Geopolitical Risk and Inflation: The Role of Energy Markets

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Abstract

Episodes characterized by heightened geopolitical tensions are often associated with adverse developments in energy markets, and particularly in oil markets. This paper investigates the consequences of different classes of geopolitical risk shocks for inflation and economic activity, focusing on the role of energy markets. By exploiting the comovement of the Caldara and Iacoviello (2022) GPR index and oil prices around selected episodes via high-frequency sign restrictions à la Jarociński and Karadi (2020) and narrative sign restrictions à la Antolín-Díaz and Rubio-Ramírez (2018), the paper disentangles the impact of geopolitical shocks associated with disruptions on energy markets from geopolitical shocks associated with economic contractions unrelated to energy markets. These two classes of shocks are associated with distinct macro consequences. A positive surprise in the GPR index associated with geopolitical macro shocks is on average contractionary and deflationary. On the other hand, a positive surprise in the GPR index associated with geopolitical energy shocks is on average contractionary and inflationary. The identification strategy is validated at sector-level by exploiting the heterogeneity in the response of 57 sectors of the US economy to different classes of geopolitical shocks. 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 in response to geopolitical macro shocks.

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

JEL Codes: E31, E32, F31, Q35, Q38, 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 macro consequences of geopolitical risk.[1] This paper investigates how geopolitical risk shocks can affect the economy and contributes to the literature by highlighting, disentangling, and quantifying the role of energy markets in their transmission.

The empirical literature has recently provided evidence that geopolitical events can have severe macroeconomic consequences. Caldara and Iacoviello (2022) developed an index of geopolitical risk (GPR) to quantify the state of geopolitical risk based on the number of articles related to adverse geopolitical events in each newspaper. Fluctuations in the GPR index, which captures unpredictable variations in geopolitical tensions, can depress industrial production and employment. The heterogeneity across different classes of geopolitical episodes remains, however, to a large extent unexplored.

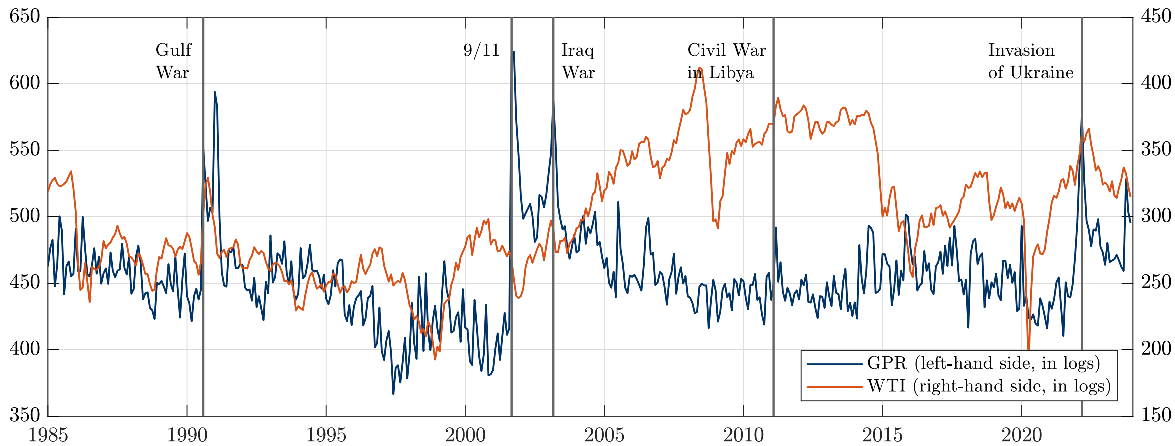
Geopolitical events can be associated with disturbances of different nature, ranging from energy disruptions to trade and financial fragmentation. Within macroeconomic models, these can be characterized as a combination of different structural shocks, with distinct macroeconomic effects. This paper investigates the heterogeneity in the nature of geopolitical risk shocks and in their macroeconomic effects, by focusing on the role of energy markets. The anecdotal evidence presented in Figure 1 suggests that heightened geopolitical tensions are frequently associated with energy market disruptions, and that they might play a pivotal role in the transmission of geopolitical shocks.

Figure 1 shows 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 monthly average of the West Texas Intermediate index (WTI) spot price deflated by US CPI (in red). During some of the most salient events, such as the outburst of the Gulf War, the Iraq War, the Civil War in Libya, and the Invasion of Ukraine, increases in the GPR are accompanied by a rise in WTI spot prices. On the other hand, in occasion of some other events, such as the 9/11, the increase in the GPR is accompanied by a drop in WTI spot prices. The paper interprets the opposite comovement between geopolitical risk and energy prices as driven by fundamentally different shocks.

In this paper, I exploit this comovement to disentangle two types of geopolitical risk shocks: those associated with disruptions on energy markets (referred to as geopolitical

[1] In this paper, I adopt the definition of geopolitical risk provided by Caldara and Iacoviello (2022), i.e. the threat, realization, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political actors that affect the peaceful course of international relations.

Figure 1 Geopolitical Risk and Oil Prices



energy shocks or GPR energy shocks) and those associated with macroeconomic contractions unrelated to energy markets (referred to as geopolitical macro shocks or GPR macro shocks). I then quantify the effects of these two shocks on a set of macroeconomic variables, illustrating their widely different implications for inflation dynamics.

The analysis proceeds in three steps. First, I disentangle geopolitical energy shocks from geopolitical macro 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 via energy markets, anticipating future energy supply disruptions. Conversely, when geopolitical news is associated with decreases in oil prices, it suggests an anticipated 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. To achieve identification of energy and macro GPR shocks, I employ a combination of sign restrictions, as well as 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 energy and macro GPR shocks lead to contractions in economic activity. However, the response of inflation differs across shocks: energy GPR shocks lead to inflationary effects, while macro GPR 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 sectoral data on output, prices, and energy intensity from 57 sectors of the US economy, I show that sectors with higher energy use relative to their value-added are more strongly affected by energy GPR shocks.

The results of this paper have relevant implications for policymakers. First, the analysis suggests that an empirical assessment of the effects of geopolitical shocks requires disentangling the underlying forces driving these movements. Ignoring the distinction between energy and macro GPR shocks can lead to misleading conclusions about the effects of individual geopolitical episodes. For instance, unconditional estimates might underestimate the inflationary consequences of the Russian invasion of Ukraine. Second, the findings suggest that the conduct of monetary policy should be contingent on the nature of the GPR shock, as energy GPR shocks could potentially lead to a trade-off between output and inflation stabilization.

The paper proceeds 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 on 57 sectors of the US economy. 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 shocks. Caldara et al. (2023) also investigate the consequences of geopolitical shocks for inflation, but do not explore the heterogeneity characterizing geopolitical shocks of different nature, and the role of energy markets for the propagation of geopolitical risk shocks.

The focus on the energy markets relates to a vast literature which analyses 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 tight 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 risk 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 risk shocks.

This paper contributes to the literature by highlighting the role of the energy markets in the transmission of geopolitical risk and developing an empirical framework to quantitatively assess their role in the propagation to economic activity and inflation.

3 Identification approach and construction of the surprise dataset

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

The adoption of a sign restrictions based 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 contractions in economic activity unrelated to energy markets. In line with this interpretation, this type of news results in a decrease in oil prices due to a reduction in overall macroeconomic activity, consequently leading to a decline in the demand for oil. 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 comove-

[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).

ment, on the other hand, is attributed to news regarding developments in energy markets, as it is associated to 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, the contribution from these shocks is 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 B.1 in the Appendix. 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 that by exploiting the comovement of the GPR index and oil prices around a list of key events in the spirit of Jarociński and Karadi (2020). This approach leverages narrative information from a list of prominent geopolitical events selected by Caldara and Iacoviello (2022) on a narrative basis. As these events are 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 a reduction of the noise-to-signal ratio[4].

Namely, the list of events exploited for the dataset construction is a refinement of the list of key geopolitical events provided by Caldara and Iacoviello (2022). As geopolitical events often arise in series, the refinement proposed in this paper focuses on the first event in the sequence. Hence, the list of events used in this paper slightly differs from the list in Caldara and Iacoviello (2022), which mainly focuses on spikes in the GPR index.

Prominent examples of the events included in the dataset are the beginning of the US involvement in the Gulf War on the 15th of January 1991, the US invasion of Afghanistan on the 3rd October 2001, the beginning of the Iraq War on the 21st of March 2003, the terrorist attacks in London on the 7th July 2005 and in Paris on the 17th of November 2015, and the Russian invasion of Ukraine on the 24th of February 2022. The full list of events is available in the Appendix.

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

[4]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.

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[5] 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.

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. This happens because the dataset includes adverse events, while geopolitical events of benign nature, such as peace agreements, are typically rare and largely anticipated. Second, the GPR surprise series presents several spikes in occasion of sudden events, such as the failed coup in USSR in August 1991, the London terror attacks in July 2005, and the Paris attacks in November 2015.[6] 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 to the border with Ukraine. On the right-hand axis, I report the daily variations in the principal component extracted from the 1- to 6-month ahead futures price variation on the selected geopolitical episode days (in blue). The joint observation of the two surprise series reveals that the comovement between the two can vary

[5] 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.

[6] 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. For this reason, this event is excluded from the surprise dataset.

significantly across episode. For instance, during the failed coup in USSR in August 1991 oil price movements have not recorded any pronounced movements (-0.24%). On the other hand, in the occasion of the Paris attacks in November 2015, oil future prices rose by more than 2.11%. Finally, in the occasion of the London terror attacks in July 2005, oil future prices dropped by 1.99%.

Figure 3 shows a scatter plot of surprises in the GPR and the oil future prices, with each dot representing a geopolitical episode. Similarly to Figure 2, the chart highlights that many positive GPR surprises are often accompanied by positive oil price surprises, and vice versa for negative surprises. Differently from the typical monetary policy announcement chart, the surprises are displayed only on two quadrants. This is because, the geopolitical episodes featured in the dataset concern only positive geopolitical risk surprises, i.e. increases in geopolitical risk. On the upper quadrant, GPR and oil prices comove positive negatively, while in the lower quadrant GPR and oil prices comove positively. Each of these quadrants contains about half of the surprises, suggesting that geopolitical risk surprises might be characterized by two roughly equally prominent channels in the data.

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.

Figure 2 Geopolitical Risk and Oil Surprises

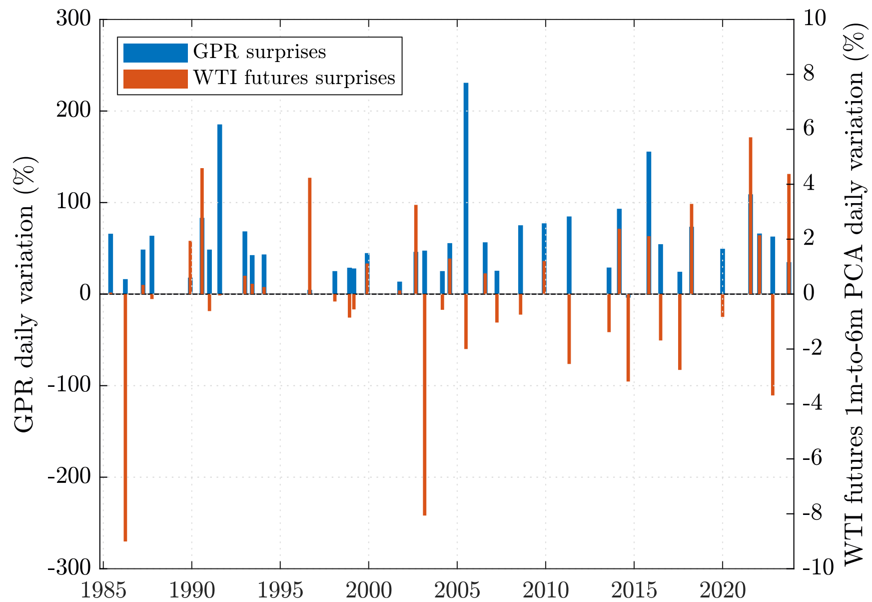
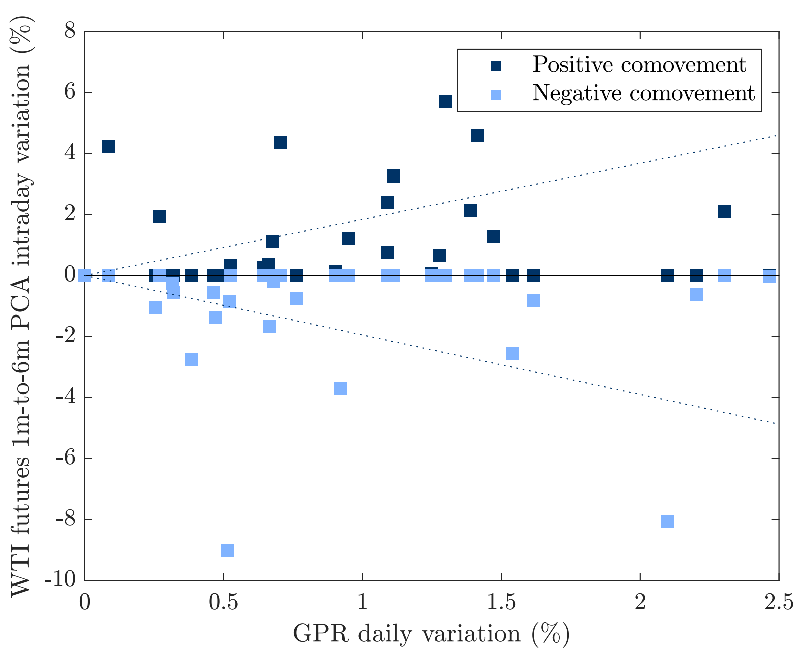


Figure 3 Comovement of Geopolitical Risk and Oil Surprises



4 The Effects of Energy and Macro GPR 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. The model allows combining elements from three popular approaches in the structural VAR literature, namely narrative, high-frequency, and sign restrictions. The narrative character is associated with the narrative approach used in the selection of the events, while the high-frequency character refers to the use of a narrow window.

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 principal component of 1-month to 6-month ahead WTI future prices around selected geopolitical episodes. When any of the 41 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. Henceforth, I will refer to this block as the "surprise block". 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. Henceforth, I will refer to this block as the "macro block". The sample includes 39 years of macroeconomic data at monthly frequency, from January 1985 to December 2023[7].

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 risk shocks can be characterized by the comovement they imply between GPR and oil surprises. Macro GPR shocks are associated with a negative comovement between GPR and oil future prices. On the other hand, energy GPR shocks are associated with a positive comovement between GPR and oil future prices.

Table 1 Scheme of selected high-frequency sign restrictions

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

Table 1 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). Furthermore, this restriction scheme also implies 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 within the macro block are left unrestricted. The model exploits Minnesota priors with a relatively low tightness, and is estimated using a Gibbs sampling algorithm with 10000 draws. The first 2000 draws are discarded, while every fourth of the remaining 8000 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. The model is estimated with 6 lags, consistent

[7]The complete list of selected geopolitical episodes, as well as the data used in the empirical exercises, are described in greater detail in the Appendix.

with the tenors of the future curve considered for the construction of the synthetic oil future surprise measure via principal component analysis.

In the following section, the responses from the sign-restricted model are compared to a comparable model identified ordering the GPR surprise first, as in Plagborg-Møller and Wolf (2021)[8]. In this specification, I treat all geopolitical risk shocks as part of a unique category, in the spirit of Caldara and Iacoviello (2022). Similarly to the previous scheme, these Cholesky ordering based restrictions impose block exogeneity, as the macro block is assumed not to affect GPR surprises. This specification can be seen as a useful benchmark to compare the results to other contributions in the literature. In Figure A.1, in the Appendix, a supplementary exercise shows the robustness of the results to the use of the poor man's sign restrictions, whereby each geopolitical surprise is fully explained either by the macro or the energy shock.

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 in three distinct cases. First, I analyze the response of the GPR index when ordered first à la Cholesky in the spirit of Plagborg-Møller and Wolf (2021). This benchmark is broadly representative of the analysis by Caldara and Iacoviello (2022), who analyze geopolitical risk shocks as a unique class of shocks, while acknowledging the variety of mechanisms they could operate through. Second, this response is compared to the impulse responses from the macro and the energy GPR shocks identified via high-frequency sign restrictions.

The first variable included in the macro block is the GPR index. Following a one standard deviation shock to the GPR, 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 shock are similar. However, the dynamics associated with the GPR energy shock are more persistent, with the GPR 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 shock to the GPR, WTI prices decline by between 2.6% and 6.3% in the first six months after the shock. The decline is persistent, lasting by 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

[8]For clarity, this specification does not use the WTI surprise series altogether.

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.

Figure 4 IRFs associated with a GPR shock identified via Cholesky ordering

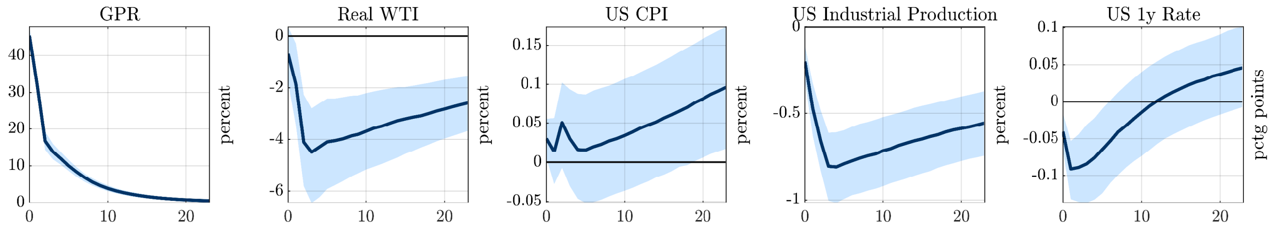
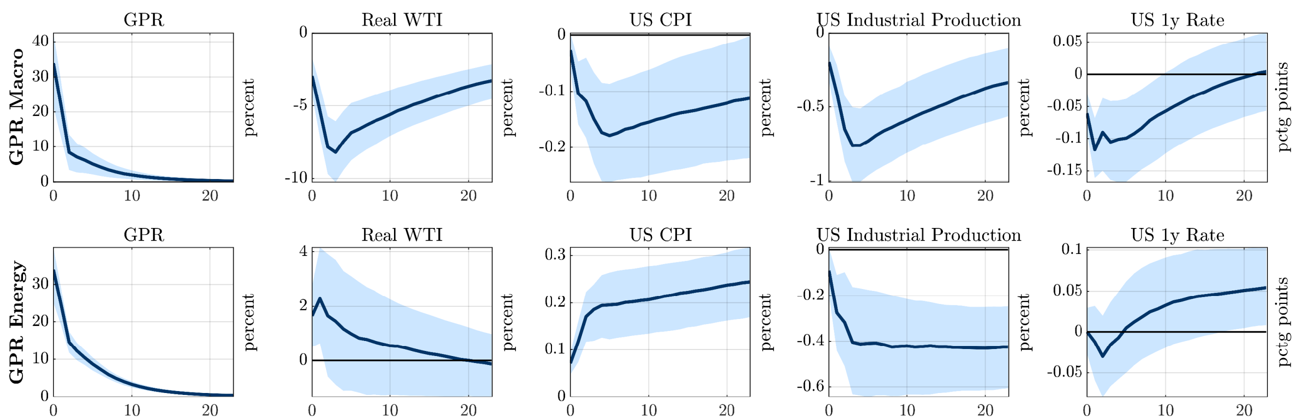


Figure 5 IRFs associated with GPR macro and GPR energy shocks identified via high-frequency sign restrictions



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 third reported variable is CPI in terms of deviations from the steady state level. The average GPR shock has a mild inflationary effect, wich becomes significant only towards the end of the considered horizon, with a magnitude between 1 and 17 basis points. This result hides a great deal of heterogeneity across classes of shocks. On one hand, the GPR macro shock is associated with a drop in CPI of between 9 and 25 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. A one standard deviation shock to the GPR depresses real industrial production by between 0.6% and 1%, reaching a trough in the first six months after the shock, and very gradually returning to the steady state in the following year. For 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. 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.

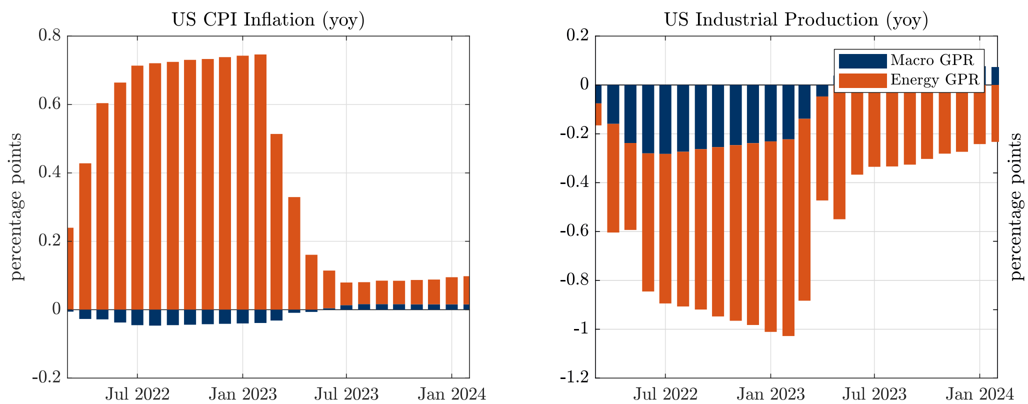
Finally, I include the 1-year sovereign yield, which sheds light on the average monetary policy response to the identified shocks. For the three shocks, the 1-year rate response is consistent with inflation dynamics, hinting at monetary policy as a potential driver of the underlying dynamics. For the 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 macro GPR shock, the 1-year rate significantly temporarily drops by between 5 and 16 basis point, while it is insignificant at the impact for the energy GPR shock. In the Appendix, I report the results from several additional variables, including oil market indicators, inflation expectation and uncertainty indicators, monthly economic activity indicators, and quarterly macro aggregates.

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

To illustrate one of the many potential policy applications of the model, I exploit the baseline model estimates to recover the impact of the Russian invasion of Ukraine on CPI inflation and industrial production in the US. The model is particularly suitable for evaluating episodes which contemplate the presence of shocks of different nature at work, as it disentangles the impact of the macro and the GPR energy shock.

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 15.42% of the GPR index increase to the GPR macro shock and the 84.58% of the increase to the GPR energy shock. On the other hand, the GPR 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 derived from the historical decomposition. Ultimately, this approach delivers a GPR macro shock associated with a 10.20% rise in the GPR index and a GPR energy shock associated with a 55.98% rise in the GPR index.

Figure 6 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.

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 0.75 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 overall negligible.

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 0.22 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 -1.03 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 detailed in Table 2. First, I impose that the both shocks exerts a positive effect on the GPR and a negative effect on real WTI prices. Second, that the GPR energy shock has a positive effect on the GPR and a positive effect on real WTI prices. Third, that all other shocks cannot affect the GPR. In other words, the GPR 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.

Table 2 Scheme of selected sign and zero restrictions

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

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 3. 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.

Table 3 Scheme of selected narrative restrictions

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 (+)

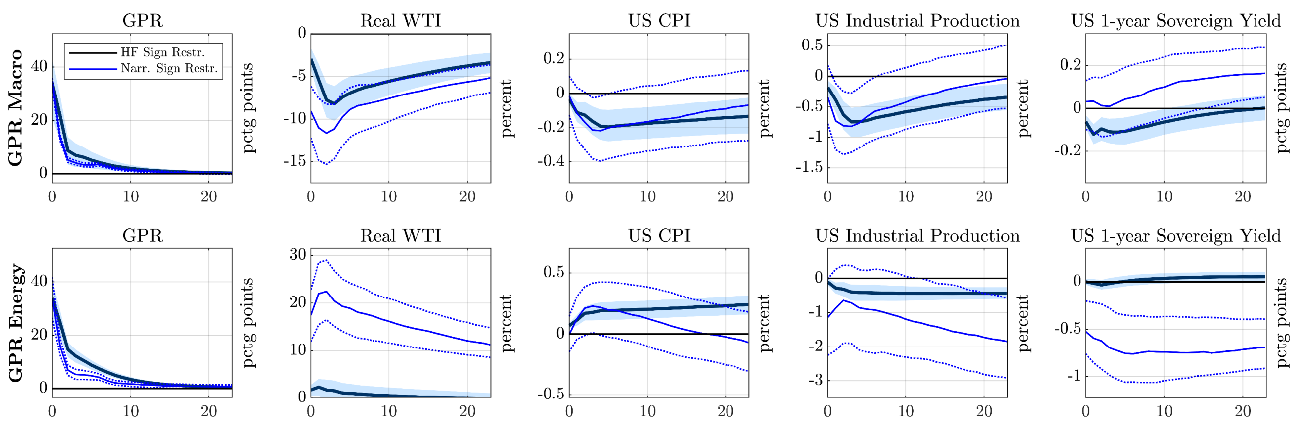
To identify the GPR energy shock, I impose the presence of a positive shock in four prominent episodes of geopolitical tension involving oil markets. First, the start of the Persian Gulf War in August 1990 with the Iraq invasion of Kuwait. Second, the beginning of the US invasion of Iraq in March 2003. 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.

4.6 Results

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.

First, I analyze the response of the model to GPR macro shocks. In response to a one standard deviation rise in the GPR, 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.

Figure 7 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).

Second, I analyze the response to the GPR energy shocks. In response to a one standard deviation rise in the GPR, 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.

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 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 gross output (measured in millions of chained 2012 US dollars) and the chain-type price indexes for gross output, respectively. The data is quarterly, and covers the period 2005-2021. These data are matched with yearly frequency information on the energy intensity of these 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). The detail of the considered sectors and the match between the BEA and the IEA data is reported into the Appendix. Sectors such as Oil and Gas Extraction and Petroleum and Coal Products are excluded, as well as transportation services[9], resulting in a total of 57 sectors.

[9]In the IEA statistics, the energy intensity of Transportation Services (including Air transportation, Rail transportation, Water Transportation, Truck Transportation, Transit and Ground Passenger Transportation, Pipeline Transportation, and Other Transportation and Support Activities) is reported jointly with the overall Services sector. This is likely to deliver a mischaracterization of the energy intensity of the Transportation Services sectors, which are typically very energy intensive as opposed to the rest of the Services sector. For this reason, I exclude these sectors from the dataset.

5.2 Average Effects

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

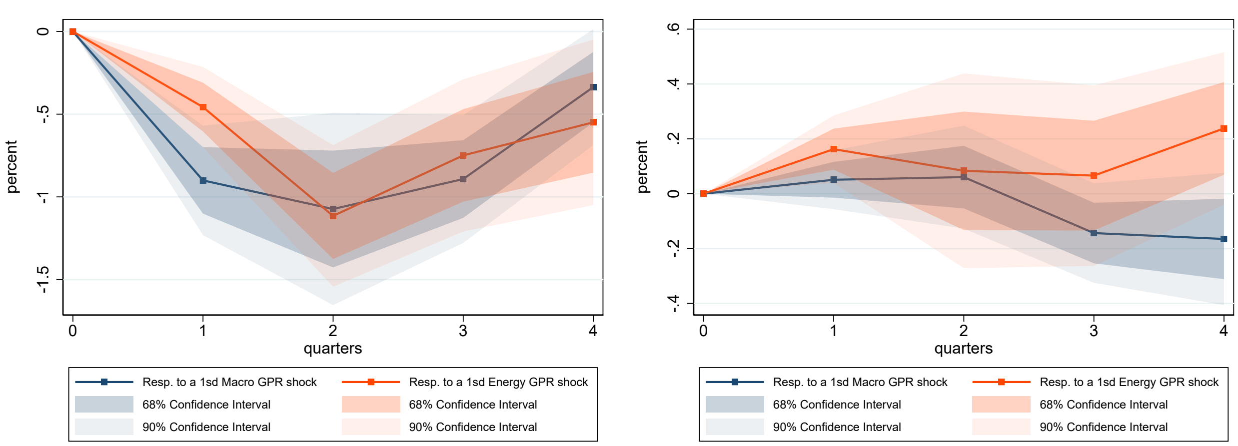
$$\Delta y_{j,t+h} = \alpha_h + \alpha_{j,h} + \beta_h \varepsilon_t + \gamma_h X_{t-1} + u_{j,t+h} \tag{4}$$

In the equation above, $y_{j,t}$ are 2-digit quarterly sectoral prices and gross output from the BEA for the period 2005-2021, α_h is a constant, $\alpha_{j,h}$ are sector-level fixed effects, $\varepsilon_t = \{\varepsilon_t^{macro}, \varepsilon_t^{energy}\}$ are the draws of the macro and energy GPR shocks associated with the median IRF (in the VAR identified via high-frequency sign restrictions), and $X_{j,t-1}$ is a vector of controls including 4 lags of the variables included in the VAR in the previous sections of the paper. j indicates the sector, t the time when the shock occurs, and h the considered horizon.

In Figure 8, 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 0.7% and 1.4% in the second quarter following the shock. A contraction of similar magnitude follows a shock to the GPR index associated with the energy component of the geopolitical risk. As in the VAR findings, the two shocks have distinct effects on the sectoral price level.

Figure 8 Average response to a one standard deviation GPR macro shock and GPR energy shock

A. Sectoral Output *B. Sectoral Prices*



On average, prices drop by up by between 0.02% and 0.2% 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 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 persistent rise in sectoral prices by between 0.1% and 0.4%, which lasts until the end of the considered horizon.

In the Appendix, I show that using the macro and the energy component of geopolitical risk obtained using the poor man methodology by Jarociński and Karadi (2020) as opposed to the median draw delivers a similar outcome. In conclusion, 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

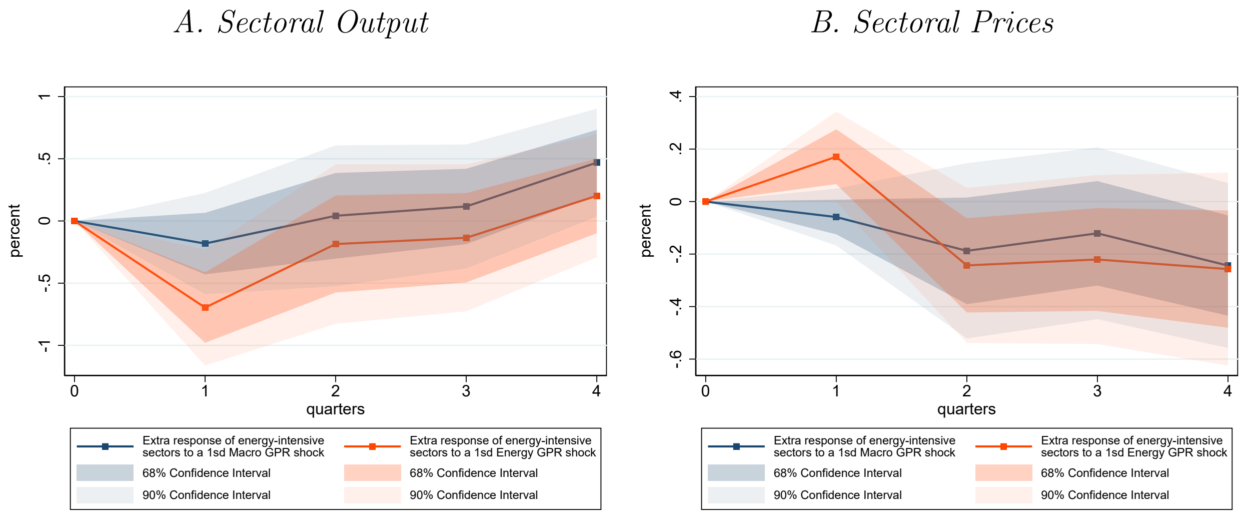
Second, I analyze the differential response of energy intensive sectors. To do so, I introduce a measure of energy intensity $EI_{j,t}$, defined as the amount of energy employed in production by sector j per unit of value added in time t, measured in MJ/USD 2015. To evaluate the differential effect of 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:

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

In the equation above, $y_{j,t}$ are 2-digit quarterly sectoral prices and gross output from the BEA for the period 2005-2021, α_h is a constant, $\alpha_{j,h}$ are sector-level fixed effects, $\alpha_{h,t}$ are time fixed effects, $\varepsilon_t = \{\varepsilon_t^{macro}, \varepsilon_t^{energy}\}$ are the draws of the macro and energy GPR shocks associated with the median IRF (in the VAR identified via sign restrictions).

In Figure 9, I show the additional response of a sector characterized by an energy intensity one standard deviation above the mean compared to the average. In this specification, sector-time fixed effects absorb all the average variation from geopolitical shocks. Hence, the responses in Figure 9 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 response of high energy-intensive sectors is not significantly different from the average response, except for the fourth quarter. 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 persistently declines by up to 0.5% more. This is a much stronger response compared to the average response (-1%).

Figure 9 Additional response with high energy-intensity use to a one standard deviation GPR macro shock and GPR energy shock



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, in none of the considered horizons, for none of the considered significance levels. However, in response to a standard deviation shock to GPR associated with the energy shock, on average sectoral prices of high energy-intensive sectors rapidly rise by up to 0.1% more. Again, this increase makes the overall response significantly larger compared to the average response of 0.2%, although the increase does not persist along the considered horizon. In the Appendix, I show that the response obtained using the macro and the energy component of geopolitical risk obtained using the poor man methodology by Jarociński and Karadi (2020) is in line with the above. These results show that the energy component of geopolitical risk 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 risk shocks for inflation and economic activity, and shows that energy markets are crucial for their transmission. The paper contributes to investigating the heterogeneity across classes of geopolitical shocks, by providing an identification strategy to isolate the energy component of geopolitical risk shocks based on state-of-the-art methodologies from the VAR literature.

The paper proposes a simple yet effective distinction between geopolitical shocks associated with disruptions on energy markets from geopolitical shocks associated with economic contractions unrelated to 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 shocks should be conditional on the composition of each individual episode in terms of structural shocks. Central banks should respond to geopolitical macro episodes by loosening interest rates, while the optimal response to energy-related geopolitical episodes is ambiguous, as they face a trade-off between output and inflation stabilization.

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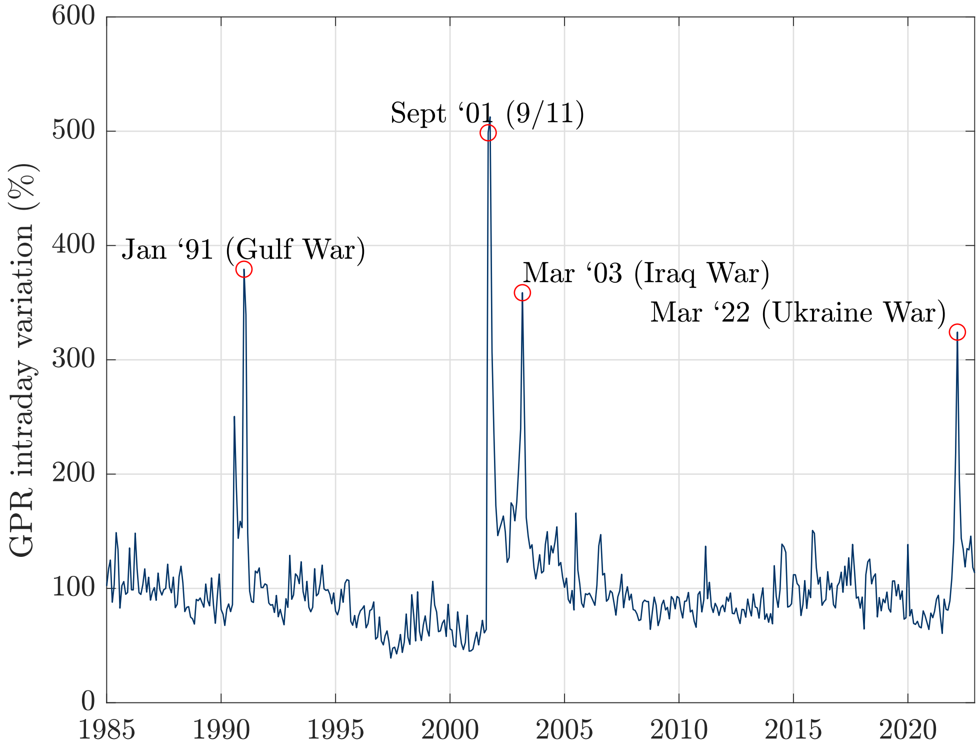
A Appendix

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)

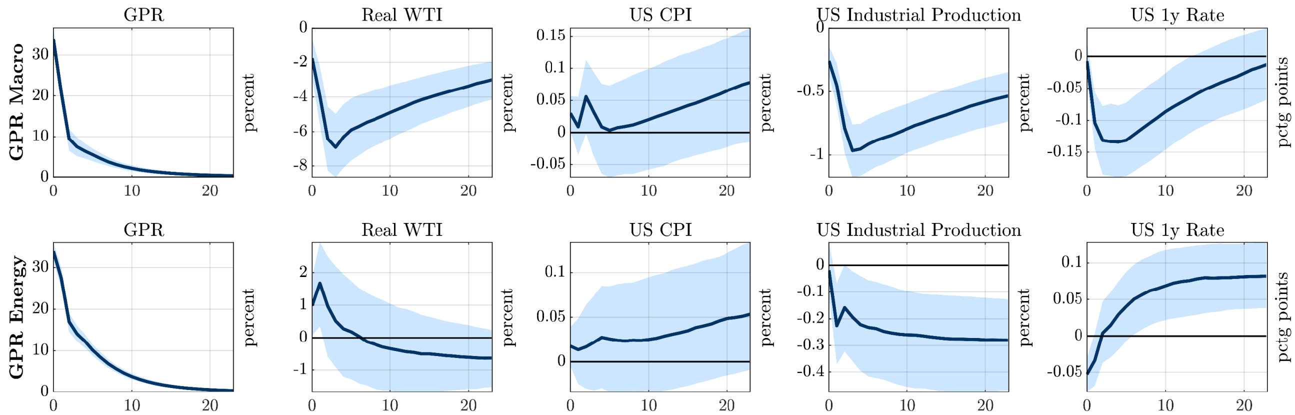


A.2 List of events[10]

Surprise date	Description
18/06/1985	TWA Hijacking
07/04/1986	US Bombing of Libya
28/04/1987	US/Russia Negotiations over Nuclear Weapons
12/10/1987	War Threats in Persian Gulf
21/12/1989	US Invade Panama
03/08/1990	Iraq Threatens US Embassy
15/01/1991	Gulf War. Iraq Fires at Israel.
09/08/1991	Ethnic Violence in Yugoslavia
20/08/1991	Failed coup in Soviet Union
14/01/1993	Air Strikes Against Iraq
28/06/1993	US Raid on Baghdad
08/02/1994	NATO Ultimatum to Serbia
03/09/1996	US Raid on Iraq
24/02/1998	US Considers Strike Against Iraq
18/12/1998	Iraq Disarmament Crisis Escalation
24/03/1999	Beginning Kosovo Air War
28/12/1999	Holidays' Terrorist Concerns
12/09/2001	9/11 Terrorist Attacks
09/10/2001	US Invades Afghanistan
27/09/2002	War Fears US / Iraq
21/03/2003	Beginning of the Iraq War
23/03/2004	Assassination of Sheik Yassin, Middle East Tensions
03/08/2004	Terrorist Threats in New York and Washington
08/07/2005	London Bombings 7/7
11/08/2006	Transatlantic Aircraft Plot
30/04/2007	War and Terrorism Concerns, Protests in Turkey
11/08/2008	South Ossetian War Escalation
28/12/2009	Flight 253 Failed Bombing Attempt
03/05/2011	US Announce Death of Osama Bin Laden
29/08/2013	Escalation of Syrian Crisis
03/03/2014	Russia Invades Crimea
02/09/2014	Escalation Ukraine/Russia
16/11/2015	Paris Terrorist Attacks
18/07/2016	Turkish Coup Attempt
21/08/2017	North Korea Tensions
12/04/2018	Syria Missile Strikes
07/01/2020	US / Iran Tensions Escalate
23/08/2021	Afghan Crisis Escalation
22/02/2022	Russia Invades Ukraine 24/02
14/11/2022	Istanbul Bombings 13/11
09/10/2023	Hamas Attacks on Israel 07/10

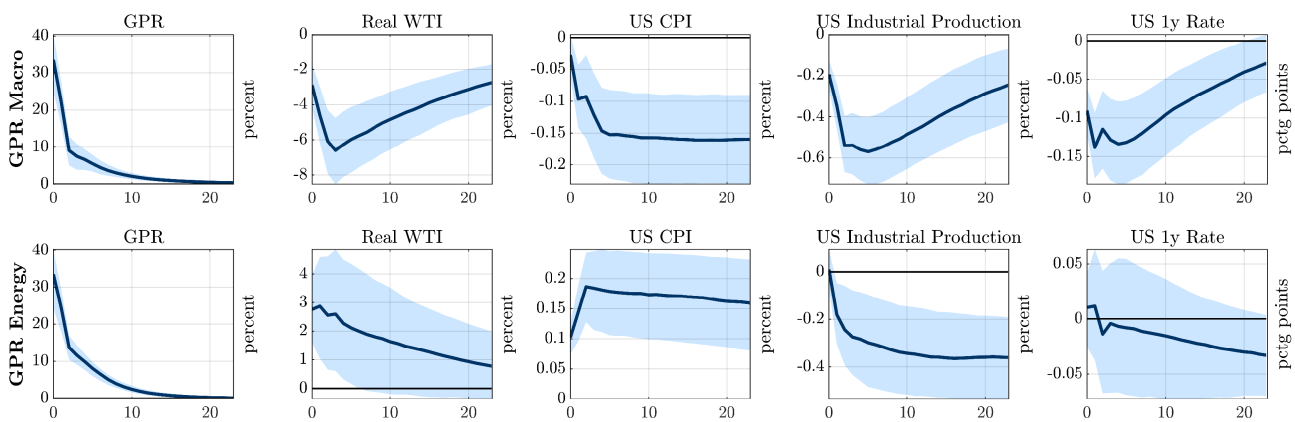
[10] This list of events builds on the list of the spikes in the GPR index collected by Caldara and Iacoviello (2022). Differently from their work, I report the date of each event based on the largest surprise in the GPR index surrounding the date of the spike, as opposed to the date of the spike itself.

Figure A.1 IRFs of the baseline variables (poor man approach)



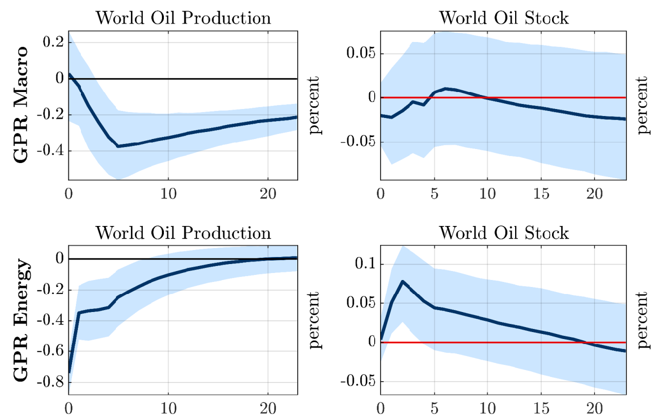
The figure(s) displays the estimated dynamic response of the baseline set of variables to GPR macro and GPR energy shocks identified with the poor man restrictions by Jarociński and Karadi (2020). Blue lines indicate point estimates and blue areas outline 68% confidence bands. The shock is associated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

Figure A.2 IRFs of the baseline variables (excluding Covid)



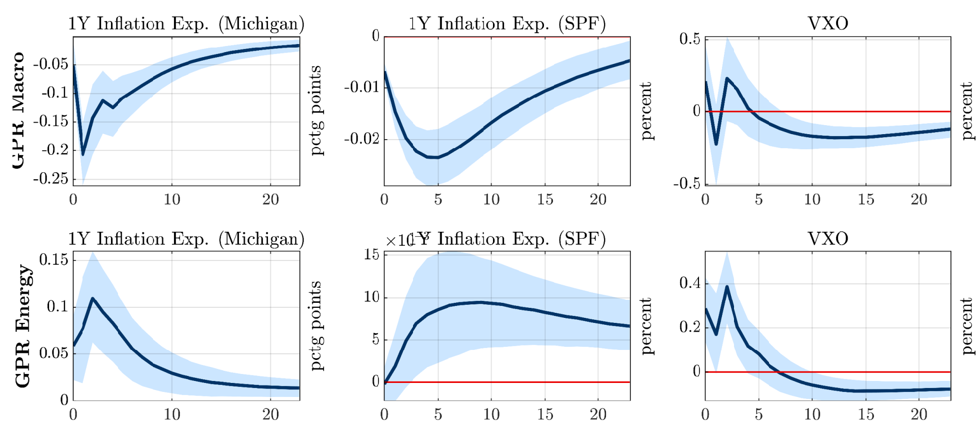
The figure(s) displays the estimated dynamic response of the baseline set of variables to GPR macro and GPR energy shocks when the geopolitical surprises occurring in 2020 are removed from the sample. Blue lines indicate point estimates and blue areas outline 68% confidence bands. The shock is associated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

Figure A.3 Oil markets



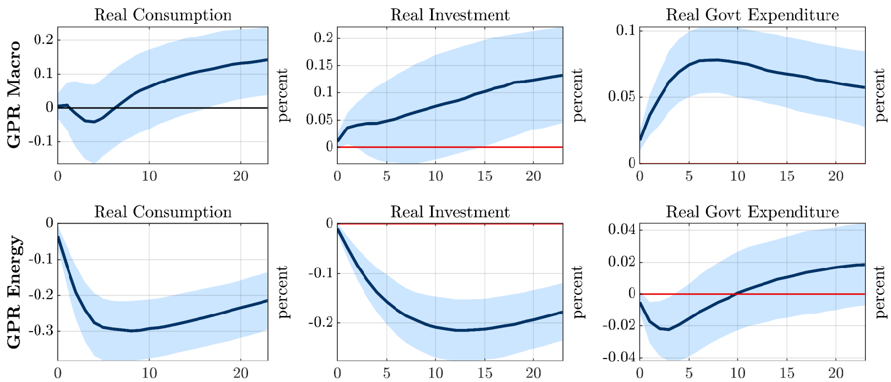
The figure(s) displays the estimated dynamic response of the baseline set of variables to GPR macro and GPR energy shocks. Blue lines indicate point estimates and blue areas outline 68% confidence bands. The shock is associated with a one standard deviation increase in the Geopolitical Risk Index (GPR).

Figure A.4 Expectations and Financial Volatility



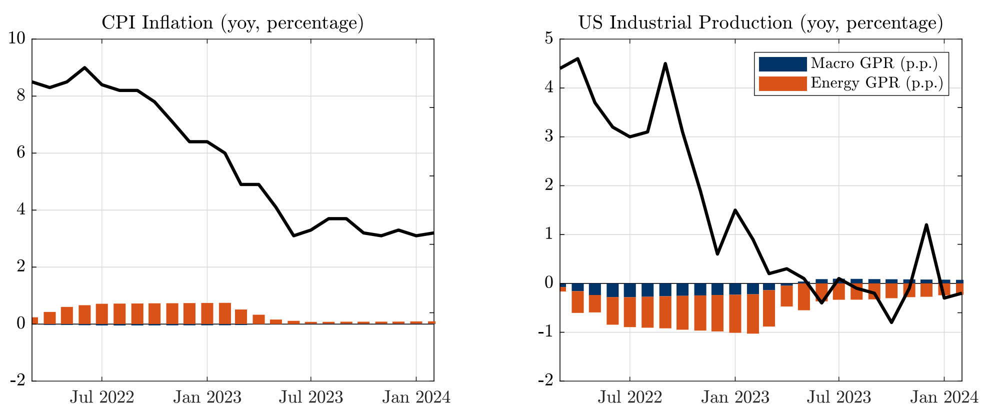
The figure(s) displays the estimated dynamic response of inflation expectations and financial volatility measures to GPR macro and GPR energy shocks. Blue lines indicate point estimates and blue areas outline 68% confidence bands. The shock is associated with a one standard deviation increase in the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

Figure A.5 Quarterly Macro Aggregates



The figure(s) displays the estimated dynamic response of world oil real consumption, investment, and government 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 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.

B Identification via Narrative Sign Restrictions: Methodological Detail

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

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

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 (B.1) by A_0^{-1}, this formulation can be compared like-for-like to the formulation as in Equation (3):

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

The matrix B can be obtained by multiplying the two matrices containing the structural parameters $A_+' = [A_1', \ldots, A_p' c']$ ($m \times n$, 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 (B.3) and (B.4):

$$\Gamma(\Theta) = (e'_{1,n}F(\Theta)'S'_1, ..., e'_{n,n}F(\Theta)'S'_n) > 0 \tag{B.3}$$

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

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:

$$e'_{j,n}\varepsilon_{t_{vt}}(\Theta) \geq 0 \quad for \quad 1 \leq v \leq s_j \tag{B.5}$$

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:

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

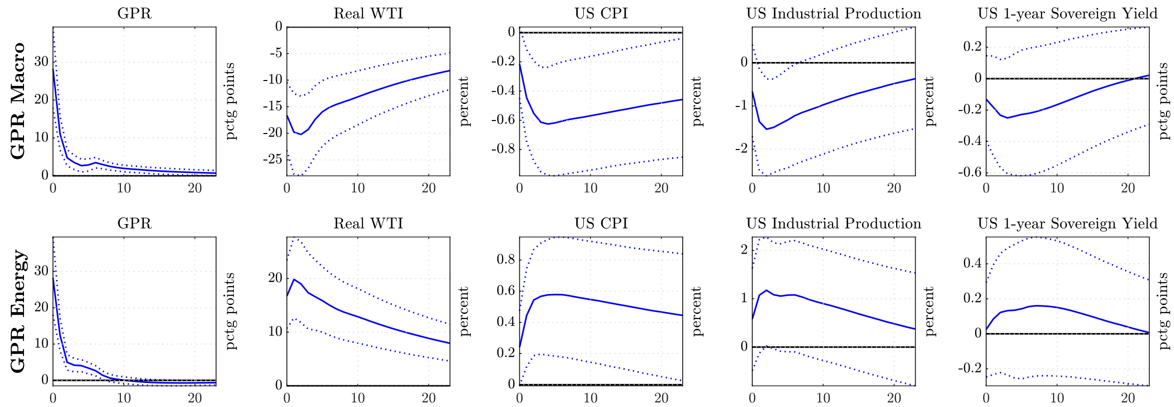
Antolín-Díaz and Rubio-Ramírez (2018) distinguish restrictions on the historical decomposition in either Type A when they impose that one shock is larger than the contributions of all other shocks in a given period or Type B restrictions when they impose that one shock is larger than the sum of the contributions 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 macro GPR and the energy GPR 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 $1 \leq v \leq s_j$:

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

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[11]. 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 6 lags, consistent with the baseline specification.

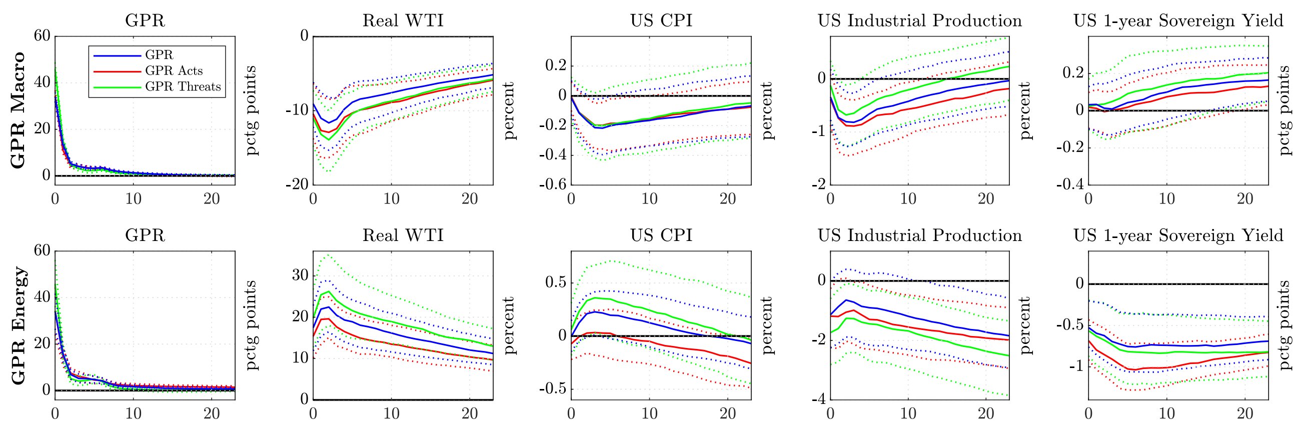
[11] The used simulation draws M are 1000 as in Antolín-Díaz and Rubio-Ramírez (2018).

Figure B.1 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 B.2 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).

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)	First principal component of the daily variation in WTI futures (1- to 6-months ahead) around selected events.	1985-2023	D
GPR Index	Caldara and Iacoviello (2022)	Monthly GPR index as in Caldara and Iacoviello (2022). The index tracks the monthly article counts related to adverse geopolitical events as a share of the total number of articles published by 10 amongst the 10 major US and UK newspapers.	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.	2005-2021	Q
Sectoral Prices	US Bureau of Economic Analysis	Chain-Type Price Indexes for Value Added by Industry.	2005-2021	Q
Sectoral Energy Intensity	International Energy Agency	Amount of energy from all sources employed in production per unit of value added.	2005-2021	Y

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

Table B.3 BEA/IEA Industry Match (1/2)

BEA Industry	IEA Industry
Farms	Agriculture, forestry and fishing
Forestry, fishing, and related activities	Agriculture, forestry and fishing
Mining, except oil and gas	Mining and quarrying
Support activities for mining	Mining and quarrying
Utilities	Services (without public administration and defence)
Construction	Construction
Wood products	Manufacture of wood and of products of wood and cork
Nonmetallic mineral products	Manufacturing (excl. coke and refined petroleum)
Primary metals	Manufacture of basic metals
Fabricated metal products	Manufacture of fabricated metal products, machinery and equipment
Machinery	Manufacture of fabricated metal products, machinery and equipment
Computer and electronic products	Manufacturing (excl. coke and refined petroleum)
Electrical equipment, appliances, and components	Manufacturing (excl. coke and refined petroleum)
Motor vehicles, bodies and trailers, and parts	Manufacture of transport equipment
Other transportation equipment	Manufacture of transport equipment
Furniture and related products	Manufacturing (excl. coke and refined petroleum)
Miscellaneous manufacturing	Manufacturing (excl. coke and refined petroleum)
Food and beverage and tobacco products	Manufacture of food products, beverages and tobacco products
Textile mills and textile product mills	Manufacture of textiles, wearing apparel, leather and related products
Apparel and leather and allied products	Manufacturing (excl. coke and refined petroleum)
Paper products	Manufacture of paper products and printing
Printing and related support activities	Manufacture of paper products and printing
Chemical products	Manufacturing of chemicals and pharmaceutical products
Plastics and rubber products	Manufacturing (excl. coke and refined petroleum)

Table B.4 BEA/IEA Industry Match (2/2)

BEA Industry	**IEA Industry**
Wholesale trade	Services (without public administration and defence)
Motor vehicle and parts dealers	Services (without public administration and defence)
Food and beverage stores	Services (without public administration and defence)
General merchandise stores	Services (without public administration and defence)
Other retail	Services (without public administration and defence)
Warehousing and storage	Services (without public administration and defence)
Publishing industries, except internet (includes software)	Services (without public administration and defence)
Motion picture and sound recording industries	Services (without public administration and defence)
Broadcasting and telecommunications	Services (without public administration and defence)
Data processing, internet publishing, and other information services	Services (without public administration and defence)
Federal Reserve banks, credit intermediation, and related activities	Services (without public administration and defence)
Securities, commodity contracts, and investments	Services (without public administration and defence)
Insurance carriers and related activities	Services (without public administration and defence)
Funds, trusts, and other financial vehicles	Services (without public administration and defence)
Housing	Services (without public administration and defence)
Other real estate	Services (without public administration and defence)
Rental and leasing services and lessors of intangible assets	Services (without public administration and defence)
Legal services	Services (without public administration and defence)
Computer systems design and related services	Services (without public administration and defence)
Miscellaneous professional, scientific, and technical services	Services (without public administration and defence)
Management of companies and enterprises	Services (without public administration and defence)
Administrative and support services	Services (without public administration and defence)
Waste management and remediation services	Services (without public administration and defence)
Educational services	Services (without public administration and defence)
Ambulatory health care services	Services (without public administration and defence)
Hospitals	Services (without public administration and defence)
Nursing and residential care facilities	Services (without public administration and defence)
Social assistance	Services (without public administration and defence)
Performing arts, spectator sports, museums, and related activities	Services (without public administration and defence)
Amusements, gambling, and recreation industries	Services (without public administration and defence)
Accommodation	Services (without public administration and defence)
Food services and drinking places	Services (without public administration and defence)
Other services, except government	Services (without public administration and defence)

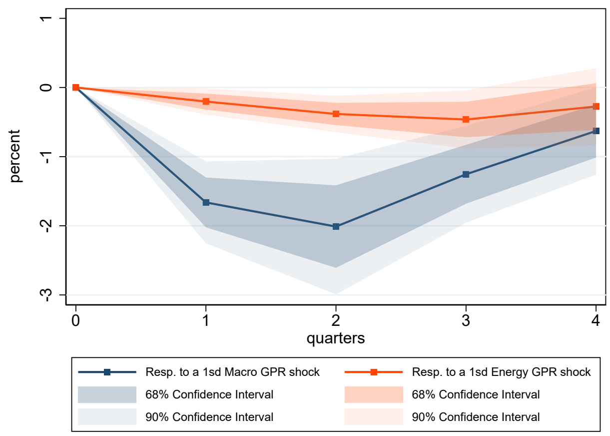
Table B.5 Data and Sources - Additional VAR Variables

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)

Figure B.3 Average response to a one standard deviation GPR macro shock and GPR energy shock identified using the poor-man approach

A. Sectoral Output



B. Sectoral Prices

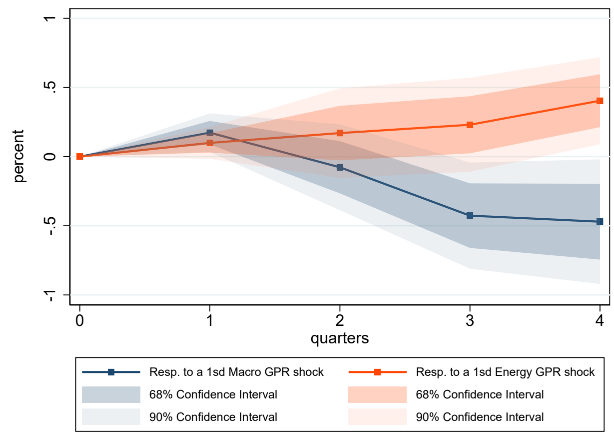
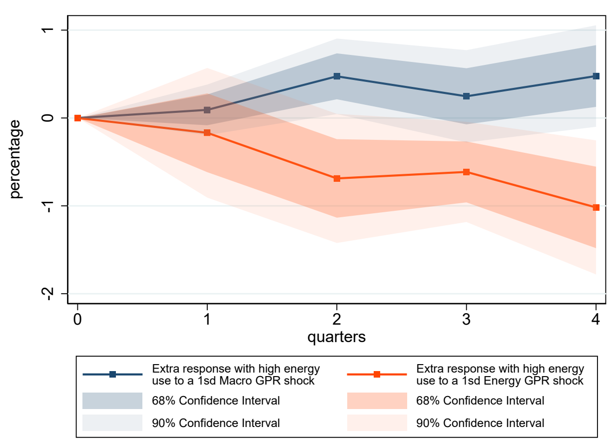


Figure B.4 Additional response of energy intensive sectors to a one standard deviation GPR macro shock and GPR energy shock identified using the poor-man approach

A. Sectoral Output



B. Sectoral Prices