Disentangling the geopolitical risk and its effects on commodities. Evidence from a panel of G8 countries

Matteo Foglia - Università degli Studi di Bari
Giulio Palomba - Università Politecnica delle Marche
Marco Tedeschi - Università Politecnica delle Marche

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GeoPolitical Risk (GPR)

Tuathail (1998a,b): GPR refers to the impact of political, economic, and social factors on the global and/or regional landscape.

GPR stems from international relations, trade disputes, and unforeseen events. It causes:

- disruptions in supply chains $\rightarrow$ increase in prices;
- currency fluctuations $\rightarrow$ speculation opportunities.

Monitoring GPR is important for policymakers and investors to reach the economic and financial stability.
The GPR influences financial markets behavior (Gkillas et al., 2018; Elsayed and Helmi, 2021);

Guidolin and La Ferrara (2010): the outbreak of military conflicts influenced the financial markets behavior.

The global GPR has been found to impact on:
- equity markets (Elsayed and Helmi, 2021);
- bond markets (Sohag et al., 2022);
- currency markets (Bossman et al., 2023);
- inflation (Caldara et al., 2023).

Major events have shaken the past two decades:
- the Global Financial Crisis (GFC) in September 2008;
- the “Whatever it takes” speech in July 2012;
- the Brexit referendum in June 2016;
- the Covid-19 pandemic in March 2020;
- the Russia-Ukraine conflict in February 2022;
Motivation

Ding et al. (2021); Gong and Xu (2022): the investigation of GPR shocks across countries is missing.

The global GPR impact the commodity sectors:

- energy (Cunado et al., 2020; Chowdhury et al., 2021);
- metals (Baur and Smales, 2020; Li et al., 2021);
- food (Hasan et al., 2022; Tiwari et al., 2021).
Motivation

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- metals (Baur and Smales, 2020; Li et al., 2021);
- food (Hasan et al., 2022; Tiwari et al., 2021).

The aim of the paper is to:

- analyze the GPR transmission across different countries in the last two decades;
- disentangle the impact of country-specific GPR on commodity market prices.
### Data

- monthly data from Jan 2001 to Oct 2022 \((T = 274)\);
- GPR indexes \((\text{Caldara et al., 2023})\);
- G8 countries;
- 13 log differences of commodity prices \(\text{(list)}\);
- 3 commodity sectors (energy, metals, food);

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Data

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- GPR indexes (Caldara et al., 2023);
- G8 countries;
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Methodology

- Time Varying Parameter VAR (TVPVAR) Koop and Korobilis (2013) and Antonakakis et al. (2020);
- Kalman filter;
- Generalized Impulse Response Functions (GIRFs);
- no window size is required;
- outlier sensitive estimated parameters;
- identification of GPR shocks over time;
- suitable model for low frequency data;
- the events that shook the last decade are accounted for.
Methodology

TVPVAR(p):

\[ y_t = A_t x_{t-1} + \varepsilon_t \]  

where \( \varepsilon_t \sim N(0, \Omega_t) \) and

\[ A_t = \begin{bmatrix} A_{1t} & A_{2t} & \ldots & A_{pt} \end{bmatrix} \quad \text{and} \quad x_{t-1} = \begin{bmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{bmatrix}. \]

We assume:

\[ a_t = a_{t-1} + \nu_t, \]

where \( \nu_t \sim N(0, \Sigma_t) \) and \( a_t = \text{vec}(A_t) \).

We estimate a TVPVAR(1).
Kalman filter

- training set: from January 2001 to December 2007 ($T_0 = 96$);
- test set: from January 2008 onward ($T_1 = 180$);
- $T_0 + T_1 = T = 274$;
- starting parameters $a_0$, $A_0$, and $\Omega_0 = T_0^{-1} E_0' E_0$;
- Initial conditions:

$$
A_t | \mathcal{I}_{t-1} = A_{t-1} \\
\varepsilon_t | \mathcal{I}_{t-1} = y_t - A_{t-1} x_{t-1} \\
\Omega_t | \mathcal{I}_{t-1} = \kappa_2 \Omega_{t-1} + (1 - \kappa_2) \frac{\varepsilon_t \varepsilon_t'}{T_0} | \mathcal{I}_{t-1} \\
\Sigma_t^* | \mathcal{I}_{t-1} = k_1^{-1} \Sigma_{t-1} = k_1^{-t} \Sigma_0,
$$

where $\kappa_1, \kappa_2$ are decay factors (Koop and Korobilis, 2014).
Kalman filter

The multivariate Kalman filter proceeds via the following steps

\[
\Omega_t = X_{t-1}'(\Sigma_t^*|\mathcal{I}_{t-1})X_{t-1} + \kappa_2\Omega_{t-1} + (1 - \kappa_2)\frac{\varepsilon_t\varepsilon_t'}{T_{t-1}},
\]

(3)

\[
K_t = (\Sigma_t^*|\mathcal{I}_{t-1})X_{t-1}\Omega_{t-1}^{-1},
\]

(4)

\[
a_t = a_{t-1} + K_t(\varepsilon_t|\mathcal{I}_{t-1}),
\]

(5)

\[
\varepsilon_t = y_t - A_t\mathbf{x}_{t-1},
\]

(6)

\[
\Sigma_t = (I_{n^2p} - C_t)\Sigma_t^*|\mathcal{I}_{t-1},
\]

(7)

where \(C_t = K_tX_{t-1}'\), \(X_{t-1} = \mathbf{x}_{t-1} \otimes I_n\), \(I_n\) is the \(n\)-dimensional identity matrix.
Results

We provide:

- 80 GIRFs:
  - 56 GPR shock transmission across countries;
  - 24 GPR shock impact to commodity prices;
- 13 step-ahead horizons;
- country GPR shares on sectors commodity prices;
Results

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- 80 GIRFs:
  - 56 GPR shock transmission across countries;
  - 24 GPR shock impact to commodity prices;
- 13 step-ahead horizons;
- country GPR shares on sectors commodity prices;
- **black** line: Global Financial Crisis, September 2008;
- **blue** line: “Whatever it takes”, July 2012;
- **red** line: Brexit, June 2016;
- **green** line: Covid-19, March 2020;
- **gray** line: Russia-Ukraine war, February 2022.
Russian GIRFs: highest magnitude in the Russia-Ukraine conflict case, in both directions.
A sudden GPR shock in Germany increase the GPR in other countries: leading role in Europe.
The Canadian GPR shock significantly increases the UK and US GPR after two months (Brexit period): significant devaluation of the British pound (Nasir and Morgan, 2018).

Shocks from other countries to Canada are quickly absorbed, meaning a low influences in the Canadian domestic situation (same behavior of Japanese GPR).
• The backlash in the UK and US GPRs is the more pronounced, especially for the **pandemic** and the **war**;
• The USA and Japan are considered relatively stable and safe economies, in comparison to the UK, therefore the domestic perceived GPR decrease.

**USA → UK  UK → USA  USA → JAP  UK → JAP**

![Graphs showing GPR shock transmission across countries](image-url)
GPR and energy sector

- 8 months to absorb shocks. Min/max around the 2 month;

### Generalized impulse response functions for economic sectors
Generalized impulse response functions for economic sectors

GPR and metals sector

GIRF magnitudes are generally lower than those of the energy sector. US, Russia, and Germany have the most relevant effects.
Generalized impulse response functions for economic sectors

GPR and food sector
GPR shares of countries

Shares over time and aggregates

Metals

Energy

Food

(d) Covid-19 pandemic

(e) Russia-Ukraine conflict
Concluding remarks:

- ongoing globalization of world markets;
- GPR transmission between G8 countries and that on commodity markets tends to be uneven;
- geographic proximity (North America and Europe) generally amplifies the mutual influence of GPR shocks;
- shocks from the Russian GPR have a more pronounced impact on European countries and the US (not vice versa);
- other factors, such as:
  - globalization (Sweidan and Elbargathi, 2022);
  - trade relationships (Gupta et al., 2019);
  - political and financial instability (Shahzad et al., 2023)
can contribute to transmitting GPR to commodity markets.
Economic Implications II

• the GPR increase generally reduce the energy prices. This result is attributable to the general contraction in demand (Assaf et al., 2021; Bossman et al., 2023);
• GPR shocks in Germany and Japan lead to higher energy prices: market speculation and commodities as safe-haven assets (Triki and Maatoug, 2021);
• our results could help policymakers and investors.
Thank you!

Any questions and/or suggestions?

m.tedeschi@pm.univpm.it
References I


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Log Differences of Commodity prices

Figure: Log differences of commodity prices

Energy

- **Crude oil**
- **Gasoline**
- **Heating oil**
- **Natural gas**

Metals

- **Copper**
- **Gold**
- **Palladium**
- **Platinum**
- **Silver**

Foods

- **Corn**
- **Oats**
- **Soybeans**
- **Wheat**
Gretl code: initialization

```gretl
matrices A_t_mean = array(t)
matrices Omega_t   = array(t)
matrices Sigma_t   = array(t)
matrices Kalman_t  = array(t)
matrices C_t       = array(t)
matrix A_pred = zeros(n^2,t)  |
matrix A_update = zeros(n^2,t)
matrix Varepsilon_t = zeros(n,n)
matrix A_col = zeros(n^2*p,1)
matrix y = zeros(n,1)

loop for i = 1 .. t  #Inizialization of arrays
    A_t_mean[i] = zeros(n,n*p)
    Omega_t[i]  = zeros(n,n*p)
    Sigma_t[i]  = zeros(n^2*p,n^2*p)
    C_t[i]      = zeros(n^2*p,n^2*p)
    Kalman_t[i] = zeros(n^2*p, n)
endloop

# Inizialization of the variables. It means the starting point of the Kalman filter where t=1
Omega_t[1] = Omega_0
Sigma_t[1] = beta_0_var
A_pred[,1] = beta_0_mean

matrix yy = x[(p+1):t,]
matrix xx = x[1:(t-p-1),]
```

Back to Methodology slide
Appendix

Gretl code: main loop

```
loop for i = 2 .. (t-1)
  if i <= (p+1)
    A_pred[i] = A_pred[,i-1]
    A_update[i] = A_pred[i]
    Sigma_t[i] = Sigma_t[i-1]
    Varepsilon_t = x[i],x[i],
    Omega_t[i] = l^2*Omega_t[(i-1)] + (1-l^2)*Varepsilon_t
  elif i>(p+1)
    Varepsilon_t = y[i-p],y[i-p]*A_t-mean(i-1)
    SSR = Varepsilon_t*Varepsilon_t
    Kron = x[i],I(n)
    Sigma_t[i] = (1/l^4)*Sigma_t[(i-1)]
    Omega_t[i] = Kron*Sigma_t[i]*Kron' + l^2*Omega_t[(i-1)] + (1-l^2)*SSR
    Kalman_t[i] = Sigma_t[i]*(Kron*inv(Omega_t[i]))
    e_hat = y[i-p], - xx[(i-p),]*A_t-mean[i]
    A_update[i] = A_pred[i] + Kalman_t[i]*e_hat'
    C_t[i] = Kalman_t[i]*Kron
    Sigma_t[i] = (I(n^2*p) - C_t[i])*Sigma_t[i]
    Omega_t[i] = l^2*Omega_t[i] + (1-l^2)*e_hat*e_hat'
  endif
A_col = decay_factor*A_update[,i-1]
print A_t-mean[i] = mshape(A_col, n, n*p)
print i | x[i],A_t-mean[i]
endloop
```