Geopolitical Risk and Inflation: The Role of Energy Markets

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Abstract

Geopolitical shocks are not all alike – different classes of geopolitical shocks can have different macroeconomic implications, particularly on inflation. This paper exploits the comovement between the Geopolitical Risk Index (GPR) and oil prices across major geopolitical events to disentangle two types of geopolitical shocks within a structural VAR model for the US economy. The VAR estimates suggest that geopolitical shocks associated with disruptions in energy markets are inflationary and contractionary. In contrast, geopolitical shocks associated with macroeconomic developments that are unrelated to energy markets are deflationary and contractionary. To support this interpretation, the paper exploits the heterogeneity across sectoral output and prices of the US economy to show that a sector's response to a geopolitical shock depends on its energy intensity. Sectors characterized by higher energy intensity are subject to larger output losses and price increases in response to geopolitical energy shocks, while the same does not hold for geopolitical macro shocks.

Keywords: Geopolitical Risk, Business Cycles, Energy, High-Frequency Sign Restrictions, High-Frequency Identification, Narrative Sign Restrictions.

JEL Codes: E31, E32, Q41, Q43.

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1 Introduction

Recent events such as the Russian invasion of Ukraine in February 2022 have sparked renewed interest in the macroeconomic consequences of geopolitical events. The empirical literature has shown that these events have significant contractionary effects.[1] However, geopolitical episodes are not all alike. They can be associated with multiple disturbances, ranging from energy market disruptions to trade and financial fragmentation. Some can hamper the supply of critical inputs, while others can affect aggregate demand. Within macroeconomic models, these can be characterized as a combination of different structural shocks. This paper shows that this distinction matters for macroeconomic outcomes, i.e. different geopolitical shocks can transmit differently to economic activity and inflation.

While energy market disruptions have been particularly prominent in recent history, energy price dynamics around geopolitical events suggest that there might be other important - and fundamentally different - shocks at play. In Figure 1, I plot the evolution of geopolitical risk and oil prices from 1985 to 2023, proxied respectively by the log of the monthly average of the GPR index developed by Caldara and Iacoviello (2022) (in blue), and the log of the West Texas Intermediate index (WTI) spot price, deflated by the US CPI (in red).

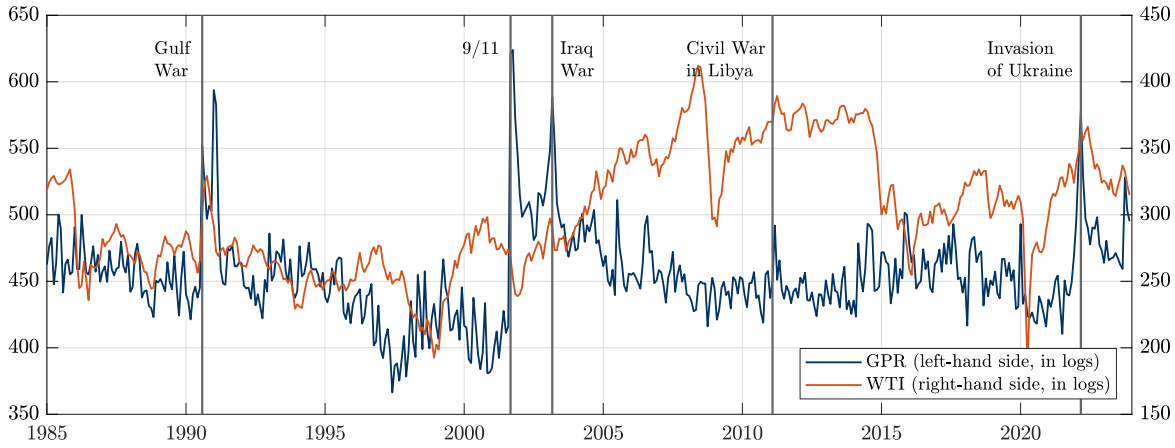


Figure 1 Geopolitical Risk and Oil Prices

During some of the most salient events in recent history, such as the outburst of the Gulf War, the Iraq War, the Civil War in Libya, and the Russian Invasion of Ukraine, increases in the GPR index are accompanied by a rise in WTI spot prices. On the other hand, in occasion of other events, such as the 9/11, the increase in the GPR index is accompanied by a drop in WTI spot prices.

[1] Caldara and Iacoviello (2022) developed an index of geopolitical risk (GPR) to quantify the contractionary effects of adverse events based on their coverage by the international press.

This paper shows that this comovement can be exploited to identify two distinct types of geopolitical shocks. The first type, referred to as geopolitical energy shocks (or GPR energy shocks), is associated with disruptions in energy markets. The second type, referred to as geopolitical macro shocks (or GPR macro shocks), encompasses macroeconomic dynamics that do not originate in energy markets. Since these shocks have different macroeconomic effects, disentangling them can shed light on the transmission of geopolitical risk to inflation and economic activity.

First, I disentangle these two shocks by exploiting the comovement between the GPR index and oil price futures. The underlying premise is that when geopolitical events lead to increases in oil prices, their transmission operates through energy markets, anticipating future energy supply disruptions. In contrast, when geopolitical news leads to decreases in oil prices, the market anticipates a contraction in overall macroeconomic activity, leading to a decline in oil demand.

Second, I quantify the impact of these shocks on the US economy using a structural VAR model. I identify the model using a combination of sign restrictions, narrative information, and high-frequency sign restrictions following the approaches proposed by Jarociński and Karadi (2020) and Antolín-Díaz and Rubio-Ramírez (2018). The empirical analysis indicates that both geopolitical energy and geopolitical macro shocks lead to contractions in economic activity. However, the response of inflation differs across shocks: geopolitical energy shocks lead to inflationary effects, while geopolitical macro shocks result in deflationary effects.

Third, I validate the identification strategy by exploiting the heterogeneity in energy intensity across different sectors of the US economy. Using US sectoral data on output, prices, and energy intensity from the BEA, I show that sectors with higher energy use relative to their value-added are more strongly affected by geopolitical energy shocks, while the same does not hold for geopolitical macro shocks. This highlights that the responses of activity and inflation to geopolitical shocks in a given sector depend on their energy intensity.

The paper is structured as follows. In Section 2, I review the main contributions in the literature related to the paper. In Section 3, I document some stylized facts and the methodology for the construction of the database. In Section 4, I describe the identification strategy, the econometric approach, and exploit the model estimates to assess the impact of the Russian invasion of Ukraine on CPI and industrial production in the US. In Section 5, I validate the identification strategy by evaluating the impact of the identified shocks sectoral US data. Finally, in Section 6, I conclude by outlining the normative and policy implications of the work.

2 Related Literature

The paper relates primarily to the geopolitical risk literature, which builds on the seminal work of Caldara and Iacoviello (2022), who develop a news-based geopolitical index and highlight the contractionary effect of geopolitical episodes for economic activity, which materializes via a reduction in investment and hours worked. Hassan et al. (2019) and Wang et al. (2023) show that this effect is more pronounced when firms have (i) greater political exposure, (ii) greater irreversible investment, and (iii) higher market power. Brignone et al. (2024) shed light on the role of non-linearities in the transmission of geopolitical risk, emphasizing the role of the precautionary saving channel. Caldara et al. (2023) investigate the consequences of geopolitical shocks for inflation, but do not explore the heterogeneity characterizing geopolitical shocks of different nature.

The focus on the energy markets relates to a vast literature which analyzes the macro consequences of shocks originating in the oil sector, including oil supply, demand, and expectations about future oil market conditions. In the last decades, the literature has developed identification schemes to identify oil-specific shocks within VAR models which exploit zero restrictions as in Kilian (2009), sign restrictions as in Kilian and Murphy (2012), Baumeister and Peersman (2013) or Baumeister and Hamilton (2019), narrative information as in Antolín-Díaz and Rubio-Ramírez (2018), Caldara et al. (2019), and high-frequency information as in Känzig (2021).

From a methodological perspective, the econometric approach used in the paper closely relates to the narrative approach and the high-frequency approach to the identification of monetary policy shocks. First, following the literature on the identification of monetary policy shocks, I identify geopolitical risk surprises by measuring the change in news-based geopolitical risk measures in a narrow window around key events selected on a narrative basis.[2] Second, I adopt the high-frequency sign restrictions approach proposed by Jarociński and Karadi (2020) jointly with narrative information using the daily comovement between variables to distinguish between the different classes of geopolitical shocks.[3] Third, in the spirit of Antolín-Díaz and Rubio-Ramírez (2018), I exploit narrative information in a structural VAR to estimate the macroeconomic effects of the distinct classes of geopolitical shocks.

This paper contributes to the literature by highlighting the role of the heterogeneity across geopolitical events in their macroeconomic transmission, and developing an empirical framework to quantitatively assess the role of different shocks in the propagation.

[2]See Kuttner (2001), Gürkaynak et al. (2005), Nakamura and Steinsson (2018), Miranda-Agrippino and Ricco (2021).

[3]See Romer and Romer (2004) or Romer and Romer (2010).

3 Identification approach and construction of the surprise dataset

This section provides an overview of the rationale underlying the identification approach, the methodology used to construct the dataset of geopolitical risk surprises, and its main features.

3.1 Identification Approach

The adoption of an identification strategy based on a narrative high-frequency sign restrictions approach is motivated by the observation that in a narrow window around geopolitical episodes, oil prices sometimes increase, and sometimes decline, as I earlier illustrated in Figure 1. The negative comovement is attributed to news associated with macroeconomic dynamics which do not originate in energy markets. In line with this interpretation, this type of news results in oil price movements associated with fluctuations in the overall macroeconomic activity via the oil demand channel. As such, I define this class of shocks as geopolitical macro shocks, or GPR macro. Based on the empirical pattern, the contribution of this shock is likely to be prevalent in episodes not characterized by severe disruptions in energy markets, like the 9/11. The positive comovement, on the other hand, is attributed to news regarding developments in energy markets, as it is associated with an increase in oil prices. For this reason, I define this class of shocks as geopolitical energy shocks, or GPR energy. Based on the empirical pattern, these shocks are likely to be prevalent in episodes like the Gulf War, the Iraq War, the Civil War in Libya, and the Invasion of Ukraine.

The rationale for constructing a dataset of GPR surprises derives from the main identification challenge of the empirical analysis in the implementation of this identification strategy - namely the reduction of the noise-to-signal ratio in the data. While in principle sign restrictions can be implemented also at monthly frequency jointly with an exogeneity restriction on the GPR index, in practice this delivers inconsistent results, as I show in Figure A.9 in the Appendix.[4] This underscores the need to improve the signal by imposing additional discipline on the data.

Such additional discipline can be imposed by exploiting narrative information, jointly with sign restrictions methodologies. The identification strategy adopted as baseline does

[4]The scheme of restrictions I refer to here is the one described in Table 3. The inconsistency derives from the observation that industrial production rises in response to an energy related geopolitical shock (the response being insignificant), at odds with the literature on the effect of geopolitical risk shocks and the literature on the effects of oil market disruptions.

that by exploiting the comovement of the daily version of the GPR index and oil prices around a list of key events in the spirit of Jarociński and Karadi (2020). As key events are by definition characterized by large fluctuations in the GPR index, in these instances, the variance of geopolitical shocks is likely to be relatively larger compared to the unconditional variance, resulting in an improvement of the signal-to-noise ratio[5].

3.2 Event Selection

The list of the key geopolitical events employed for the dataset is selected following a narrative approach, in the spirit of the work of Romer and Romer (2004, 2010). Based on narrative information from qualitative sources,[6] I select those events whose date corresponds unequivocally to the date of the first large surprise in the daily GPR index series. To construct the list of events, I adopt the following procedure.

First, I consider the list of events associated with spikes in the daily GPR index provided by Caldara and Iacoviello (2022)[7]. Second, I extend the list to include the latest geopolitical events. This process leads inter alia to the inclusion of the Afghan crisis in August 2021, the Russian invasion of Ukraine in February 2022, the Istanbul bombing in November 2022, and the attacks of Hamas on Israel in October 2023[8]. Third, I examine each one of the considered episodes to establish the date of coverage of the concerned event, based on narrative information from the archive of major newspapers. The main challenge here is that geopolitical events often arise in sequence, sometimes leading to a gradual escalation of the geopolitical risk. To rule out the possibility that the rise in geopolitical risk is anticipated by the market, I focus on the event associated with a large GPR surprise in the sequence.[9]

Table 1 illustrates the list of selected events, which includes 42 distinct key geopolitical

[5]Alternatively, similar results can be achieved by combining sign restrictions with restrictions on the historical decomposition in the spirit of Antolín-Díaz and Rubio-Ramírez (2018), as I will show later.

[6]To this purpose, I mostly exploit narrative information from the same list of newspaper employed for the construction of the GPR index, i.e. the Chicago Tribune, the Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, the Los Angeles Times, The New York Times, USA Today, The Wall Street Journal, and The Washington Post.

[7]See Figure 2 at page 1202 in Caldara and Iacoviello (2022).

[8]Additionally, I include the protests in Tripoli in February 2011, which marked the beginning of the Libyan Civil War. This episode is not included in the list by Caldara and Iacoviello (2022), but the GPR series shows a clear spike around the relevant date, and it is regarded as a significant event in the oil shocks literature—for example (see Antolín-Díaz and Rubio-Ramírez, 2018).

[9]This leads to some minor differences with the dates reported by Caldara and Iacoviello (2022). Namely, (i) I anticipate the date of the US bombing of Libya in 1986 to the 7th of April, date in which the Berlin attacks which led to the Libya bombing were covered by newspapers; (ii) I postpone the date of the Persian Gulf War outburst to Monday 12th October, as the attacks occurred during a weekend; (iii) I select the 3rd August 1990, date in which the Iraqi invasion of Kuwait was covered by major newspapers, rather than reporting the Iraq threats to the US Embassy on the 8th August 1990, and so on.

events. The list of events mostly includes wars, terror attacks, and international crises. Some notable examples are the start of the US involvement in the Gulf War, the US invasion of Afghanistan in October 2001, the beginning of the Iraq War in March 2003, the terrorist attacks in London in July 2005 and in Paris in November 2015, and the Russian invasion of Ukraine in February 2022.

3.3 Surprise Construction

Based on this list of events, I construct a series of GPR surprises by taking the difference of the value of the GPR index on the day of the selected geopolitical episode (t) and the value of the GPR index on the day before the episode ($t-1$):

$$Surprise_t^{gpr} = GPR_t - GPR_{t-1} \tag{1}$$

On the other hand, I construct a series of oil price surprises by taking the (log) difference of the close price of the h-month ahead of WTI crude futures contracts on the day (t) of the geopolitical episode and the price on the last trading day before the episode ($t-1$):

$$Surprise_{ht}^{oil} = log(F_t^h) - log(F_{t-1}^h) \tag{2}$$

Following Känzig (2021), I extract a first principal component from the surprises on the futures curve using maturities from one month to six months[10] to capture the role of expectations on the oil market. Daily surprises are then aggregated into a monthly series. If there is only one event in a month, the monthly surprise has the same value as the daily one. In the few cases where there are multiple events within the same month, daily surprises are cumulated to obtain a monthly frequency variable. If oil price data are not available for a given event, I exclude that event from the list.[11]

Figure 2 shows the dataset of surprises from a historical perspective. Consistent with Figure 1, on the left hand-side, I report the daily variations in the GPR index on the selected geopolitical episode days (in blue). The series exhibits two important features. First, all reported events are associated with an increase in the GPR index. This happens because

[10] I do not consider maturities from 7 months up to 1-year as their price changes infrequently in the first part of the sample, hinting at potential liquidity issues.

[11] For instance, following the 9/11 in September 2001, the New York Mercantile Exchange was closed for three days, hence WTI future prices are not available for those dates. Similarly, on 1st September 2014, US stock markets were closed in observance of Labor Day, which is a federal holiday celebrated on the first Monday of September each year.

Event No.	Surprise Date	Description	GPR surprise
1	18/06/1985	TWA Hijacking	124.75
2	07/04/1986	Berlin Attacks, U.S. Bombing of Libya	51.42
3	27/04/1987	US/Russia Negotiations over Nuclear Weapons	52.59
4	12/10/1987	War Threats in Persian Gulf	68.06
5	21/12/1989	US Invades Panama	27.09
6	03/08/1990	Iraqi invasion of Kuwait	141.53
7	15/01/1991	US Congress Authorizes Iraq War	220.38
8	09/08/1991	Ethnic Violence in Yugoslavia	40.47
9	20/08/1991	Failed coup in Soviet Union	206.04
10	14/01/1993	Air Strikes Against Iraq	127.92
11	28/06/1993	US Raid on Baghdad	66.17
12	08/02/1994	NATO Ultimatum to Serbia	64.24
13	03/09/1996	US Raid on Iraq	8.65
14	24/02/1998	US Considers Strike Against Iraq	31.47
15	18/12/1998	Iraq Disarmament Crisis Escalation	52.12
16	24/03/1999	Beginning Kosovo Air War	32.03
17	28/12/1999	Holidays' Terrorist Concerns	67.65
18	12/09/2001	9/11 Terrorist Attacks	571.44
19	09/10/2001	US Invades Afghanistan	90.18
20	13/09/2002	War Fears US / Iraq	111.32
21	18/03/2003	Beginning of the Iraq War	209.74
22	23/03/2004	Assassination of Sheik Yassin, Middle East Tensions	46.42
23	03/08/2004	Terrorist Threats in New York and Washington	147.16
24	08/07/2005	London Bombings	422.55
25	11/08/2006	Transatlantic Aircraft Plot	109.20
26	30/04/2007	War and Terrorism Concerns, Protests in Turkey	25.34
27	11/08/2008	South Ossetian War Escalation	76.39
28	28/12/2009	Flight 253 Failed Bombing Attempt	94.85
29	22/02/2011	Protests in Tripoli, Start of Civil War in Libya	54.83
30	03/05/2011	US Announces Death of Osama Bin Laden	153.94
31	29/08/2013	Escalation of Syrian Crisis	47.28
32	03/03/2014	Russia Invades Crimea	109.15
33	01/09/2014	Escalation Ukraine/Russia	70.51
34	16/11/2015	Paris Terrorist Attacks	230.42
35	18/07/2016	Turkish Coup Attempt	66.43
36	21/08/2017	North Korea Tensions	38.42
37	10/04/2018	Syrian War Escalation	111.08
38	07/01/2020	US / Iran Tensions Escalate	161.47
39	23/08/2021	Afghan Crisis Escalation	130.06
40	22/02/2022	Russia prepares for Ukraine invasion	138.78
41	14/11/2022	Istanbul Bombings	92.02
42	09/10/2023	Hamas Attacks on Israel	70.48

Table 1 List of selected geopolitical events

the dataset includes only adverse events, as geopolitical events of benign nature, such as peace agreements, are typically rare and often anticipated. Second, the GPR surprise series presents several spikes in the occasion of sudden events, such as the failed coup in the USSR in August 1991, the London terror attacks in July 2005, and the Paris attacks in November 2015. These spikes do not necessarily coincide with those of the series presented in Figure 1, as geopolitical events might present a build-up phase. Notable examples are the US invasion of Iraq, which was publicly discussed at the United Nations and the US Congress before taking place, or the Russian invasion of Ukraine, which was preceded by a phase of building tension due to the gradual accumulation of Russian troops at the frontier between the two countries. On the right-hand axis, I report the principal component of the daily variation of the first six tenors of the future curve around selected geopolitical event days (in blue). The joint observation of the two surprise series reveals that the comovement between the two can vary significantly across episode. For instance, during the failed coup in the USSR in August 1991, oil prices showed little reaction, with only a slight decrease of 0.23%. In contrast, after the Paris attacks in November 2015, oil futures surged by more than 2%. Similarly, following the London terror attacks in July 2005, oil futures experienced a decline of approximately 2%.

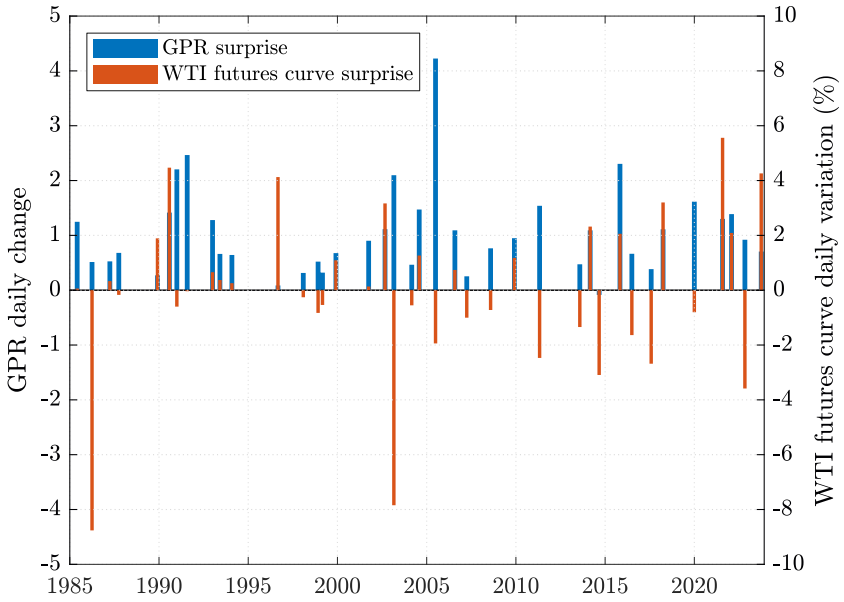


Figure 2 Geopolitical Risk and Oil Surprises

The figure highlights the comovement of geopolitical risk and WTI price surprises around selected geopolitical episodes. Each couple of bars represents one of the episodes detailed in Table 1. On the left axis, I display the change in the daily GPR index. On the right axis, I display the percentage change in the price of the 1-month ahead WTI future contract.

There are two explanations to this phenomenon. One concerns noise in oil markets, which

might create oil price fluctuations in either way, the other is the presence of distinct shocks which systematically affect oil prices during geopolitical episode days. I present evidence supporting the latter, and propose an econometric framework to decompose surprises into distinct shocks and track their propagation through the economy.

4 The Effect of GPR Energy and GPR Macro Shocks

This section explains the methodology used to estimate the VAR model including GPR and oil price surprises on top of standard macroeconomic and financial variables, and how the structural shocks of interest are identified. This class of VAR models allows combining elements from three popular identification approaches in the structural VAR literature, namely narrative, high-frequency, and sign restrictions. First, the narrative character is associated with the narrative approach used in the selection of the events. Second, the high-frequency character refers to the use of a narrow window for the measurement of the surprises. Third, sign restrictions are applied to disentangle the role of GPR macro and GPR energy shocks in driving GPR and WTI surprise series.

4.1 Baseline Model Specification

The baseline VAR model specification is described by Equation (3):

$$\begin{pmatrix} s_t \\ y_t \end{pmatrix} = \begin{pmatrix} 0 \\ c_y \end{pmatrix} + \sum_{l=1}^{p} \begin{pmatrix} 0 & 0 \\ B_p^{YS} & B_p^{YY} \end{pmatrix} \begin{pmatrix} s_{t-p} \\ y_{t-p} \end{pmatrix} + \begin{pmatrix} u_t^s \\ u_t^y \end{pmatrix} \tag{3}$$

$$\begin{pmatrix} u_t^s \\ u_t^y \end{pmatrix} \sim \mathcal{N}(0, \Sigma)$$

On the left-hand side, $s_t = \begin{pmatrix} s_{1t} & s_{2t} \end{pmatrix}'$ indicates a 2×1 vector of surprises, where s_{1t} is the log of daily variation of the geopolitical risk index around the list of selected geopolitical episodes, while s_{2t} is the surprise in the price of the 1-month ahead WTI future contract around selected geopolitical episodes. When any of the selected geopolitical episodes occurs in the concerned month t, the surprise series s_{1t} and s_{2t} take a value equal to the sum of the surprises occurred in that month. If no surprises occur in the concerned month t, s_{1t} and s_{2t} take zero value. The $n \times 1$ vector y_t includes a set of US and global macro variables at monthly frequency. Finally, u_t^s (2×1) and u_t^y $(n \times 1)$ are two vectors of normally distributed

reduced-form residuals.

The set of considered variables contains the monthly average of the GPR index, real WTI spot prices, US CPI from the US Bureau of Economic Analysis, US Industrial Production and US 1-Year Treasury Rate from the Board of Governors of the Federal Reserve System. The sample includes 39 years of macroeconomic data at monthly frequency, from January 1985 to December 2023.

4.2 Identification via High-Frequency Sign Restrictions

The identification strategy builds on two assumptions. First, GPR and oil surprises are only driven by the two identified shocks, and other shocks do not systematically affect them. Second, the identification builds on the idea that the nature of the geopolitical shocks can be characterized by the comovement they imply between GPR and oil surprises. GPR macro shocks are associated with a negative comovement between GPR and oil future prices. On the other hand, GPR energy shocks are associated with a positive comovement between GPR and oil future prices.

	Macro GPR	**Energy GPR**	**Other Shocks**
GPR surprises	+	+	0
WTI surprises	−	+	0
other variables	unrestricted	unrestricted	unrestricted

Table 2 Scheme of selected high-frequency sign restrictions

Table 2 provides an overview of the identifying restrictions. These restrictions divide each surprise into two components: a geopolitical macro shock (associated with a rise in GPR and a drop in real WTI prices) and a geopolitical energy shock (associated with a rise in GPR and a rise in real WTI prices). On the other hand, the two zeros on the third column reflect the fact that business cycle frequency shocks are assumed not to affect the surprise variables within the days characterized by geopolitical episodes. All the rest of the relations are left unrestricted. The model exploits Minnesota priors with a relatively low tightness and six lags, consistent with the considered tenors of the oil future curve. Sampling is performed using a Gibbs sampling algorithm with 10000 draws. The first 2000 draws are discarded, while every fourth of the remaining 8000 draws are kept, for a total of 2000 draws. The

posterior draws of the shocks are computed with the use of a uniform prior on the space of rotations, as in Rubio-Ramírez et al. (2010). Having backed out the admissible set of structural shocks, the Fry and Pagan (2011) methodology is applied to pin down the draw associated with the median target response.

4.3 Results

In this section, I discuss the main results of the empirical analysis, by looking at the impact of a one standard deviation shock to the GPR index.

The first considered variable is the GPR index. Following a one standard deviation shock to the GPR index, the level of geopolitical risk remains particularly elevated in the first three months, for then declining gradually in the first two years after the shock. The dynamics associated with the GPR macro and the GPR energy shock are similar. However, the dynamics associated with the GPR energy shock are more persistent, with the GPR index remaining 15% above its steady state level for the first six months, as opposed to two months.

Second, the model studies the response of WTI prices deflated by US CPI. Following a one standard deviation GPR macro shock, WTI prices decline persistently, with prices remaining depressed for more than two years after the shock. These dynamics are similar to those exhibited by the GPR macro shock, although for the latter they are more pronounced, reaching levels between 6% and 10% in the first six months after the shock. The response associated with the GPR energy shock, is instead positive, reaching an increase of between 0.5% and 4% in the second month after the shock. The response is, however, less gradual than the one associated with the GPR macro shock.

The third reported variable is CPI in terms of deviations from the steady state level. On one hand, the GPR macro shock is associated with a drop in CPI of between 9 and 26 basis, on the other hand the GPR energy shock is associated with a very significant and persistent rise of between 12 and 27 basis points. This response is crucial to understand the heterogeneity in the nature of the two shocks in question, with the GPR macro shock exhibiting the typical features of a demand shock, and the GPR energy shock exhibiting the typical features of a supply shock.

The fourth variable analyzed by the model is industrial production. For both the macro and the GPR energy shock, the response is also contractionary, but the profile of the response is rather different. For the GPR macro shock, industrial production falls in the first six months by between 0.5% and 1%, with the effect of the shock fading away in the first year.

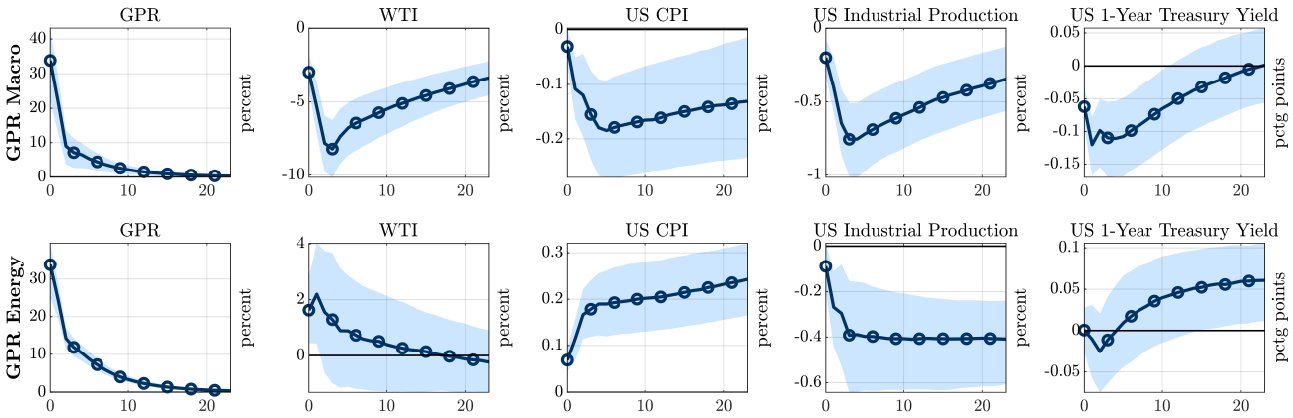


Figure 3 The macroeconomic effects of GPR macro and GPR energy shocks

The figure(s) displays the estimated dynamic response to GPR macro and GPR energy shocks. Black lines indicate point estimates and blue areas outline 68% confidence bands. The shock is associated with a one standard deviation increase in the Geopolitical Risk Index (GPR).

The GPR energy shock response instead features a gradual drop up to between -0.2% and -0.7%, which reaches the trough only after one year, with GPD remaining depressed up to the end of the considered horizon.

Finally, I include the 1-year sovereign yield, which sheds light on the average monetary policy response to the identified shocks. For the three shocks, the 1-year rate response is consistent with inflation dynamics, hinting at monetary policy as a potential driver of the underlying dynamics. For the joint GPR shock, the 1-year rate significantly declines by between 5 and 13 basis point in response to a one standard deviation shock to the GPR, and it rapidly turns insignificant. For the GPR macro shock, the 1-year rate significantly temporarily drops by between 5 and 16 basis point, while it is insignificant at the impact for the GPR energy shock. For completeness, in the Appendix I report the results obtained including a set of additional variables, including measures of economic activity, government spending, oil market indicators, inflation expectations, and proxies for financial volatility. For robustness, I also report the responses obtained using what is referred to as the poor man's approach in Jarociński and Karadi (2020), whereby each geopolitical surprise is fully explained either by the macro or the energy shock based on their comovement with the WTI future curve surprise.

4.4 Estimating the Impact of the 2022 Invasion of Ukraine on CPI Inflation and Industrial Production in the US

To illustrate a potential policy application of the model, I exploit the baseline estimates to recover the impact of the Russian invasion of Ukraine on CPI inflation and industrial production in the US. The model is well-suited for analyzing episodes involving multiple types of shocks, as it can distinguish the impact of energy market disruptions alongside other macroeconomic factors. This allows for a clearer understanding of how different forces can contribute to drive economic outcomes during periods of geopolitical tension.

To estimate the impact of the Russian invasion of Ukraine, it is first necessary to recover the size of the two structural shocks associated with GPR dynamics in the concerned period. The most straightforward approach would be (i) estimating a historical decomposition of the GPR surprise series, (ii) decomposing the surprise series into the two structural shocks, and (iii) projecting the associated impulse response function over the considered horizon. However, this approach would tend to underestimate the overall impact of the shock, since Russia had gradually accumulated its troops at the frontier since a few days and the risk of invasion was largely anticipated, resulting in a smaller surprise at the impact. In quantitative terms, the GPR index rose by 66.19% on the day of the invasion, with the historical decomposition attributing the 16.29% of the GPR index increase to the GPR macro shock and the 83.71% of the increase to the GPR energy shock. On the other hand, the GPR index rose by 83.13% between January 2022 and March 2022. In the spirit of a back-of-the-envelope calculation, I calibrate the shock so to match the full extent of the January 2022 – March 2022 GPR variation while retaining the shares of the two shocks derived from an historical decomposition performed on the daily surprises. Ultimately, this approach delivers a GPR macro shock associated with a 13.57% rise in the GPR index and a GPR energy shock associated with a 69.72% rise in the GPR index.

Based on this calibration, I use the median response to illustrate the impact of the outburst of the conflict on CPI inflation and industrial production in the US, which I express here in year-on-year terms for it to be more intuitive for the interpretation of CPI inflation dynamics. I assume that the shock occurs in March 2022 (period 0), and study its propagation in the following months. The GPR energy shock is associated with a rapid growth in the inflation rate in the months following the shock, reaching the maximum impact in July 2022 at 0.42 percentage points. The effect on CPI inflation persists up to the first quarter of 2023. Then, CPI inflation starts to rapidly decline up to June 2023, when the effect dissipates. The effect of the GPR macro shock on CPI inflation, on the other hand, is

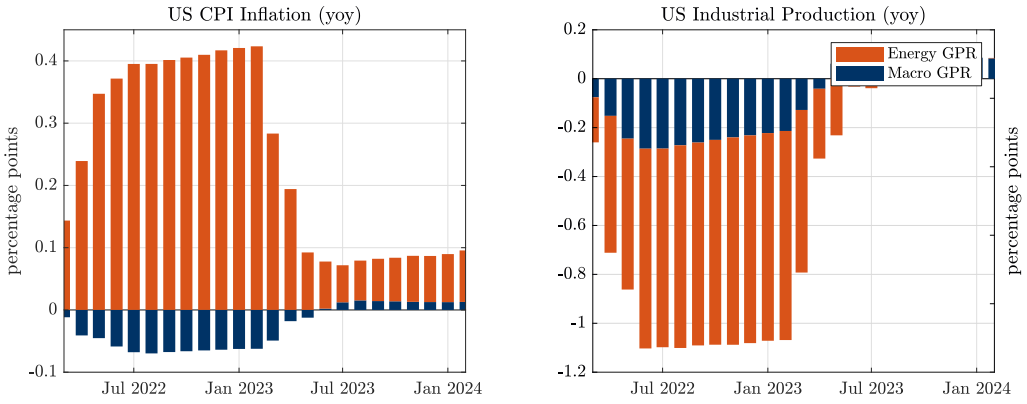


Figure 4 Impact of the Russian Invasion of Ukraine in February 2022

The figure displays the decomposition of the response of CPI inflation and industrial production to a GPR macro and a GPR energy shocks calibrated so to match the difference in the level of the GPR index between January and March 2022 in shares proportional to their contribution in the historical decomposition.

limited, and quantifiable in about -0.05%.

The effect on US industrial production is the result of the joint action of both shocks. The GPR macro shock implies a contraction up to 0.30 percentage points in June 2022, which persists up to the first quarter of 2023. The effect associated with the GPR energy shock is more rapid in the initial phase, and more gradual in its build-up phase, reaching the trough in March 2023 with a contribution of -0.81 percentage points. March 2023 also marks the trough of the overall response, for a total of -1.11 percentage points. The effect of the GPR energy shock is very persistent, fading away very gradually and extending beyond the considered horizon of 24 months. These results are broadly consistent with the observation that CPI in the US rose only by about 1% from the outburst of the war to the peak of the inflation wave in June 2022.

4.5 Identification via Narrative Sign Restrictions

This section explores the robustness of the results of the paper to alternative identification assumptions. While the baseline identification strategy builds on the idea that different shocks can be identified based on the comovement of oil prices and the GPR index around key geopolitical episodes, in this section I will show that using the narrative sign restrictions by Antolín-Díaz and Rubio-Ramírez (2018) can yield results in line with the baseline estimates. This methodology combines narrative information with sign and zero restrictions to identify the structural shocks in a Bayesian VAR model along the lines of the one presented in Section 4. The methodology is detailed in the Appendix.

Let us start from the sign and zero restrictions, which are outlined in Table 3. First, I impose that the both shocks exerts a positive effect on the GPR index and a negative effect on real WTI prices. Second, that the GPR energy shock has a positive effect on the GPR index and a positive effect on real WTI prices. Third, that all other shocks cannot affect the GPR index. In other words, the GPR index is exogenous to the rest of the model, being exclusively driven by GPR macro and GPR energy shocks. Differently from the previous exercise, it is important to note that these restrictions are imposed at monthly frequency.

	Macro GPR	**Energy GPR**	**Other Shocks**
GPR	+	+	0
WTI	–	+	unrestricted
other variables	unrestricted	unrestricted	unrestricted

Table 3 Scheme of selected sign and zero restrictions

Let us now move to the narrative restrictions. I impose a set of restrictions on the historical decomposition of the model, which I detail in Table 4. The narrative restrictions I impose belong to two different classes: (i) sign-based narrative restrictions, which impose the sign of the contribution of a given shock in a given period, and (ii) historical decomposition narrative restrictions, which discipline the size of the contribution of a given shock in a given period. These restrictions are particularly useful to (i) discipline the response of industrial production and (ii) shrink the set of admissible draws derived from the imposition of the zero and sign restrictions detailed above.

I impose this set of narrative restrictions drawing from narrative information on the five selected episodes illustrated in Figure 1. To identify GPR macro shocks, it is sufficient to impose the presence of a large contribution of the GPR macro shock in September 2001, the month of the 9/11. This restriction reflects the uncertainty in financial markets and more broadly the shock in the global economic and financial community following the events of the 11th of September 2001. At the same time, one can exclude with reasonable certainty the presence of a strong energy component in September 2001, as oil markets have experienced a period characterized by downward pressures in the months following the 9/11, with WTI prices dropping from 26$/bbl in September to 19$/bbl in November. Note that this restriction does not exclude the presence of a positive energy component in the historical decomposition, but rather of a *dominant* energy component.

Event date	Description	Type of shock	Restriction
August 1990	Start of the Persian Gulf War	Energy	Sign (+)
September 2001	9/11	Macro	Top Contributor to GPR
March 2003	Beginning of the Iraq War	Energy	Sign (+)
February 2011	Civil War in Libya	Energy	Sign (+)
March 2022	Russian Invasion of Ukraine	Energy	Sign (+)

Table 4 Scheme of selected narrative restrictions

To identify the GPR energy shock, I impose the presence of a positive shock in four prominent episodes of geopolitical tension involving oil markets. First, the start of the Persian Gulf War in August 1990 with the Iraq invasion of Kuwait. Second, the beginning of the US invasion of Iraq in March 2003. Third, the outburst of the Civil War in Libya in February 2011. Lastly, the Russian invasion of Ukraine in February 2022. The first three episodes are borrowed from Antolín-Díaz and Rubio-Ramírez (2018), which use them to discipline an oil supply shock. All of these episodes, however, originate from a geopolitical rationale, and can be reasonably characterized as geopolitical shocks.

Let us now analyze the results of the estimation based on the narrative sign restrictions approach. In Figure 5, I report in black the impulse responses from the estimation via high-frequency sign restrictions, and in blue the impulse responses from the narrative sign restrictions. In response to a one standard deviation rise in the GPR associated with a GPR macro shock, real WTI prices drop by between 7.5% and 15%, US CPI drops by between 0% and 0.4%, and industrial production drops by between 0.2% and 1.2%. Finally, the response of the 1-year sovereign yields is not significant. Overall, the responses highlighted by the model identified via narrative sign restrictions are in line with those identified by the baseline model, with the oil price and industrial production responses being significantly less pronounced compared to the baseline case.

On the other hand, in response to a one standard deviation rise in the GPR associated with a GPR energy shock, real WTI prices rise by between 15% and 30%, US CPI rises by between 0% and 0.4%, while industrial production drops by between 0% and 0.75%. Finally, the 1-year sovereign yield drops by between 0.5% and 3%, although the uncertainty surrounding this estimate is relatively large, and the response becomes significant only towards the end of the IRF horizon. Overall, the model identified with narrative sign restrictions displays a very pronounced response of WTI prices, significantly larger and more pronounced than the baseline model. Consistently, this is associated with a larger contraction of industrial activity, and a more pronounced drop in sovereign yields, but not with a more inflationary response of CPI.

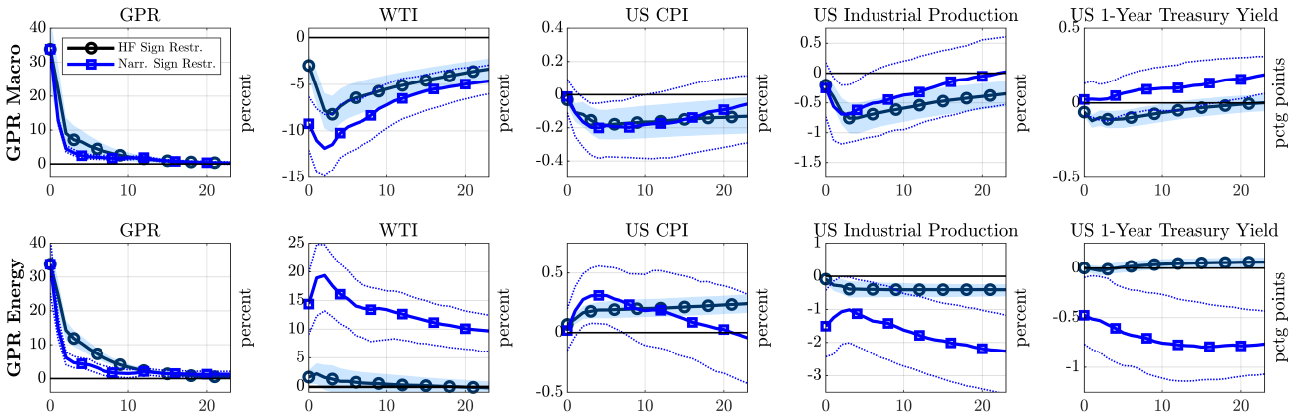


Figure 5 IRFs ASSOCIATED WITH GPR MACRO AND GPR ENERGY SHOCKS

The figure(s) displays the estimated dynamic response to GPR macro and GPR energy shocks. Black lines indicate point estimates, the blue areas and the dotted blue lines indicate 68% confidence bands. The shock is associated with a one standard deviation increase in the Geopolitical Risk Index (GPR).

These results highlight that the response of the economy to the GPR macro and GPR energy shocks identified with narrative sign restrictions are broadly consistent with the response of the model identified by high-frequency sign restrictions.

5 Heterogeneous Effects of GPR Macro and GPR Energy Shocks Across Sectors

In this section, I empirically investigate the response of sectoral output and prices in the US economy to validate the interpretation of the shocks. To this purpose, I evaluate whether the sectors of the US economy are more strongly affected by the energy component of geopolitical risk when their energy intensity is higher.

5.1 Data

The sector-level data on output and prices employed in the analysis are sourced from the Bureau of Economic Analysis. The selected aggregates for measuring output and prices are real value added (measured in millions of chained 2012 US dollars) and the chain-type price indexes for value added, respectively. The data is quarterly, and covers the period 2005q2-2021q4. These data are matched with yearly frequency information on the energy intensity of the US manufacturing sectors measured as the ratio of the aggregate amount of energy employed by these sectors from all sources as a ratio of the value added produced by these

sectors (in MJ/USD 2015), provided by the International Energy Agency (IEA). These data cover 24 of the 64 sectors available in the BEA dataset. The set of sectors covered by the IEA dataset includes Farms, Forestry, Fishing, Mining, Support activities for mining, Utilities, Construction, Wood products, Nonmetallic mineral products, Primary metals, Fabricated metal products, Machinery Computer and electronic products, Electrical equipment, Motor vehicles, Other transportation equipment, Furniture and related products, Miscellaneous manufacturing, Food and beverage and tobacco products, Textile products, Apparel and leather, Paper products, Printing, Chemical products, Plastics and Rubber products.

5.2 Average Effects

First, I analyze the average response of the considered sectors using a panel local projections specification as follows:

$$\Delta y_{j,t+h} = \alpha_h + \alpha_{j,h} + \alpha_{h,q} + \beta_h \varepsilon_t + \gamma_h X_t + u_{j,t+h} \tag{4}$$

In the equation above, $y_{j,t}$ are 2-digit quarterly sectoral prices and value added from the BEA for the period 2005q2-2021q4, α_h is a constant, $\alpha_{j,h}$ are sector-level fixed effects, $\alpha_{h,q}$ are quarter fixed effects, $\varepsilon_t = \{\varepsilon_t^{macro}, \varepsilon_t^{energy}\}$ are the draws of the GPR macro and GPR energy shocks associated with the median IRF (in the VAR identified via high-frequency sign restrictions), and $X_{j,t}$ is a vector of controls including four lags of the macro GPR and energy GPR shocks and four lags of the variables included in the VAR in the previous sections of the paper, i.e. the year-on-year differences of the GPR index (in logs), the WTI deflated by US CPI (in logs), US CPI (in logs), US Industrial Production (in logs) and the 1-Year Treasury Rate. The index j indicates the sector, t the time when the shock occurs, and h the considered horizon. Errors are clustered two-ways, by time and by sector.

In Figure 6, I show the average response of the sectors is line with the findings of the VAR exercise. In response to a one standard deviation shock to the GPR index associated with its macro component, output declines on average by between 0.6% and 2% in the second quarter following the shock. The contraction which follows the energy GPR shock is more pronounced, reaching a trough between -0.4% and -1.5%. As in the VAR findings, the two shocks have distinct effects on the sectoral price level.

On average, prices drop by up by between 0.1% and 0.3% in response to a one standard deviation GPR shock associated with the macro component of geopolitical risk. This occurs starting from the third quarter, while at the impact the response is insignificant, in line

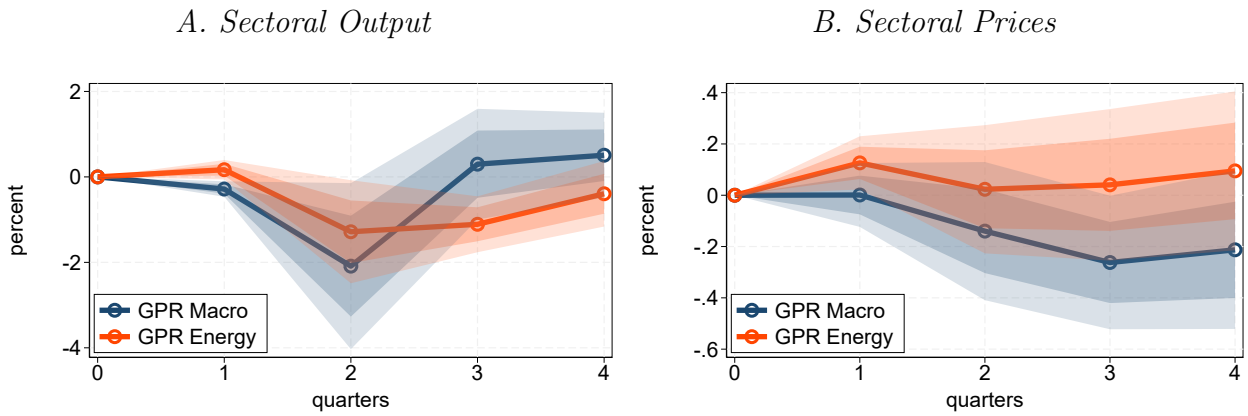


Figure 6 Average effect of a GPR macro shock and a GPR energy shock

The figure(s) displays the average effect of sectoral value added and prices to a one standard deviation GPR macro and GPR energy shocks. Solid lines indicate point estimates, and shaded areas outline respectively 68% and 90% confidence bands.

with the typical New Keynesian model response of the price level to a demand shock, due to the role of nominal rigidities. On the other hand, the effect of a shock to the GPR index associated with the energy component of geopolitical risk is associated with a rise in sectoral prices by between 0.7% and 1.8%, which loses significance towards the end of the considered horizon.

Overall, the evidence from the average response of the sectors of the US economy to geopolitical shocks, is corroborative of the VAR findings: geopolitical shocks are always contractionary, although geopolitical shocks associated with the macro component of geopolitical risk are deflationary, while shocks associated with the energy component of geopolitical risk are inflationary.

5.3 Heterogeneous Effects: The Role of Energy Intensity

Second, I analyze the differential response of the energy intensive sectors. To do so, I introduce an energy intensity dummy $EI_{j,t}$, which takes value one if the energy intensity in a given sector-year is greater than the median across sectors, and zero otherwise. To evaluate the differential effect of sectors subject to a high-energy use in a given time period, I augment the previous specification with an interaction term and time fixed effects in the following way:

$$\Delta y_{j,t+h} = \alpha_h + \alpha_{j,h} + \alpha_{h,t} + \alpha_{h,q} + \beta_h \varepsilon_t EI_{j,t} + \gamma_h X_t + u_{j,t+h} \tag{5}$$

In the equation above, $y_{j,t}$ are 2-digit quarterly sectoral prices and value added from the BEA for the period 2005q2-2021q4, α_h is a constant, $\alpha_{j,h}$ are sector-level fixed effects, $\alpha_{h,t}$ are time fixed effects, $\alpha_{h,q}$ are quarter fixed effects, $\varepsilon_t = \{\varepsilon_t^{macro}, \varepsilon_t^{energy}\}$ are the draws of the GPR macro and GPR energy shocks associated with the median IRF (in the VAR identified via sign restrictions). The vector X_t includes four lags of the GPR macro and the GPR energy shocks, as well as four lags of the interaction term. Errors are clustered two-ways, by time and by sector.

In Figure 7, I show the additional response of a sector characterized by an energy intensity one standard deviation above the median. In this specification, sector-time fixed effects absorb all the common variation from geopolitical shocks. Hence, the responses in Figure 7 can be interpreted as deviations from the average response. In response to a one standard deviation shock to the GPR index associated with its macro component, the median response of high energy-intensive sectors is relatively larger, but the relative effect is overall not significantly different from the average response. However, in response to a standard deviation shock to GPR associated with the energy shock, on average the sectoral output of high energy-intensive sectors declines very persistently until reaching a trough between -0.5% and -1.5% at the end of the considered horizon. This is a much stronger response compared to the average response (between -0.4% and -1.5%).

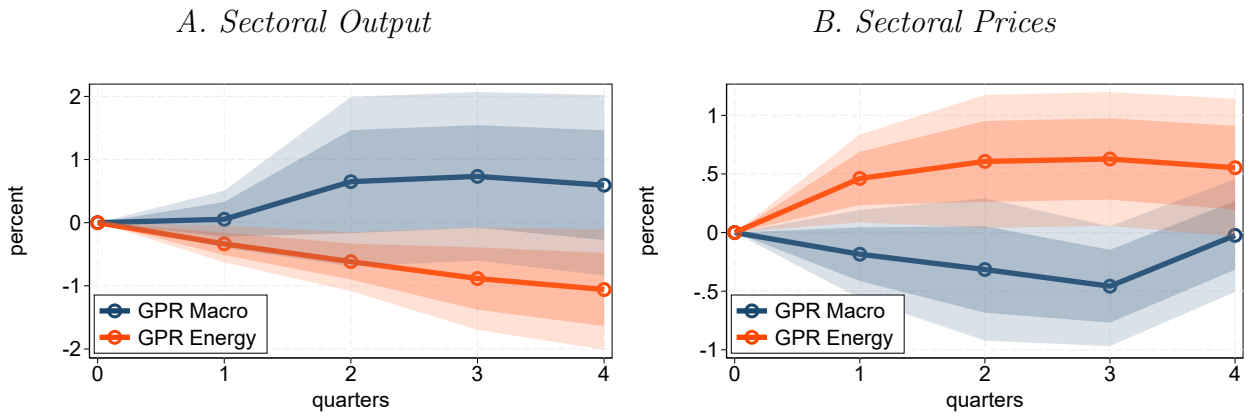


Figure 7 Relative effect of a GPR macro shock and GPR energy shock

The figure(s) displays the relative effect of a one standard deviation GPR macro and GPR energy shocks on value added and prices of high-intensive sectors compared to the average response. Solid lines indicate point estimates, and shaded areas outline respectively 68% and 90% confidence bands.

A similar pattern emerges for sectoral prices. In response to a one standard deviation shock to the GPR index associated with the macro component, the response of high energy-intensive sectors is not significantly different from the average response (except for the third

quarter at 68% confidence level). However, in response to a standard deviation shock to the GPR index associated with the energy shock, on average sectoral prices of high energy-intensive sectors rise persistently by up to 0.6% more. This additional increase makes the overall response much larger compared to the average response of 0.1%, suggesting that most of the inflationary response might be driven by energy-intensive sectors. These results show that the energy component of geopolitical shocks affects more strongly more energy intensive sectors, by validating the interpretation of the GPR energy shock as such.

6 Conclusion

This paper explores the consequences of different classes of geopolitical shocks for inflation and economic activity, and shows that energy markets are crucial for their transmission. The paper contributes to investigating the heterogeneity across geopolitical shocks, by providing an identification strategy to isolate the energy component of geopolitical shocks based on state-of-the-art methodologies from the VAR literature.

The paper proposes a simple and effective distinction between geopolitical shocks associated with disruptions on energy markets from geopolitical shocks associated with macroeconomic dynamics which do not originate in energy markets. These two shocks are associated with distinct macro implications.

One of the main insight from the analysis is that geopolitical risk episodes should not all be treated equally for policy analysis purposes, as interpreting them as a unique class of shocks might be misleading for inferring the macro implications of individual geopolitical episodes. The findings of the empirical analysis suggest that a rise in geopolitical risk is always contractionary for economic activity, irrespective of its nature. However, a rise in the GPR index is deflationary when associated with geopolitical macro shocks and inflationary when associated with geopolitical energy shocks. The magnitudes of these effects are estimated to be economically meaningful from a policymaking perspective.

Finally, the findings of this paper come with important implications for monetary policy. The conduct of monetary policy in response to geopolitical events should be conditional on their composition in terms of structural shocks. Central banks should respond to geopolitical macro shocks by loosening interest rates, while the optimal response to energy-related geopolitical shocks is a priori ambiguous, as they face a trade-off between the stabilization of output and inflation.

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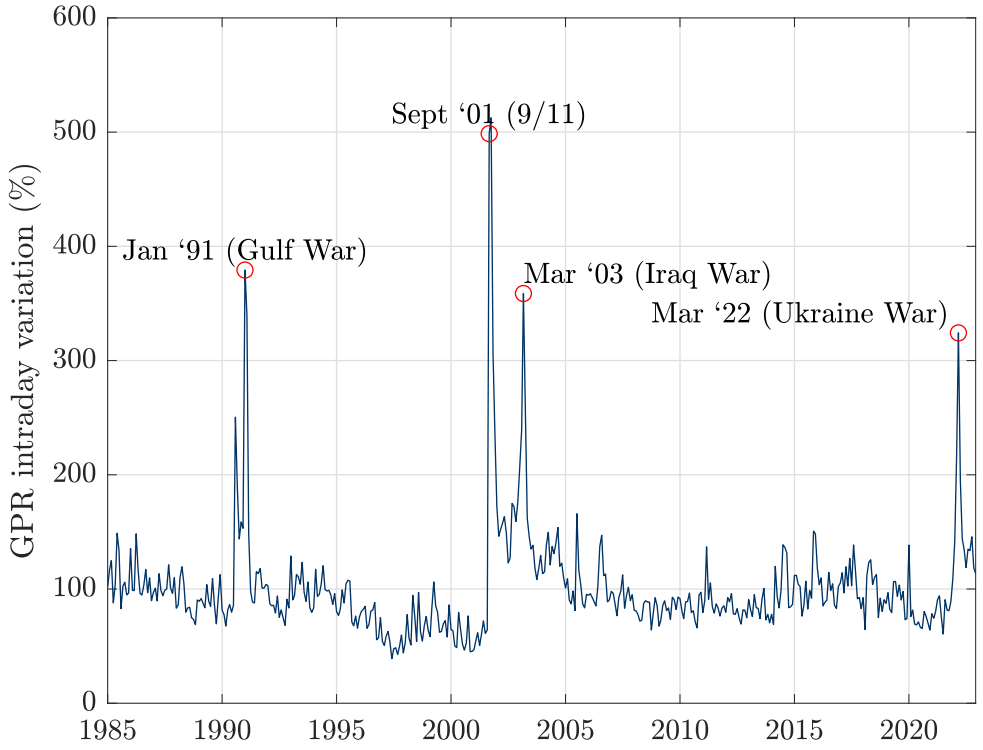
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A Additional Details and Results

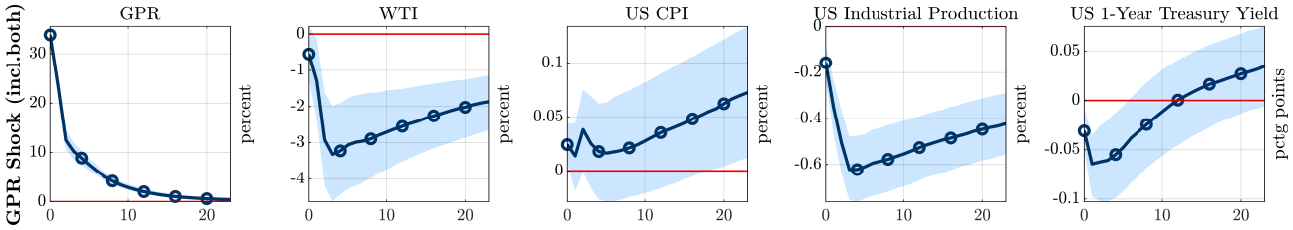
A.1 The Caldara-Iacoviello Geopolitical Risk Index (GPR)

- The GPR index is calculated by counting the number of articles related to adverse geopolitical events in each newspaper for each day/month (as a share of the total number of news articles)



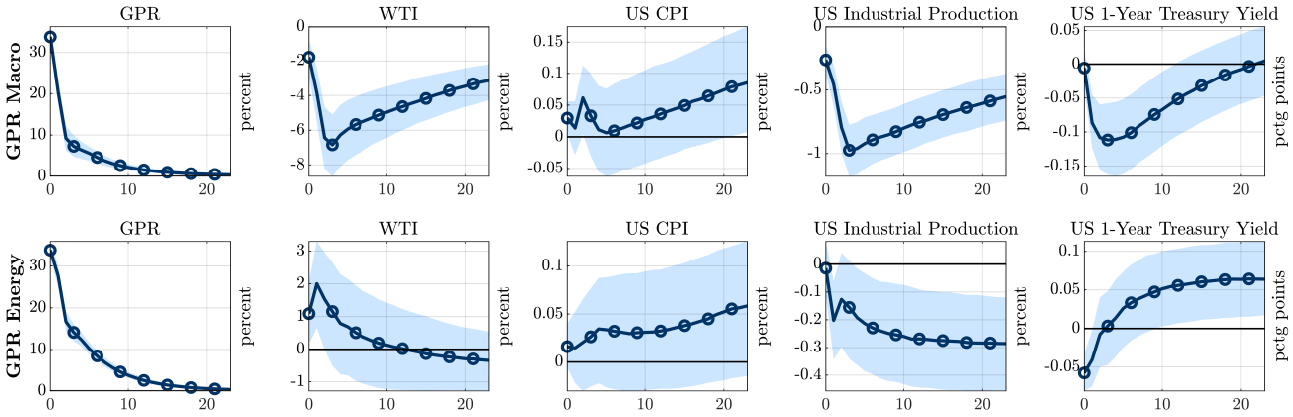
A.2 Additional Results

Figure A.1 IRFs associated with a GPR shock identified via Cholesky ordering



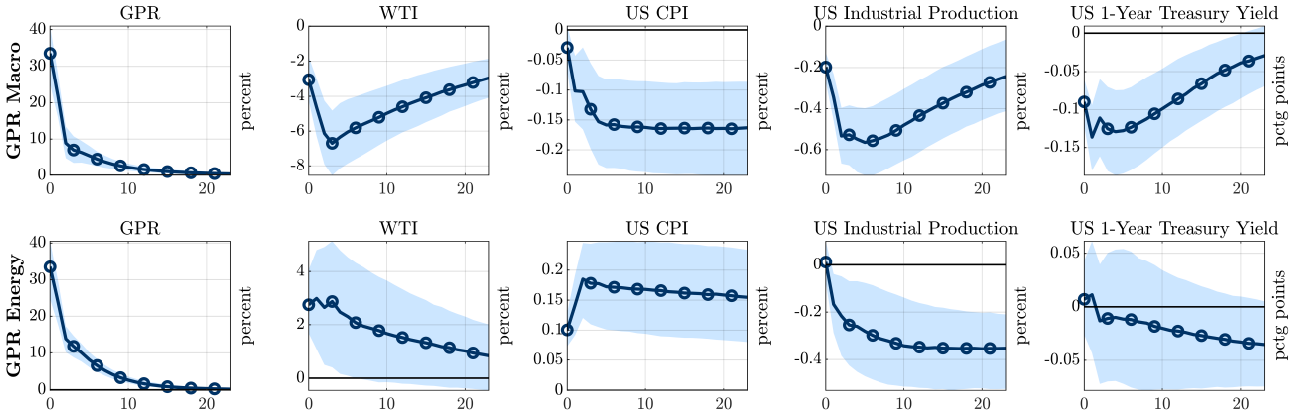
The figure(s) displays the estimated dynamic response to a model where GPR surprises are ordered first. Black lines indicate point estimates and blue areas outline 68% confidence bands. The shock is associated with a one standard deviation increase in the Geopolitical Risk Index (GPR).

Figure A.2 IRFs of the baseline variables (poor man's approach)



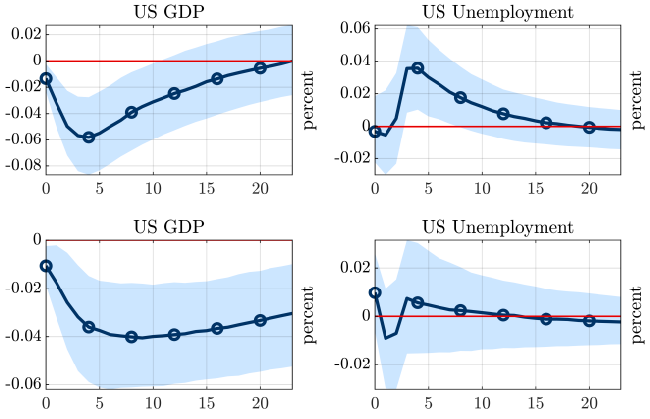
The figure(s) displays the estimated dynamic response of the baseline set of variables to GPR macro and GPR energy shocks identified using what is referred to as the poor man's approach by Jarociński and Karadi (2020). Blue lines indicate point estimates and blue areas outline 68% confidence bands. The shock is associated with a one standard deviation increase in the Geopolitical Risk Index (GPR).

Figure A.3 IRFs of the baseline variables (excluding Covid)



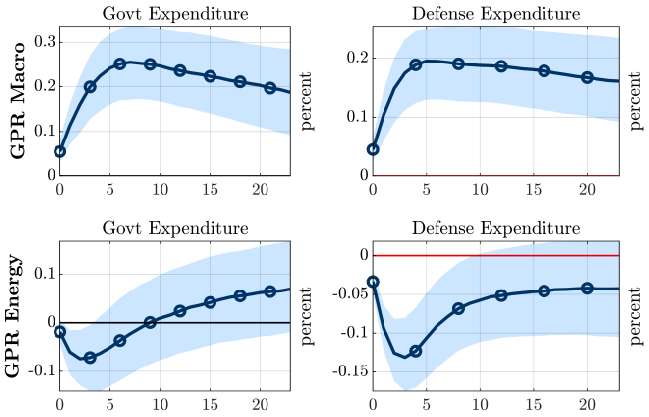
The figure(s) displays the estimated dynamic response of the baseline set of variables to GPR macro and GPR energy shocks when the geopolitical surprises occurring in 2020 are removed from the sample. Blue lines indicate point estimates and blue areas outline 68% confidence bands. The shock is associated with a one standard deviation increase in the Geopolitical Risk Index (GPR).

Figure A.4 Measures of Economic Activity



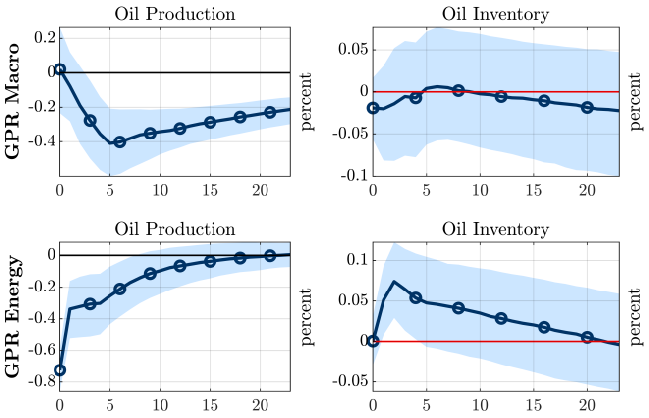
The figure(s) displays the estimated dynamic response of GDP and unemployment. Blue lines indicate point estimates and blue areas outline 68% confidence bands. The shock is associated with a one standard deviation increase in the Geopolitical Risk Index (GPR).

Figure A.5 Government Spending



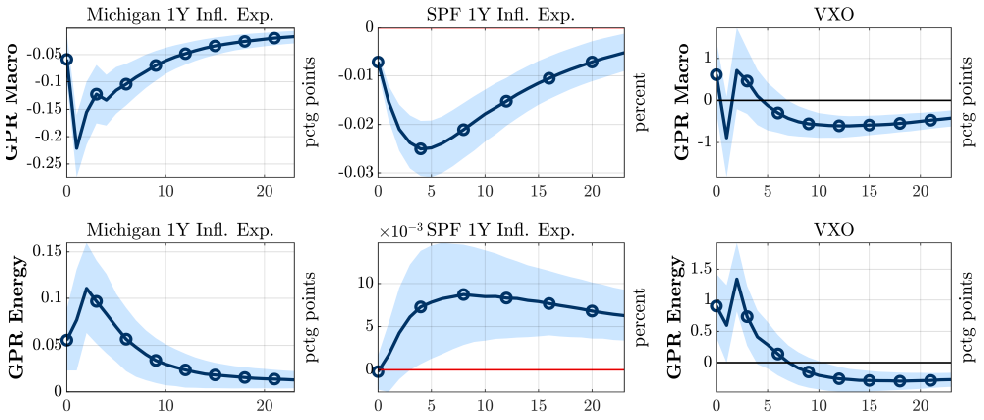
The figure(s) displays the estimated dynamic response of government spending and defense spending to GPR macro and GPR energy shocks. Blue lines indicate point estimates and blue areas outline 68% confidence bands. The shock is associated with a one standard deviation increase in the Geopolitical Risk Index (GPR).

Figure A.6 Oil markets



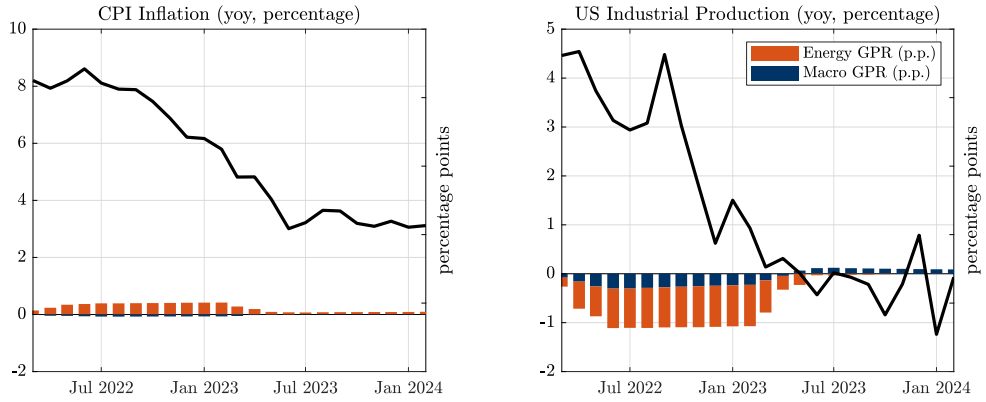
The figure(s) displays the estimated dynamic response of the baseline set of variables to GPR macro and GPR energy shocks. Blue lines indicate point estimates and blue areas outline 68% confidence bands. The shock is associated with a one standard deviation increase in the Geopolitical Risk Index (GPR).

Figure A.7 Expectations and Financial Volatility



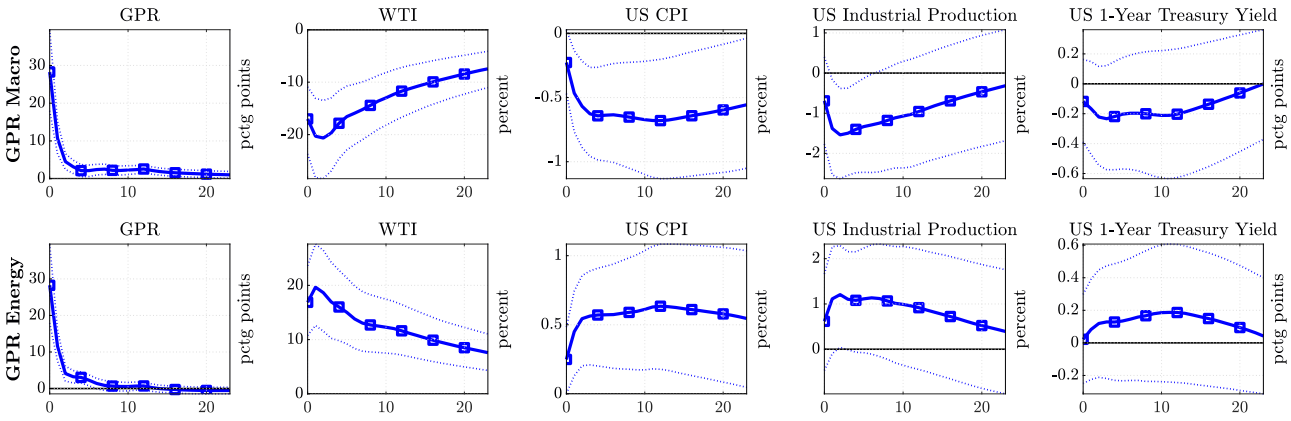
The figure(s) displays the estimated dynamic response of inflation expectations and financial volatility measures to GPR macro and GPR energy shocks. Blue lines indicate point estimates and blue areas outline 68% confidence bands. The shock is associated with a one standard deviation increase in the Geopolitical Risk Index (GPR).

Figure A.8 Impact of the Russian Invasion of Ukraine in February 2022



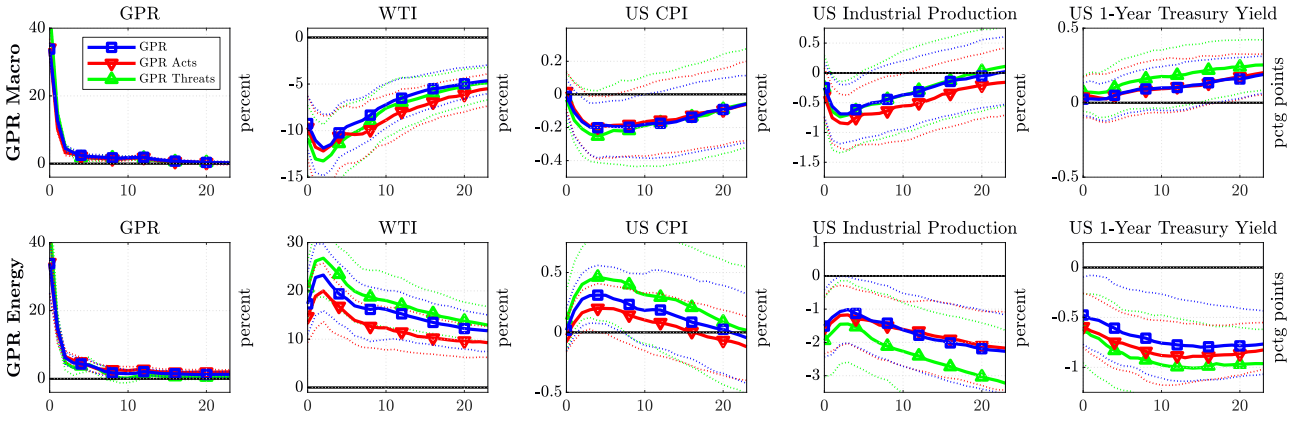
The figure displays the decomposition of the response of CPI inflation and industrial production to a GPR macro and a GPR energy shocks calibrated so to match the difference in the level of the GPR index between January and March 2022 in shares proportional to their contribution in the historical decomposition.

Figure A.9 IRFs associated with the GPR macro and GPR energy shocks identified via simple sign restrictions



The figure(s) displays the estimated dynamic response to GPR macro and GPR energy shocks. The solid blue lines indicate point estimates, and the dotted blue lines indicate 68% confidence bands. The shock is associated with a one standard deviation increase in the Geopolitical Risk Index (GPR).

Figure A.10 IRFs associated with the GPR macro and GPR energy shocks identified via narrative sign restrictions



The figure(s) displays the estimated dynamic response to GPR macro and GPR energy shocks. Solid lines indicate point estimates, and dotted lines indicate 68% confidence bands. The shock is associated with a one standard deviation increase in the Geopolitical Risk Index (GPR).

A.3 Identification via Narrative Sign Restrictions: Methodological Note

Consider the structural VAR specification proposed by Antolín-Díaz and Rubio-Ramírez (2018), which can be describe as in Equation (A.1):

$$y_t' A_0 = c' + \sum_{l=1}^{p} y_{t-l}' A_l + \varepsilon_t' \quad with \quad \varepsilon_t \sim \mathcal{N}(0, I_n) \quad \text{(A.1)}$$

On the left-hand side, y_t indicates a $n \times 1$ vector of US macro variables at monthly frequency, and A_0 is an invertible $n \times n$ matrix of structural parameters. The variables included in the vector y_t are the same used in the exercise performed in Section 4 (except for the surprises). On the right-hand side, c is a $1 \times n$ vector of structural parameters, p is the number of lags of the model, A_l is a matrix of structural parameters, ε_t indicates a $1 \times n$ vector of structural shocks. By multiplying both sides of Equation (A.1) by A_0^{-1}, this formulation can be compared like-for-like to the formulation as in Equation (3):

$$y_t' = c' + x_t' B_l + u_t' \quad with \quad u_t \sim \mathcal{N}(0, \Sigma) \quad \text{(A.2)}$$

The matrix B can be obtained by multiplying the two matrices containing the structural parameters $A_+' = [A_1', ..., A_p' c']$ ($m \times n$, where $m = np + 1$) and A_0 ($n \times n$) so that $B = A_+ A_0^{-1}$ ($m \times n$). The reduced form residuals can be obtained as $\varepsilon_t' A_0^{-1}$ with $\mathbb{E}[u_t' u_t'] = \Sigma = (A_0 A_0')^{-1}$. Finally, the matrix $\Theta = (A_0, A_+)$ contains the value of the structural parameters. Within this framework, I impose four classes of restrictions: (i) sign restrictions on the structural parameters, (ii) zero restrictions on the structural parameters, (iii) narrative sign restrictions on the sign of shocks in a given period, and (iv) narrative sign restrictions on the relative magnitude of shocks within the historical decomposition.

Zero and sign restrictions impose constraints on the coefficients of the matrix of the structural parameters Θ. Following the notation of Arias et al. (2018), sign and zero restrictions on the structural parameters can be expressed as in Equation (A.3) and (A.4):

$$\Gamma(\Theta) = (e_{1,n}' F(\Theta)' S_1', ..., e_{n,n}' F(\Theta)' S_n') > 0 \quad \text{(A.3)}$$

$$\Gamma(\Theta) = (e'_{1,n}F(\Theta)'S'_1, ..., e'_{n,n}F(\Theta)'S'_n) = 0 \tag{A.4}$$

Recalling that $\Theta = (A_0, A_+)$ and defining $e_{j,n}$ as the jth column of I_n for $1 \leq i, j \leq n$ and $h \geq 0$, imposing sign and zero restrictions on the structural parameters boils down to pinning down the values of S_j and $F(\Theta)$ which comply with the selected restrictions. To impose restrictions on the structural parameters, it is possible to define $F(\Theta) = \Theta$ and S_j as an $s_j \times r_j$ matrix of +1 and -1 for sign restrictions, and of zeros for zero restrictions.

Sign restrictions on structural shocks impose constraints on the sign of a given structural shock in a given period. For instance, in the case of a positive shock, one can assume that the sign of the jth shock at the sj episode occurring at date $t = 1, ..., t_{s_j}$ is positive:

$$e'_{j,n}\varepsilon_{t_v t}(\Theta) \geq 0 \quad for \quad 1 \leq v \leq s_j \tag{A.5}$$

Likewise, narrative sign restrictions can be implemented by imposing a negative sign. However, the dataset only features positive geopolitical risk surprises (increases in geopolitical risk), hence no negative sign restrictions on the structural shocks are imposed.

The last class of restrictions exploited for the identification are the narrative restrictions on the historical decomposition. Historical decomposition-based narrative restrictions impose a restriction on the relative magnitude of the contribution of a particular shock in a given period compared to other shocks individually, or compared to the sum of their contributions.

To describe this class of restrictions analytically, it is useful to start from the definition of historical decomposition. The historical decomposition calculates the cumulative contribution of each shock to the observed unexpected change in the variables between two periods. Defining $L_k(\Theta)$ as the impulse response function given the set of structural parameters Θ, the historical decomposition can be characterized as:

$$H_{i,j,t,t+h}(\Theta, \varepsilon_t, ..., \varepsilon_{t+h}) = \sum_{l=0}^{h} e'_{i,n}L_l(\Theta)e_{j,n}e'_{j,n}\varepsilon_{t+h-l} \tag{A.6}$$

Antolín-Díaz and Rubio-Ramírez (2018) distinguish restrictions on the historical decom-

position in either Type A when they impose that one shock is larger than the contributions of all other shocks in a given period or Type B restrictions when they impose that one shock is larger than the sum of the contributions of all other shocks in a given period. In the context of this paper, this distinction is irrelevant as I am going to impose this restriction on the GPR index, which due to the exogeneity restrictions is exclusively driven by two shocks, i.e. the GPR macro and the GPR energy shocks. For simplicity, I characterize here the narrative restriction on the historical decomposition exploited in the paper as a Type A restriction, i.e. the contribution of the jth shock to the i_vth variable between t_v and $t_v + h_v$ is larger in absolute value than the contribution of any other j'th shock to the i_vth variable between t_v and $t_v + h_v$ for $1 \leq v \leq s_j$:

$$|H_{i_v,j,t_v,t_v+h_v}(\Theta, \varepsilon_{t_v}(\Theta), ..., \varepsilon_{t_v+h_v(\Theta)})| > max_{j' \neq j} |H_{i_v,j',t_v,t_v+h_v}(\Theta, \varepsilon_{t_v}(\Theta), ..., \varepsilon_{t_v+h_v(\Theta)})| \quad \text{(A.7)}$$

The estimation approach follows the algorithm proposed by Antolín-Díaz and Rubio-Ramírez (2018), except that Minnesota priors are employed as opposed to uniform priors for consistency with the baseline specifications. The algorithm proceeds as follows. First, B and Σ are drawn from the normal-inverse-Wishart posterior of reduced-form parameters and Q from a distribution $O(n)$, where Q is the set of all orthogonal n $\times$ n matrices. Second, the compliance of each draw with the restrictions is verified. Third, if the draw is satisfied, a weight is assigned to the draw based on the proportion of simulated draws M of structural residuals associated with the reduced-form parameter draw which satisfy the restrictions[12]. If not, the draw is discarded. Fourth, the algorithm re-draws B, Σ and Q from posterior until the desired number of draws is achieved as in the first step, by re-weighting the draws based on the importance weights assigned during the third step. The model is estimated with 12 lags, consistent with the baseline specification.

[12]The used simulation draws M are 1000 as in Antolín-Díaz and Rubio-Ramírez (2018).

B Data and Sources

Table B.1 Data and Sources - Baseline VAR Variables

Data	Source	Description	Sample	Freq
GPR surprises	Own calculations based on Caldara and Iacoviello (2022)	Daily variation in the GPR index around selected events.	1985-2023	D
WTI futures surprises	New York Mercantile Exchange (NYMEX)	Daily variation in the price of the 1-month ahead WTI future contract around selected events.	1985-2023	D
GPR Index	Caldara and Iacoviello (2022)	Monthly GPR index as in Caldara and Iacoviello (2022).	1985-2023	M
Real WTI Spot Price	International Energy Agency	Monthly average of the West Texas Intermediate Spot price, deflated with US CPI, and expressed in logs	1985-2023	M
US Real Industrial Production	US Bureau of Economic Analysis	Inflation-adjusted index of US industrial production, seasonally adjusted, deflated with US CPI, and expressed in logs.	1985-2023	M
US CPI	US Bureau of Economic Analysis	Inflation measure derived from the change in the weighted-average price of a basket of common goods and services.	1985-2023	M
US 1-Year Treasury Yield	Board of Governors of the Federal Reserve System	Monthly average of the 1-Year US government benchmark bid yield, close price.	1985-2023	M

Legend: D=Daily, W=Weekly, M=Monthly, Q=Quarterly, Y=Yearly

Table B.2 Data and Sources - Sectoral Data

Data	Source	Description	Sample	Freq
Sectoral Output	US Bureau of Economic Analysis	Chain-Type Quantity Indexes for Value Added by Industry.	2005q2-2021q4	Q
Sectoral Prices	US Bureau of Economic Analysis	Chain-Type Price Indexes for Value Added by Industry.	2005q2-2021q4	Q
Sectoral Energy Intensity	International Energy Agency	Amount of energy from all sources employed in production per unit of value added.	2005q2-2021q4	Y

Legend: D=Daily, W=Weekly, M=Monthly, Q=Quarterly, Y=Yearly

Table B.3 Data and Sources - Additional VAR Variables

Data	Source	Description	Sample	Freq
World Oil Production	US Bureau of Labor Statistics	Number of unemployed persons as a percentage of the labor force, seasonally adjusted.	1985-2023	M
World Oil Stock	Own calculations based on OECD and EIA data	US crude oil inventories (EIA) by the rescaled by the ratio of OECD petroleum stocks over US petroleum stocks (EIA) as in Kilian and Murphy (2014).	1985-2023	M
1Y Inflation Expectations (Michigan)	Michigan Surveys of Consumers	Number of unemployed persons as a percentage of the labor force, seasonally adjusted.	1985-2023	M
1Y Inflation Expectations (SPF)	Survey of Professional Forecasters	Number of unemployed persons as a percentage of the labor force, seasonally adjusted.	1985-2023	Q
VXO	Chicago Board Options Exchange	CBOE S&P 100 Volatility Index, Close Price.	1986-2021	M
US Real Consumption	US Bureau of Economic Analysis	Real personal consumption expenditures per capita. Seasonally adjusted, interpolated via cubic splines, and expressed in logs.	1985-2023	Q
US Real Investment	US Bureau of Economic Analysis	Real non-residential gross private domestic investment per capita. Seasonally adjusted, interpolated via cubic splines, and expressed in logs.	1985-2023	Q
US Real Govt Expenditure	US Bureau of Economic Analysis	Real government consumption expenditures and gross investment per capita. Seasonally adjusted, interpolated via cubic splines, and expressed in logs.	1985-2023	Q

Legend: D=Daily, W=Weekly, M=Monthly, Q=Quarterly, Y=Yearly
Quarterly variables are interpolated as in Miranda-Agrippino and Rey (2020)