and equities, as equities are forward-looking financial assets that respond immediately to news about future economic conditions (Fama, 1990).

Estimation methodology

Identification by a combination of proxy IV and sign restrictions implies that the reduced-form representation of the VAR in equation (3) is augmented with a measurement equation. Let us consider the first equation in the matrix equation (2):

$$A_{0,1}y_t = A_{+,1}x_t + e_{FD,t}, \quad (4)$$

where, for concreteness, for oil [natural gas] we have included the forward-looking demand shock (FD) [current demand shock (CD)] identified using the proxy IV. Then, a measurement equation links the proxy IV (m_t) with the FD [CD] structural shock:

$$m_t = \beta e_{FD,t} + \sigma_v v_t, \quad v_t \sim i.i.d N(0,1) \quad (5)$$

where v_t is a measurement error orthogonal to all structural shocks of the VAR model, e_t .

The model estimation uses the ECB BEAR toolbox (Dieppe and others, 2016), with the following priors:

1. The prior of the reduced-form VAR coefficients is a Normal-Wishart distribution $B|\Sigma \sim N(b_0, \Sigma \otimes \Phi_0), \Sigma \sim IW(S_0, \alpha_0)$. Φ_0 is a diagonal matrix where for any lag ℓ of variable j , its diagonal entry equals $\frac{1}{\sigma_j^2} \left(\frac{\lambda_1}{\ell \lambda_3} \right)$. The parametrization for the prior distribution is $b_0 = 0.8$ for each variable's own first lag and 0 otherwise, $\lambda_1 = 1$ and $\lambda_3 = 1$. σ_j^2 is pre-computed as the OLS residual variances of univariate AR(p) regressions run on each endogenous variable. S_0 is a diagonal matrix with diagonal elements that come from the individual AR regressions, $\alpha_0 = n + 2$, where n is the number of variables.
2. For the measurement equation, BEAR follows Caldara and Herbst (2019) and imposes a prior $N(0,1)$ for β and an $IG(s_1, s_2)$ for the standard deviation of the measurement error σ_v^2 with $s_1 = 2$ and $s_2 = 0.02$ for oil. For natural gas, we use the high relevance prior option in BEAR which imposes that half of the variation in the proxy can be attributed to measurement error.

The BEAR toolbox applies the Metropolis-within-Gibbs algorithm of Caldara and Herbst (2019). In this algorithm, the proxy IV pins down column b_1 , the elements of the reduced-form matrix that correspond to the FD shock, and the sign and magnitude restrictions enter in a second step inside the algorithm as rotation matrices. BEAR then checks the responses given by each iteration. If the sign and relative magnitude restrictions are respected, it keeps the draw, otherwise it rejects it. We simulate 2000 iterations, with the first 200 used as burn-in.

Part IV. Macroeconomic impact of energy price shocks: Local Projections

The dynamic effects of oil and LNG shocks are estimated using the local projection method of Jordà (2005). A separate panel regression is estimated for each horizon $h = 0, \dots, 24$. Oil and LNG shocks, as well as each of the four shock types, are entered separately.

Consumer Price Index

For CPI, the dependent variable is the cumulative change in the logarithm of the price level from the fixed pre-shock month $t - 1$ to horizon $t + h$:

$$100[\log(CPI_{i,t+h}) - \log(CPI_{i,t-1})]$$

For each horizon h , the estimated specification is:

$$100[\log(CPI_{i,t+h}) - \log(CPI_{i,t-1})] = \alpha_i + \beta_h Shock_t + \theta_h Covid_t + \delta_h(Shock_t \times Covid_t) + \sum_{l=1}^{12} \phi_{l,h} \pi_{i,t-l} + \varepsilon_{i,t+h}$$

where α_i denotes country fixed effects, $Shock_t$ denotes one of the SVAR-identified oil or LNG shocks, and $\pi_{i,t-l}$ denotes twelve lags of monthly CPI inflation. Standard errors are clustered at the country level. To account for the exceptional macroeconomic conditions during the onset of the COVID-19 pandemic, all specifications include a COVID-19 dummy equal to one between March 2020 and June 2020 and zero otherwise, as well as an interaction between the dummy and the shock variable. This allows the pandemic period to affect both the level of the dependent variable and the transmission of commodity-market shocks. Outside the COVID-19 window, β_h measures the impact oil or LNG shocks have on the cumulative percentage change in the CPI level at horizon h relative to $CPI_{i,t-1}$. During March-June 2020, the corresponding shock coefficient is $\beta_h + \delta_h$.

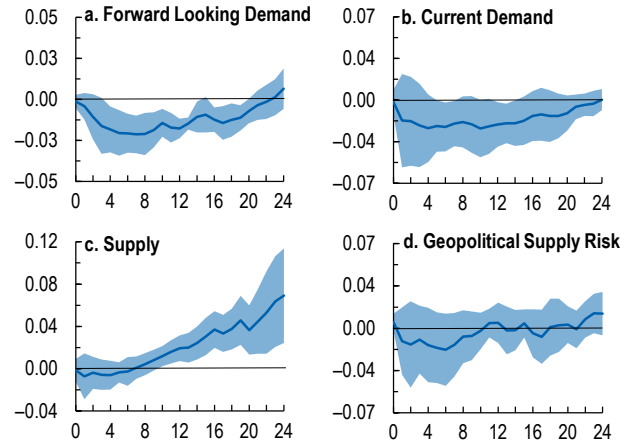
Unemployment rate

For unemployment, the dependent variable is the unemployment rate in levels at horizon $t + h$. The estimated specification is:

$$u_{i,t+h} = \alpha_i + \beta_h Shock_t + \theta_h Covid_t + \delta_h(Shock_t \times Covid_t) + \sum_{l=1}^{12} \phi_{l,h} u_{i,t-l} + \varepsilon_{i,t+h}$$

where $u_{i,t+h}$ is the unemployment rate and the controls comprise twelve lags of unemployment. Standard errors are clustered at the country level. Outside the COVID-19 window, β_h measures the

Online Annex Figure 1.1.1. Unemployment Responses to Oil Shocks in Advanced Oil-importing Economies
(Percent change; monthly horizon on the x-axis)



Sources: Haver Analytics; and IMF staff calculations.

Notes: Local projection estimates of unemployment responses to oil shocks in advanced oil-importing economies. The sample includes advanced oil-importing economies (pre-ChatGPT sample).

percentage-point effect of the shock on unemployment at horizon h relative to the counterfactual unemployment path absent shock. During March-June 2020, the corresponding shock coefficient is $\beta_h + \delta_h$.

In both specifications, country fixed effects absorb time-invariant cross-country heterogeneity, while the twelve-monthly lags account for persistence in inflation and unemployment. The sequence $\{\beta_h\}_{h=0}^{24}$ traces the baseline dynamic response over a two-year horizon.

Additional results

Figure 1.1.1 presents the effect of oil shocks on the unemployment rate for the pre-ChatGPT release (June 2007-October 2022)

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