# The Effects of Geopolitical Oil Price Shocks

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# Disclaimer

The findings, interpretations, and conclusions in our materials do not necessarily reflect the views of the World Bank Group

# Motivation

Plenty of historical evidence suggests a tight link between episodes of exceptionally elevated geopolitical tensions and movements in oil prices. For instance:

- The 1973 Arab-Israeli war
- The Iranian Revolution in 1978-1979
- The Gulf war in 1990-1991
- The Russian invasion of Ukraine
- The recent Lebanon attacks

All thes events implied sharp changes in oil prices

# The relationship is hard to measure

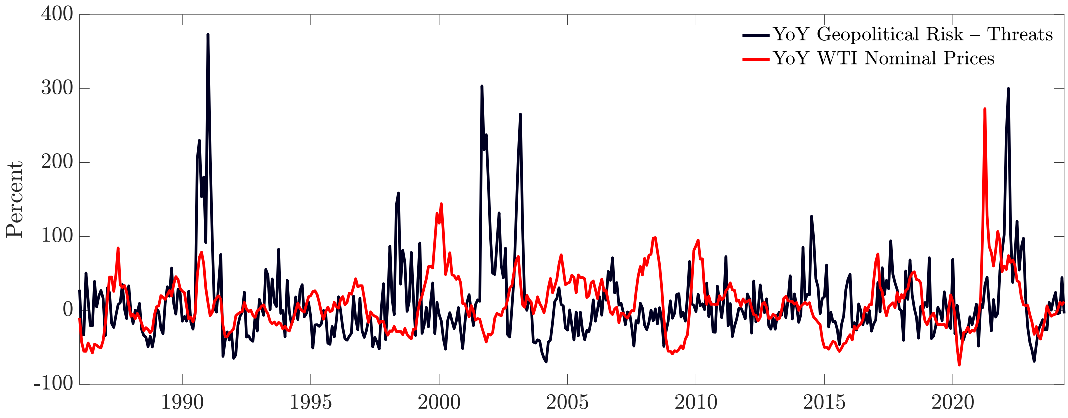


Figure: The figure shows the year-on-year growth rate of the monthly geopolitical risk index for threats by Caldara and Iacoviello (2022) and the WTI nominal prices. The correlations between these variables when is 0.0907.

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1. We use high-frequency data to construct a series of **oil price surprises** around episodes of extraordinarily sharp increases in geopolitical tensions.
2. We employ this series as an instrument in a Proxy SVAR model to identify the effects of **geopolitical oil price shocks** on the global oil market and in the US economy.

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2. We employ this series as an instrument in a Proxy SVAR model to identify the effects of **geopolitical oil price shocks** on the global oil market and in the US economy.
3. Using local projections, we extend our analysis to study the **spillovers** of these types of shocks to economic activity, inflation, and commodity prices in the world.

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- The threshold is close to choose two standard deviations from the mean, 182%
- Out of the total sample of days (14,294), approximately 3 percent of them (395) are classified as episodes of elevated geopolitical risk.

# Instrument

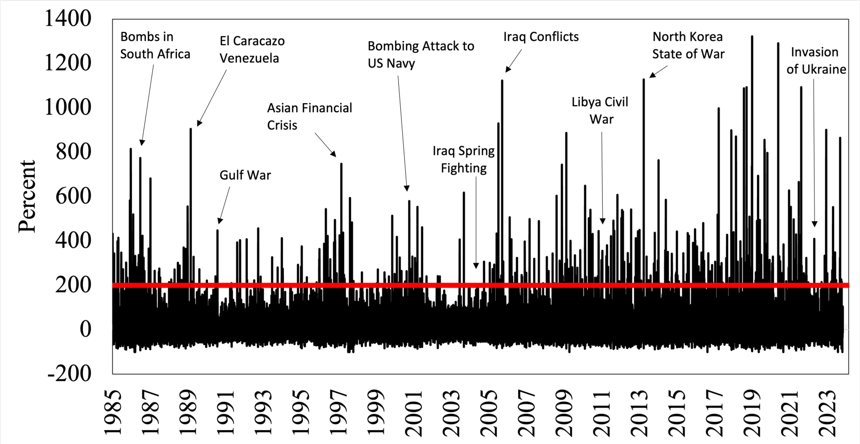



Figure: The figure shows the day-on-day growth rate of the GeoThreat index by Caldara and Iacoviello (2022). The threshold of 200 percent identifies elevated geopolitical risk. A total of 395 days out of 14,294 days (2.8 percent) are elevated in geopolitical risk.

# Instrument

Our series of geopolitical oil price surprises is designed to capture oil price fluctuations around the episodes of elevated increases in geopolitical risk and is constructed by taking the (log) difference between the price of oil futures on the day after and the day before the index of geopolitical risk rises above the 200 percent threshold:

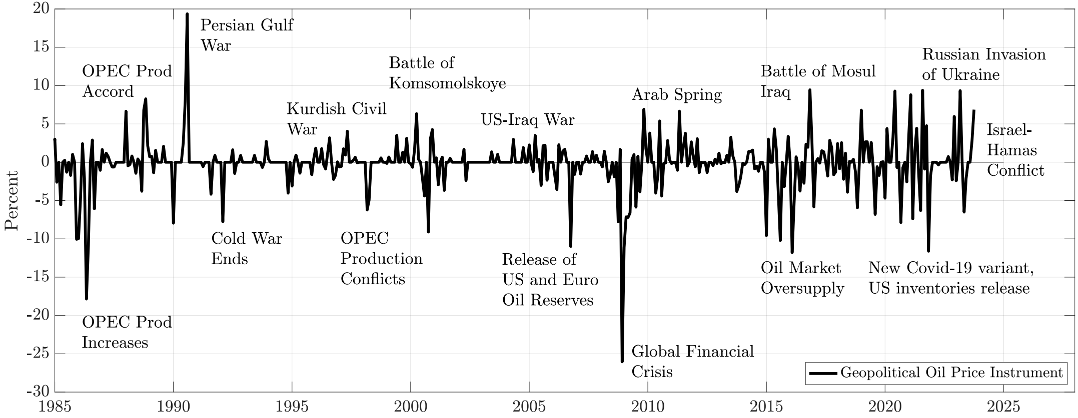
$$Surprise_{d+1} = F_{d+1} - F_{d-1},$$

where the subscript $d$ indicates the day of the high geopolitical risk event, respectively, and $F_d$ is the one-month ahead oil futures contract on day $d$.

We adopt the one-day window around the heightening of geopolitical risk since oil prices take a few hours to react to geopolitical risk increases.

We use the one-month maturity for the oil price contracts since it is sensitive to short-run changes in oil prices.

# Instrument



Percent
20
15
10
5
0
-5
-10
-15
-20
-25
-30
1985
1990
1995
2000
2005
2010
2015
2020
2025
Persian Gulf War
OPEC Prod Accord
Battle of Komsomolskoye
Kurdish Civil War
US-Iraq War
Arab Spring
Battle of Mosul Iraq
Russian Invasion of Ukraine
Israel-Hamas Conflict
Cold War Ends
OPEC Production Conflicts
Release of US and Euro Oil Reserves
Oil Market Oversupply
New Covid-19 variant, US inventories release
OPEC Prod Increases
Global Financial Crisis
Geopolitical Oil Price Instrument

# Proxy SVAR Model

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$$
\begin{aligned}
\mathbf{y_t} &= \mathbf{\Phi x_{t-1}} + \mathbf{B}\boldsymbol{\varepsilon}_\mathbf{t} \\
\mathbf{y_t} &= (x_{1,t}, x_{2,t}, x_{3,t}, \ldots, x_{n,t})' \\
\mathbf{x_{t-1}} &= (1, y_{t-1}, y_{t-2}, \ldots, y_{t-12}) \\
\boldsymbol{\varepsilon}_\mathbf{t} &= (\varepsilon_t^{x1}, \varepsilon_{2t}^{x2}, \varepsilon_{3t}^{x3}, \ldots, \varepsilon_{nt}^{xn})'
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$$

$$
\mathbf{B} = \begin{bmatrix}
b_{1,1} & b_{1,2} & b_{1,3} & \cdots & b_{1,n} \\
b_{2,1} & b_{2,2} & b_{2,3} & \cdots & b_{2,n} \\
b_{3,1} & b_{3,2} & b_{3,3} & \cdots & b_{3,n} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
b_{n,1} & b_{n,2} & b_{n,3} & \cdots & b_{n,n}
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\mathbf{B} = \begin{bmatrix} b_{1,1} & b_{1,2} & b_{1,3} & \cdots & b_{1,n} \\ b_{2,1} & b_{2,2} & b_{2,3} & \cdots & b_{2,n} \\ b_{3,1} & b_{3,2} & b_{3,3} & \cdots & b_{3,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ b_{n,1} & b_{n,2} & b_{n,3} & \cdots & b_{n,n} \end{bmatrix}
$$

For expositional purposes and without loss of generality, we assume that oil prices is ordered first is the model. Using our external instrument of geopolitical oil price surprises, we can estimate the entries of the first column in the impact matrix **B**.

# Data

We are using monthly data that range from 1975M1 to 2023M10. We have a model with eight variables:

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1. **Real oil price:** WTI prices deflated by U.S. CPI (FRED)
2. **Oil production:** Thousands of barrels per day (EIA)
3. **Oil inventories:** OECD countries (Kilian and Murphy (2014))
4. **Crude capacity utilization:** Maximum output that oil plants can maintain over time (FRED)
5. **Macroeconomic uncertainty:** measure of 1-month ahead macro uncertainty (Jurado, Ludvigson, and Ng (2015))
6. **Financial uncertainty:** measured with excess bond premium (BGFRS)
7. **US industrial production:** Monthly series (FRED)
8. **US CPI:** Consumer Price Index (FRED)

# Results:

# Instrument and Shock Diagnosis

# Instrument and shock diagnostics

- The $F$-test for the coefficient associated between our geopolitical instrument and oil prices estimated from the first stage of the procedure is equal to **20.10.**

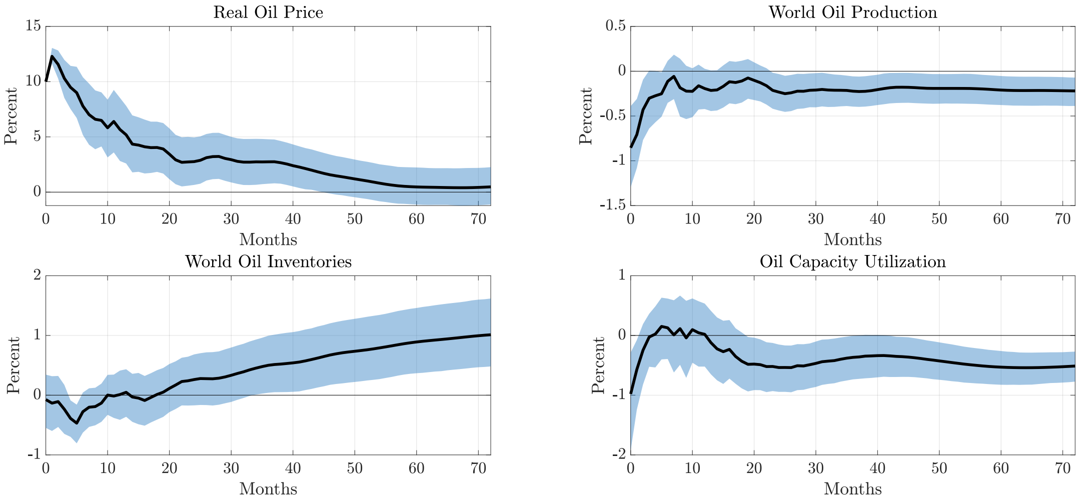
- We also regress our instrument and the identified geopolitical oil price shock on other shocks and instruments to test for its orthogonality. We find that the majority of the coefficients are statistically **insignificant**, suggesting that our shock does not exhibit a strong correlation with most of the other series: Estimations

  - Demand shocks
  - Supply shocks
  - Specific oil consumption shocks
  - Inventories shocks
  - Financial variables
  - Uncertainty measures

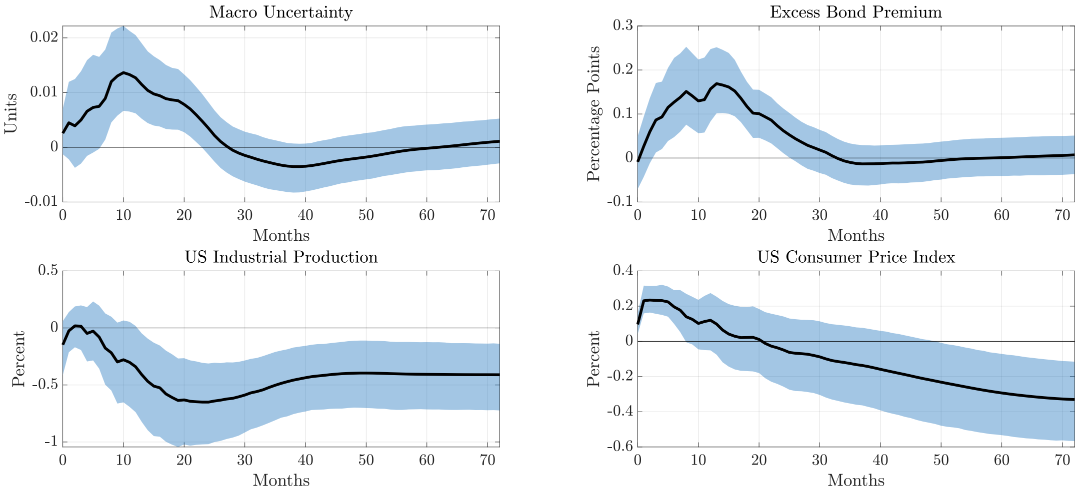
# Results:

# Oil and Macroeconomic Variables

# Oil market variables



# Uncertainty and macroeconomic variables



# Effects of the geopolitical oil price shock

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- During the Libya Civil War of 2011, real oil price rose from 40.63 USD/B to 49.10 USD/B, and production decreased by 1.38%. This implies an inverse *elasticity* of **15.6**.

# Historical Decomposition

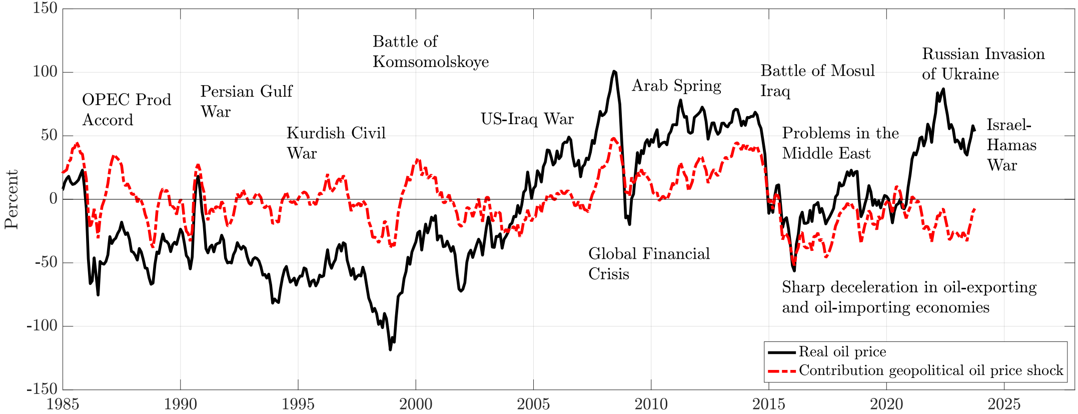



Figure: Historical decomposition of the geopolitical oil supply shock. The figure shows the cumulative historical contribution of geopolitical oil price shocks to the real price of oil together with the actual real price of oil (in percent deviations from mean).

# Results:

# Spillovers of geopolitical oil price shocks

# Spillovers

We extend our analysis and study the transmission of geopolitical oil price shocks across countries and commodities, focusing on the spillovers to:

1. National industrial production indexes
2. National CPI indexes
3. Other commodity markets

We study the impact of an increase in the geopolitical oil supply shock using the following local-projection model:

$$y_{i,t+h} \quad = \quad \beta_0^i + \psi_h^i GeoShock_t + \sum_{l=1}^{L} \beta_{h,l}^i \mathbf{y}_{t-l} + \xi_{i,t,h} \qquad \text{for } h = 0, 1, 2, ..., H, \quad (1)$$

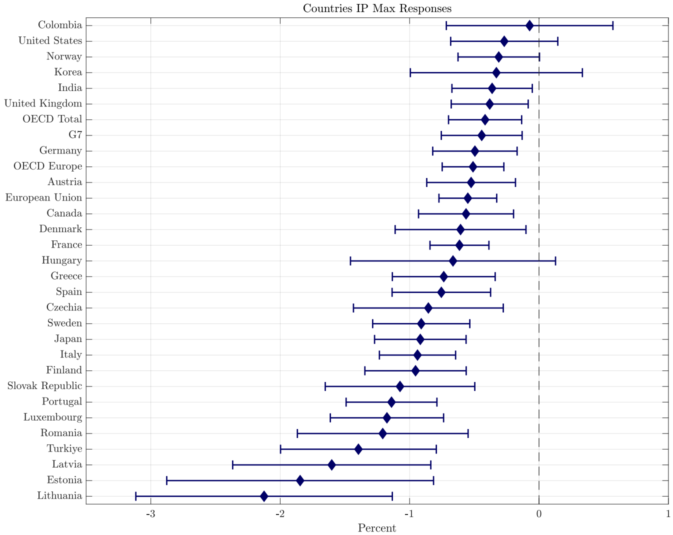
# Spillovers – Characteristics of countries

To reconcile our results for National Industrial Production and Price Indexes, we analyze two key characteristics of individual countries:

- **Domestic Factor:** The ratio of energy inventories to total inventories within the country.
- **Foreign Factor:** The ratio of foreign energy purchases to total foreign purchases.

For other commodity prices, we assess market-specific oil intensity to better understand the impact of energy shocks across different sectors.

# Spillovers – Industrial production



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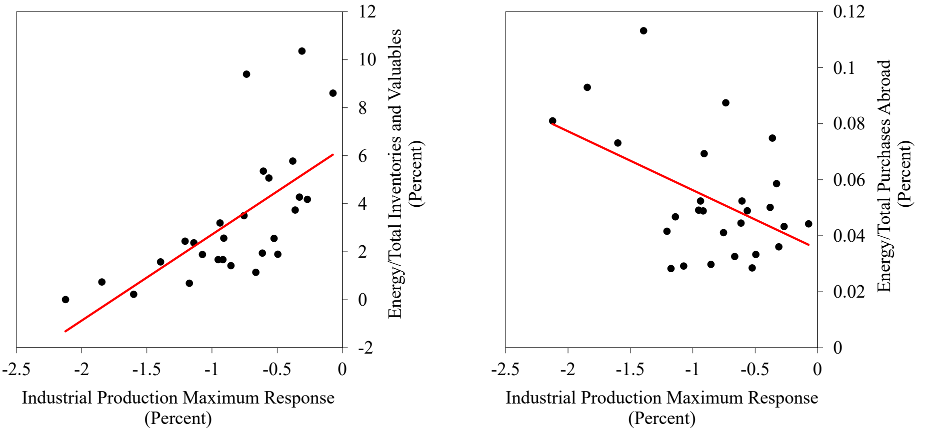
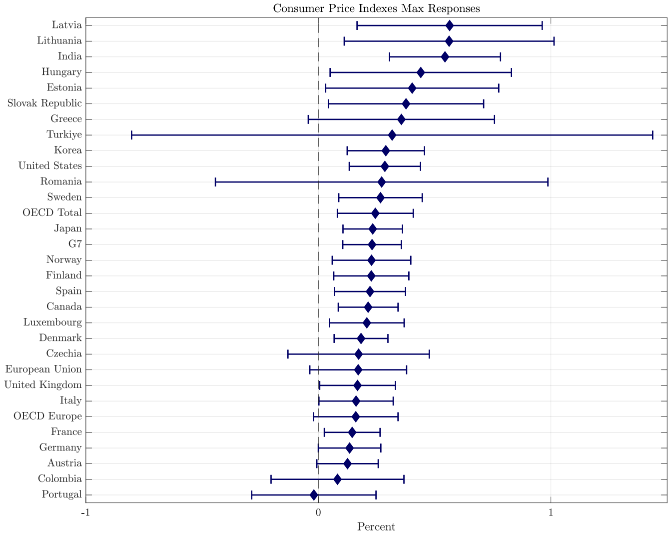



Figure: The left (right) panel of the figure shows the relationship between the energy inventories (energy purchases abroad) of the countries as a portion of the total inventories (total purchases abroad), and the maximum response of the industrial production of each country.

# Spillovers – Inflation



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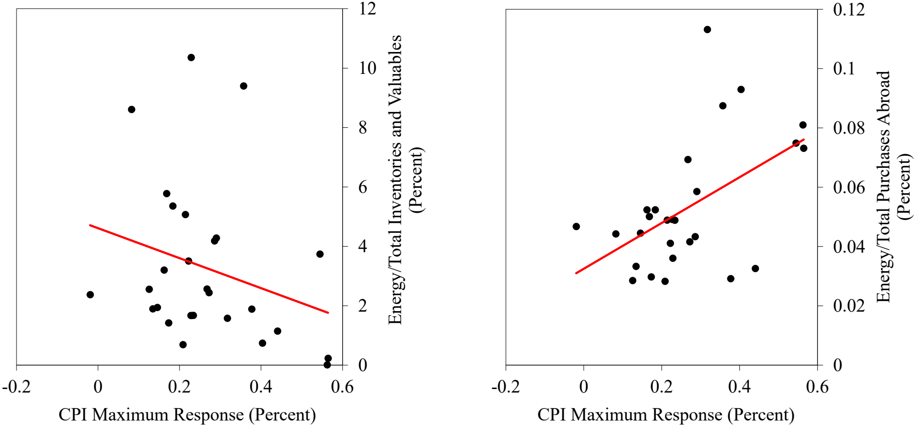


Figure: The left (right) panel of the figure shows the relationship between the energy inventories (energy purchases abroad) of the countries as a portion of the total inventories (total purchases abroad), and the maximum response of the headline consumer price index of each country.

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- We also observe notable effects on other base metals, such as copper and aluminum.

# Conclusions

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- The shocks significantly **spillover** to industrial production and price indexes across several countries and propagate to several commodity markets.
- Next steps: other versions of the instrument, study possible non-linearities...

# Thank you!

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# Appendix

# Data

- For all variables, we are introducing the data to the model as log levels.
- Data are adjusted for the Covid-19 months using the method proposed by Hamilton (2022). Procedure
- Our results are robust when:
  - Using either model (benchmark or extended)
  - Using data sample from 1984M4 to 2023M10
  - Using data sample without Covid-19 observations (i.e., dropping off 2020M1-2020M7)

# Results:
# Instrument and Shock Diagnosis

# Shock orthogonality Back

| Other Shocks/Indexes | Geopolitical Shock | Source |
|---|---|---|
| | (1) | (2) |
| Oil supply news instrument | 0.29 | (Känzig, 2021) |
| | (1.39) | |
| Oil supply news shock | 0.53 | (Känzig, 2021) |
| | (0.48) | |
| Economic activity shock | 0.07 | (Baumeister & Hamilton, 2019) |
| | (0.67) | |
| Oil consumption demand shock | 3.08 | (Baumeister & Hamilton, 2019) |
| | (3.31) | |
| Oil inventories demand shock | -0.21 | (Baumeister & Hamilton, 2019) |
| | (1.09) | |

Table: Regression between the instrument constructed in this paper (geopolitical instrument) and other instruments and structural shocks identified in previous papers. Standard errors in parenthesis.

# Shock orthogonality Back

| | | |
|---|---|---|
| Oil supply shock | -1.75<br>(1.19) | (Baumeister & Hamilton, 2019) |
| Oil demand shock | 0.71<br>(0.86) | (Caldara, Cavallo, & Iacoviello, 2019) |
| Oil supply shock | -1.23<br>(0.65) | (Caldara et al., 2019) |
| CBOE Volatility Index (VIX) | -0.10<br>(20.86) | Chicago Board Options Exchange's (CBOE) |
| Economic Policy Uncertainty | -28.91<br>(87.87) | (Baker, Bloom, & Davis, 2016) |

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# Covid-19 Observations Adjustment Back

The Covid-19 pandemic brought a series of observations with an atypical behavior. Some papers have commented on the necessity of adjusting the data before conducting any econometric exercise.

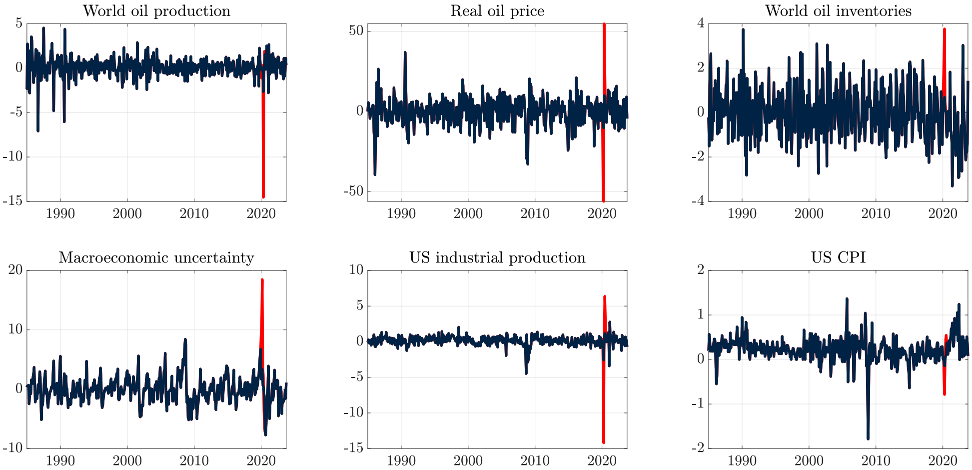
1. Some papers have suggested to ignore the Covid-19 observations, for example, Schorfheide and Song (2021)
2. Some other work suggest to *"de-Covid"* the data from the health shock that the pandemic represented by using Covid-19 indicators. For example, Ng (2021)
3. Others suggest to think of observations during the Covid-19 pandemic as having a variance-covariance matrix that is multiplied by a large scale factor during the pandemic, for example, Lenza and Primiceri (2020) and Hamilton (2023)

# Covid-19 Observations Adjustment Back

I follow Hamilton (2023) to adjust the data.

1. I follow this procedure because it allows to downweight the Covid-19 observations by dividing them by a scale parameter without completely ignoring them
2. It takes into account the variance of all variables as a system instead of performing an univariate analysis
3. The adjustment is a straight forward idea because it uses a constant scale factor for all the months of the pandemic regime Procedure
4. It can be estimated using maximum likelihood
5. I conduct this procedure for obtain an adjusting factor of 4.7 for the oil market

# Covid Adjustment



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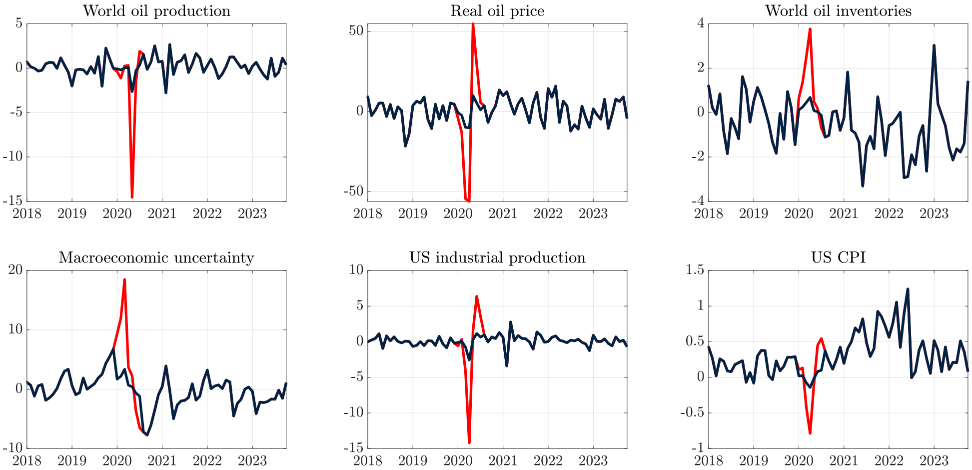
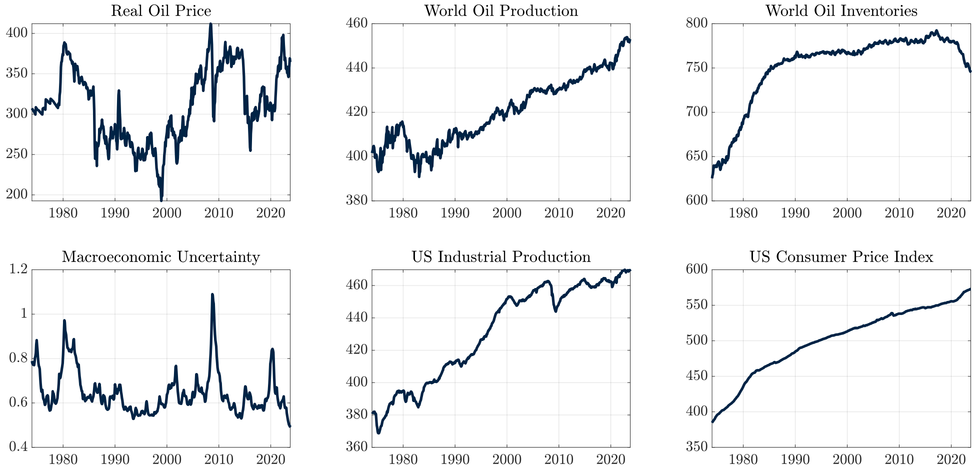


# Variables of Interest Adjusted by Covid-19 Variance



# Covid-19 Observations Adjustment – Procedure

We follow Hamilton (2023) to adjust the data and we use a constant scale factor for all the months of the pandemic regime, such that:

$$\Omega_2 = \delta^2 \Omega_1$$

where $\Omega_2$ is the variance-covariance matrix during the pandemic regime, $\Omega_1$ is the matrix during normal times, and $\delta$ is the scale parameter that takes a value greater than one ($\delta_t > 1$) during the Covid-19 months and equal to one ($\delta_t = 1$) during normal times. Here, we can write the log likelihood as

$$\begin{aligned} \mathcal{L}(\Pi_1, \Omega_1, \delta) &= -\frac{Tn}{2} log(2\pi) - \frac{T_2 n}{2} log \delta^2 - \frac{T}{2} log \left|\Omega_1\right| \\ &\quad -\frac{1}{2} \sum_{t=1}^{T} (y_t^* - \Pi_1 x_{t-1}^*)' \Omega_1^{-1} (y_t^* - \Pi_1 x_{t-1}^*) \end{aligned}$$

Where $\Pi_1$ are the parameter that characterize the normal times, $y_t^*$ and $x_{t-1}^*$ are the adjusted series by the scale parameter $\delta$ ($y_t^* = y_t/\delta$ and $x_{t-1}^* = x_{t-1}/\delta$), $T$ is the total number of observations, and $T_2$ the number of observations from the Covid regime. Lenza and Primiceri (2020) used Bayesian methods to proceed with the estimation of their adjustment.

# Covid-19 Observations Adjustment – Procedure

An advantage of Hamilton's approach is that his simpler version can be estimated using maximum likelihood. If we knew $\delta$, the MLE of $\Pi_1$ and $\Omega_1$ would be given by:

$$\hat{\Pi}_1 = \left(\sum_{t=1}^{T} y_t^* x_{t-1}^{*'}\right)\left(\sum_{t=1}^{T} y_t^* x_{t-1}^{*'}\right)^{-1} \tag{2}$$

$$\hat{\Omega}_1 = T^{-1}\sum_{t=1}^{T}\left(y_t^* - \hat{\Pi}_1 x_{t-1}^*\right)\left(y_t^* - \hat{\Pi}_1 x_{t-1}^*\right)' \tag{3}$$

If we knew the value of $(\Pi_1, \Omega_1)$ we can estimate the value of $\delta$ by taking the derivative of the log likelihood equation with respect to $\delta$:

$$\hat{\delta}^2 = (T_2 n)^{-1}\sum_{t=1}^{T}(y_t - \Pi_1 x_{t-1})'\Omega_1^{-1}(y_t - \Pi_1 x_{t-1})\mathbb{1}(Covid) \tag{4}$$

Where $\mathbb{1}(Covid)$ is an indicator variable for the Covid regime. Equations 2, 3, and 4 represent a zigzag algorithm to find the MLE of $(\Pi_1, \Omega_1, \delta)$. We start by guessing a value for $\hat{\delta}^{(1)}$ to get a weighted regression estimates of $(\Pi_1^{(1)}, \Omega_1^{(1)})$ from equations 2 and 3 to get a better estimate of $\hat{\delta}^2$, and iterate until we reach a fixed value from the iteration, that would be the MLE of $(\Pi_1, \Omega_1, \delta)$.

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# References I

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