On the Nonlinear Interplay of Geopolitical Risk, Commodity Prices and Macroeconomic Activity

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Abstract

The interaction between fluctuations in commodity prices and macroeconomic activity is often interconnected with geopolitical events. This paper aims to contribute to the literature by exploring the joint dynamics of geopolitical risk, commodity prices, and economic activity at the global level (G7 and commodity-dependent economies) and in the Euro Area. Our SVAR-based findings show that although the response to a geopolitical risk shock is generally negative for economic activity across all countries, commodity price shocks are contractionary for G7 economies and expansionary for commodity-dependent ones. Additionally, we find that these two external shocks explain an important share of the variance of output and economic confidence in the Euro Area. Further, state-dependent local projections indicate that the level of geopolitical risk affects the sign and size of the responses to a geopolitical risk shock.

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1 Introduction

The relevance of fluctuations in commodity prices for the dynamics of inflation and the macroeconomy in general has become hard to oversee. These fluctuations are often linked to geopolitical tensions, such as the Russian aggression war on Ukraine or the conflicts in the Middle East, and to the state of the global economy more generally. Yet, the dynamic interaction between geopolitical risk, commodity prices and macroeconomic activity is far from being fully understood. We aim exactly at exploring such interaction and its potential non-linearities.

Our study entails a revision of at least three seemingly disconnected literature strands in empirical and international macroeconomics: The interaction between energy prices and the macroeconomy, the analysis of macro-financial dynamics from a frequency-domain perspective, and the role of geopolitical risk in the global economy. Regarding the first strand, the study of the linkages between energy prices (specifically crude oil prices) and the macroeconomy starts with Hamilton (1983, 1996, 2003), who did pioneer work on the impact of oil market dynamics on national macroeconomic developments through the lens of time series analysis, mostly suggesting that hat US recessions were often preceded by increases in the price of oil. Kilian (2009) proposed an influential structural vector autoregression (SVAR) model of the global crude oil market whereby the source of the oil shock matters for the size of the US economy response. Similarly, Blanchard and Galí (2009) also used a SVAR model (with a rolling sample) and a New Keynesian framework[1] to analyze why response of advanced economies to oil price shocks varied significantly over time. Such time variation of oil price effects is also found in the work of Baumeister and Peersman (2013), who relied on a Bayesian time-varying SVAR. Later on, the literature has moved to the discussion of appropriate econometric identification in the context of SVAR models (e.g., Kilian and Murphy, 2012; Baumeister and Hamilton, 2019), and the interplay between energy markets and global economic conditions (e.g., Kilian and Zhou, 2018; Kilian, 2019; Hamilton, 2021; Baumeister et al., 2022)[2]. In parallel, there is also a plethora of country-specific studies attempting to quantify the effects of oil price shocks on the macroeconomy (e.g., see for a review Baumeister and Kilian, 2016 from an international perspective).

Regarding the second strand of the literature, the development and application of methods for analyzing time scales and measuring the frequency, amplitude, and turning points of cycles in macroeconomic variables (beyond the business cycle) has also gained popularity in the last decade. This is is most notable in the context of the financial cycle literature (i.e., on the comovement of stock markets, credit volumes and house prices), where it is common to find frequency domain analysis that uncover empirical aspects which would otherwise remain uncovered under

[1] An adaptation of this framework can be found in Bjørnland et al. (2018). In a related contribution, Fernández et al. (2018) analyzed the role of commodity prices in explaining business cycles in emerging market economies.

[2] Alquist et al. (2020) explored a similar question with a different empirical methodology

time-domain approaches (see Proaño and Quero Virla, 2024 for a literature review with a focus on time scales, and Strohsal et al., 2018, 2019; Proaño et al., 2025 for examples on the use of spectral analysis techniques[3]). In the context of commodity prices, *commodity supercycles* have been put forward in the academic discussion and are widely used term in the financial market jargon. In the frequency-domain tradition, Jerrett and Cuddington (2008) and Erten and Ocampo (2013) applied the methodology of Christiano and Fitzgerald (2003) to analyze commodity prices and found cycles with a duration of 20-30 years, while in the time-domain, Fernández et al. (2023) identified commodity supercycles and quantified their importance, concluding that the world shock that drives the commodity-price supercycle does have an effect in shaping short- and medium-run business cycle fluctuations (in developed and emerging economies), but does not play a central role in it. More recently, Juvenal and Petrella (2024) analyzed the linkages between commodity prices and the global financial cycle in the time domain.

Lastly, we must consider the role of geopolitical aspects in the global economy as a nascent research agenda in international macroeconomics[4]. Notably, Caldara and Iacoviello (2022) proposed a geopolitical risk index which is derived from the sentiment of leading English-speaking newspapers. At the macroeconomic level, their work shows that higher risk increases the probability of an economic disaster and is associated with lower investment and employment. Moreover, the practice of governments using economic power in existing financial and trade relationships to achieve geopolitical and economic objectives has been studied by Clayton et al. (2024a,b) in a quantitative framework. Similarly, Broner et al. (2023) proposed a quantitative model of model of hegemonic power and globalization, while Gopinath et al. (2025) explored empirically how geoeconomic fragmentation has produced changes in international trade and foreign direct investment linkages.

Accordingly, we address the research topic outlined previously using a combination of methods. Our analysis starts with a Bayesian SVAR model model with recursive identification (and *hierarchical prior selection* following Giannone et al., 2015) to explore the interaction between geopolitical risk, commodity prices and economic activity in the global economy. These initial findings allow us, as a second step, to introduce *sign and zero restrictions* (Rubio-Ramirez et al., 2010) in a Bayesian SVAR model for the Euro Area, which is the most open economy among large counterparts. Finally, we use a frequentist state-dependent local projections framework (Auerbach and Gorodnichenko, 2013) to explore if the global economy responds differently to the shocks of interest depending on the overall level of geopolitical risk. Additionally, we conduct a frequency domain causality test in Appendix B.

[3]Studies in this tradition have shown that the financial cycle have considerably longer duration than the standard business cycle, and the existence of time scales (i.e., some empirical relationships only hold at certain frequencies).

[4]Also drawing on earlier ideas from international relations and political science fields.

The rest of the paper is organized as follows: Section 2 provides a review of the related literature. Thereafter, we describe the data and formulate our methodology in Sections 3 (along with extended information in Appendix A) and 4. Results are presented in Section 5 (with additional analyses and robustness checks in Appendices B and C), followed by our concluding remarks in Section 6.

2 Literature Overview

Commodity price shocks produce differentiated macroeconomic effects depending on the economic structure of the country under consideration and its level of commodity dependence[5]. Standard economic intuition[6] suggests that advanced economies, which generally do not depend on commodities, are negatively impacted by surges in commodity prices because they put pressure on the domestic prices of energy, food, and raw materials, dampening both consumption and production. For instance, the New Keynesian model by Blanchard and Galí (2009) introduces crude oil is an input in households' consumption and in firms' production. An increase in the real price of oil leads to an increase in the consumption price relative to the domestic output price. On the production side, output is a decreasing function of the real price of oil, given employment and technology. Domestic inflation and GDP follow AR(1) processes with the same first order coefficient as the real price of oil. In a related contribution, Bjørnland et al. (2018) proposed and estimated a New Keynesian model where oil is introduced through the production function in the intermediate goods sector (as an input in production, and also through the share of oil relative to capital in production). The price of oil in determined in the foreign sector and depends on global oil-specific demand and supply forces. The results of the estimation point to the fact that a one-s.d. increase in the oil price generates a decrease in US GDP within two years due to an increase in production costs. This effect lowers profits and reduces capital accumulation and investment by firms, and eventually also affects consumption by households. On the other hand, commodity-dependent economies, generally emerging ones or exceptional cases such as Norway and Australia, sharply benefit from commodity price increases via three channels (even if the commodity price increase is caused by a geopolitical risk event[7]): the increased attainment of hard currency due to commodity exports, the increased economic activity in the commodity sector itself, and higher taxes and royalties paid to the government as a result of such activity. Some of these aspects have been featured in the quantitative models of Drechsel and Tenreyro (2018) and Agenor (2016).

[5] According to the threshold proposed by the UNCTAD (2023), countries are considered to be commodity-dependent if more than 60% of their merchandise export value comes from commodities.

[6] Most quantitative models in leading journals have addressed specifically the role of oil price fluctuations, however, their practical implications can be easily extended to the case any commodity.

[7] See International Monetary Fund (2025), p. 45.

These theoretical notions behind the macroeconomic effects of commodity price shocks also have a counterpart in the empirical literature, such as especially including Kilian (2009), Blanchard and Galí (2009), Baumeister and Peersman (2013), Fernández et al. (2018), Fernández et al. (2023), Juvenal and Petrella (2024).

Conversely, the macroeconomic implications of geopolitical events are significantly less understood because the development of modern quantitative models and empirical analyses is still in its infancy and has multiple connections to other social sciences.

Starting with the concept of *geoconomics*, Clayton et al. (2024a,b) describe it as a strategy through which "*governments use their countries' economic strength from existing financial and trade relationships to achieve geopolitical and economic goals*". This definition is close to the notion of *economic statecraft* (Baldwin, 1985), which is commonly used in political science to describe the use of economic means to pursue foreign policy goals. The authors use quantitative economic models to explain geopolitical dynamics how government use economic power from financial and trade relationships to achieve geopolitical and economic goals, and how hegemonic nations influence other countries by threatening the suspension or alteration of financial and trade relationships, but they do not focus on explaining how changes in geopolitical conditions affect macroeconomic outcomes. Mohr and Trebesch (2025), on the other hand, put together an extensive literature review and define geoeconomics more broadly as "*the field of study that examines the links between geopolitics and economics*", slightly closer to the definition of Thoenig (2024), namely, "*the study of the interaction between trade, diplomacy, and geopolitics*".

In the realm of geoeconomics, geopolitical risk arises as one of the most important concepts of the emerging literature. The leading definition in economics is the one provided by Caldara and Iacoviello (2022, p. 1197), which refers to 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*". Drawing on earlier work by Baker et al. (2016), which provides an index of economic policy uncertainty derived from US-based newspaper articles, the indices of global and country-specific geopolitical risk provided by Caldara and Iacoviello (2022) are also based on newspaper articles from 10 leading outlets in English language (6 from the US, 3 from the UK, and 1 from Canada). The authors explore the effects of these indices in a series of SVAR models and regressions.

Although the definition of Caldara and Iacoviello (2022) is almost uncontested in economics, there is disagreement on how geopolitical risk should be captured in an index. For instance, Bondarenko et al. (2024) rejected the idea of a universal English-based geopolitical risk index, and rather propose the computation of country-specific indices that are based on local-language sources. The authors claim that local-language indices capture geopolitical risk shock better. Alternatively, Hassan et al. (2019) measure political risk perceptions at the firm level using earnings call texts.

These measures coexist in the literature while, at the same time, new concepts and measures continue to appear. Fernández-Villaverde et al. (2024) derived an index of *geoeconomic fragmentation* using a broad set of indicators in a dynamic factor model, while Clayton et al. (2025) used large language models to extract signals of *geoeconomic pressure* from large textual corpora. Broner et al. (2025) used UN voting data to find that hegemonic countries foster international political alignment, which in turn enhances globalization.

In the light of these vibrant discussions, we must point out that the paradigm adopted in this paper remains close to the definition and measurement put forward by Caldara and Iacoviello (2022). Nevertheless, beyond the definitions and measurements, the effects of geopolitical risk shocks are believe to be negative for the economy. A recent report of the International Monetary Fund (2025) suggests that the effects of geopolitical risk on the macroeconomy are transmitted via a *market sentiment channel* (e.g., higher uncertainty) and an *economic channel* (e.g., trade or financial restrictions, as well as physical and civilian damage). Both channels have implications for growth, inflation, asset prices, and commodity prices. Some examples of the effect through these channels are provided by Caldara and Iacoviello (2022), who found that geopolitical events have a negative impact on private investment, and by Gopinath et al. (2025), who suggest that geopolitical risk disrupts international trade relationships and linkages. However, such effects can also be evidenced by political events, such as an increase in public debt or in public expenditure to fund a military buildup, which in turn also influences macroecononomic expectations and growth.

In conjuction, geopolitical risk and commodity price[8] shocks share a common feature: Typically, they do not originate in the domestic economy and may therefore be labelled as *external* shocks. In this regard, terms-of-trade shocks have been highlighted as a source of business cycle fluctuations in open economies (Fernández et al., 2017, Schmitt-Grohé and Uribe, 2018), which in turn posits the idea that at least part of the initial aggregate impact of these shocks might be influenced by the export basket type and the openness to trade at the time of the shock.

3 Sample Description

We address our research questions by analyzing a sample for the global economy, and another one for the Euro Area. The global sample runs from 1990 Q1 to 2023 Q3, while the Euro Area one runs from 1999 Q1 to 2023 Q3, in both cases, at quarterly frequency. Subsections 3.1 and 3.2 provide details about the selection of variables.

[8]Here, it is important to consider that although geopolitical risk can indeed affect commodity prices, there are other determinants behind price and quantity fluctuations in commodity markets. See Baumeister et al. (2022)

Further robustness checks (with a shorter sample running up to 2019 Q4) are presented in Appendix C.

3.1 Global Sample

As a measure of geopolitical tensions, we include the geopolitical risk index (GPR) of Caldara and Iacoviello (2022), which comprises the sentiment of 10 leading English-speaking newspapers on 8 dimensions of risk (war threats, peace threats, military buildups, nuclear threats, terror threats, beginning of war, escalation of war, terror acts. We use the global index of geopolitical risk, labelled in their database as the "recent" index, and not the country-specific indices which represent the contribution of specific country to global geopolitical risk. The index has two main components, *Threats* and *Acts*, which are shown in Figure 2 for reference but not used in the estimation.

As a proxy of global economic activity, we constructed GDP-weighted[9] indices of seasonally adjusted log real GDP for G7 (GDPG7) and commodity-dependent (GDPDep) economies. Based on the UNCTAD (2023) definition, the sample of dependent economies includes Brazil, Argentina, Saudi Arabia, South Africa, and Chile. The sample of G7 countries, which do not depend on commodities, includes the US, Japan, Germany, the UK, France, Italy and Canada. Considering the differences in the economic structure across countries outlined in our literature review section, we refrained from using the indicator of global real activity by Kilian (2009) or the world industrial production index by Baumeister and Hamilton (2019), to fully uncover the heterogeneity across country groups. Further, as a measure of commodity prices, we include World Bank's commodity price index (COMM), deflated with the seasonally adjusted US consumer price index in line with the standard practice in the literature (e.g., see Fernández et al., 2023, Juvenal and Petrella, 2024, and Ponomareva et al., 2024)[10]. COMM comprises a basket of commodities in the energy (67% weight in the index, including crude oil, coal, and natural gas) and non-energy (33% weight in the index, including agriculture, fertilizers, base metals, and minerals) segments, so the dynamics of the index are dominated by fluctuations in energy prices as shown in Figure 2.

Additionally, we include the CBOE VIX index (VIX) as a proxy of global financial conditions (e.g., see Strohsal et al., 2019; Proaño et al., 2025; Miranda-Agrippino and Rey, 2022) and the monetary policy rate of the US (InterestUS). A monetary policy variable was constructed by splicing the effective federal funds rate in the periods of 1990 Q1-2008 Q2 and 2022 Q3-2023 Q3, and the Shadow Rate for the US by Wu and Xia (2016) for the period 2008 Q1-2022 Q2. Hence, it captures the overall monetary policy stance even in the years when the US Federal Reserve operated

[9]The weights for the average are fixed over the whole sample using GDP in constant 2015 USD, in 2023, for each country.

[10]In the empirical literature of oil price shocks, following Kilian (2009), it is also standard to deflate crude oil prices with the US consumer price index.

at the zero lower bound and conducted quantitative easing.

With the exception of the monetary policy rate, all series enter the estimation in their natural logarithmic form.

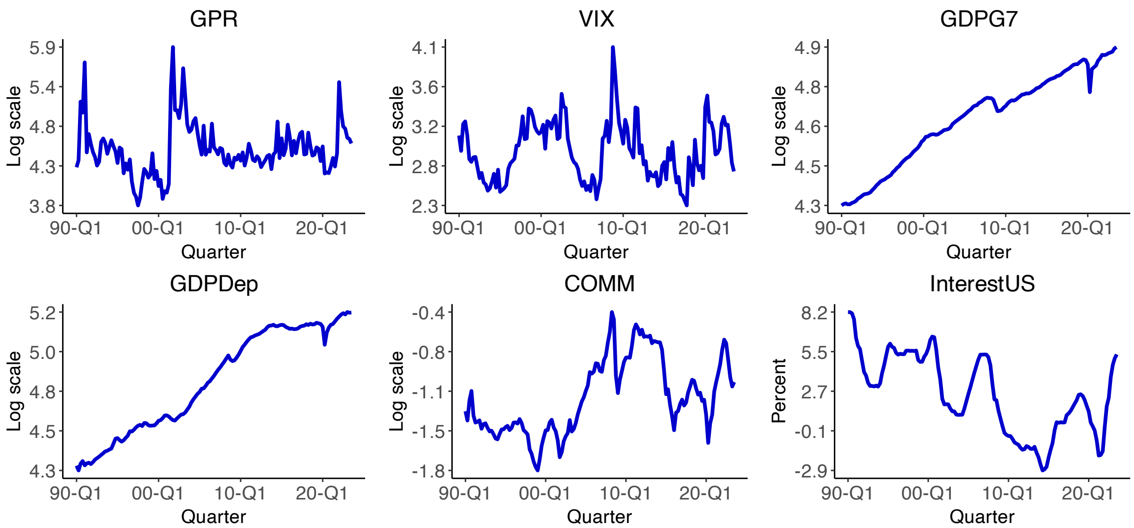

Figure 1: Global Variables from 1990 Q1 to 2023 Q3

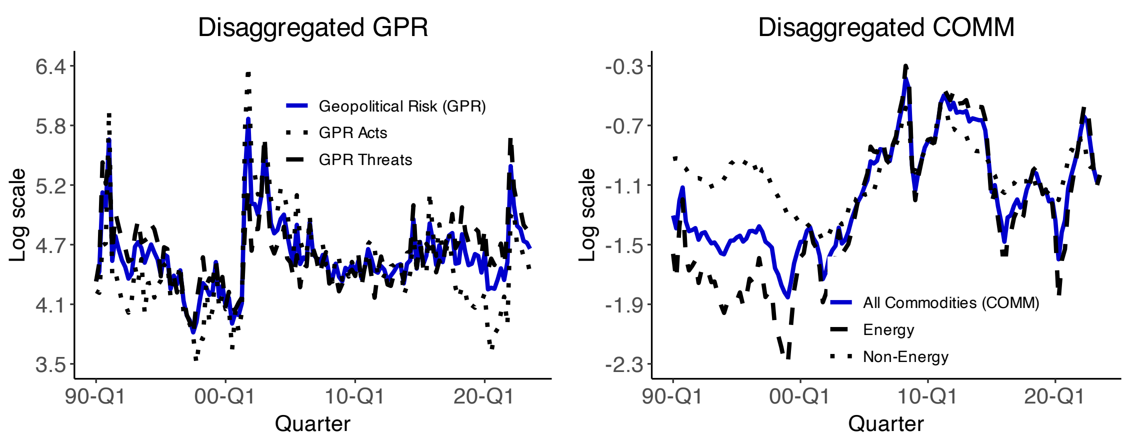

Figure 2: Disaggregated Geopolitical Risk and Real Commodity Prices from 1990 Q1 to 2023 Q3

3.2 Euro Area Sample

We include a geopolitical risk index (GPR) and a real commodity price index (COMM), as described in the previous subsection. Regarding domestic variables, we include the policy rate of the European Central Bank (InterestEA) to reflect the monetary policy stance, the seasonally adjusted real GDP for the Euro Area (GDPEA) to account for economic activity, and composite indices of business (BusinessEA) and consumer confidence (ConsumerEA) as a proxy of economic expectations.

Analogous to the procedure we used to construct the monetary policy rate of the US for the global sample, we spliced the ECB monetary policy rate in the periods 1999 Q1-2008 Q2 and 2022 Q3-2023 Q3, and the Shadow Rate for the Euro Area by Wu and Xia (2016) for the period 2008 Q1-2022 Q2, to reflect the periods of unconventional monetary policy.

All series enter the model in their natural logarithmic form in the estimation, except for monetary policy rate.

4 Econometric Strategy

Our analysis combines the insights from various econometric methodologies. The global sample is analyzed through a recursively-identified SVAR model and state-dependent local projections. An additional frequency-domain analysis Appendix B. Further, the Euro Area sample is analyzed through sign-and-zero restricted SVAR model.

4.1 Baseline Bayesian SVAR

SVAR models with recursive identification are standard in empirical macroeconomics (Kilian and Lütkepohl, 2017). Consider the following reduced-form VAR(p) model:

$$y_t = a_0 + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t, \tag{1}$$

where $y_t, t = 1, \ldots, T$ is a K-dimensional time series (being K the number of variables in the model). a_0 is an intercept vector, A_i are $K \times K$ parameter matrices, and u_t is a K-dimensional zero mean white noise process with covariance matrix $\mathbb{E}(u_t, u_t') = \Sigma_u$ such that $u_t \sim (0, \Sigma_u)$. The structural-form counterpart (SVAR) is then given by,

$$B_0 y_t = a_0 + B_1 y_{t-1} + \ldots + B_p y_{t-p} + w_t, \tag{2}$$

or by

$$y_t = a_0 + \underbrace{B_0^{-1} B_1}_{A_1} y_{t-1} + \ldots + \underbrace{B_0^{-1} B_p}_{A_p} y_{t-p} + \underbrace{B_0^{-1} w_t}_{u_t}, \tag{3}$$

where w_t denotes a mean zero serially uncorrelated error term, also called vector of structural shock, assumed to be unconditionally homoskedastic unless otherwise stated. $B_i, i = 0, \ldots, p$

are $K \times K$ coefficient matrices, and B_0 is the so-called matrix of contemporaneous relationships (with its inverse B_0^{-1} being the structural multiplier matrix). The variance-covariance matrix of w_t is normalized as $\mathbb{E}\left(w_t w_t'\right) \equiv \Sigma_w = I_k$ such that the reduced-form error-covariance matrix is $\mathbb{E}\left(u_t u_t'\right) \equiv \Sigma_u = B_0^{-1} B_0^{-1\prime}$. In the first part of the analysis using the global sample, we follow a recursive identification scheme, as it is not only the most common way of disentangling w_t from u_t [11], but it is also standard in the literature of oil price (Blanchard and Galí, 2009, Kilian, 2009) and geopolitical risk (Caldara and Iacoviello, 2022, Bondarenko et al., 2024,Brignone et al., 2025) shocks.

The vector of time series y_t comprises 6 variables in the following order: [GPR, VIX, GDPG7, GDPDependent, COMM, InterestUS][12]. The variables enter the model in the specified order, and in natural logarithm (with the exception of GDP series and the interest rate). The model is estimated with 2 lags considering information criteria for lag length. As it has become common in the literature, GPR is ordered first and its considered the most exogenous variable, in line with Caldara and Iacoviello (2022), Bondarenko et al. (2024), and Brignone et al. (2025). In a recursive identification scheme, this empirical choice comes at the cost of assuming that economic activity reacts contemporaneously to a geopolitical risk shock (i.e., within a quarter). Moreover, we order the global financial cycle variables (VIX) after GPR but before economic activity, as Caldara and Iacoviello (2022) and Proaño et al. (2025). The rationale behind the ordering of the remaining variables is that economic activity affects commodity prices (jointly with geopolitical forces which are ordered first) and that the US central bank reacts to global changes with a lag. Finally, we are specifically interested in the responses to shocks from both geopolitical risk and commodity prices.

Estimation is conducted through the Bayesian estimation approach[13]. In this sense, we use the Minnesota prior (Litterman, 1979, 1986), belonging to the normal-inverse-Wishart family and with significant popularity in macroeconomic applications. Similar to Bondarenko et al. (2024), we slightly adjust the random walk assumption of the prior by setting the prior mean to 0.5 for the reduced form equations of the variables that are rather stationary, and equal to 1.0 otherwise (i.e., for the GDP series, which are non-stationary). The overall tightness of the prior and the decay parameter were set to 0.3 and 2, respectively, following Brignone et al. (2025).

The remaining structure of the prior is treated hierarchically following Giannone et al. (2015). Namely, consider a model described by a likelihood function $\rho\left(y|\theta\right)$ and a prior distribution $\rho_\gamma\left(\theta\right)$, where $y \equiv \left[y_{p+1} + \ldots + y_T\right]'$, θ is a vector of model parameters, and γ collects the hyperparameters (i.e., the coefficients that parameterize the prior distribution but do not directly affect the

[11] I.e., we orthogonalize the latter by defining the lower-triangular $K \times K$ matrix P with positive main diagonal such that $PP' = \Sigma_u$, whereby P is then the lower-triangular Cholesky decomposition of Σ_u

[12] For variable definitions and motivation, please see Section 3

[13] For a more detailed treatment of the Bayesian framework in the context of SVAR models, see Koop and Korobilis (2010), Bauwens and Korobilis (2013), and chapters 5 and 13 of Kilian and Lütkepohl (2017)

likelihood). The hyperparameters can be chosen by interpreting the model as a hierarchical model: replacing $\rho_\gamma(\theta)$ with $\rho(\theta|\gamma)$ and evaluating their posterior. With the use of Bayes's law, such posterior can be obtained by

$$\rho(\gamma|y) \propto \rho(y|\gamma) \cdot \rho(\gamma), \tag{4}$$

where $\rho(\gamma)$ denotes the prior density on the hyperparameters, or hyperpriors, while $\rho(y|\gamma)$ is the so-called marginal likelihood (ML) and corresponds to

$$\rho(y|\gamma) = \int \rho(y|\theta, \gamma)\, \rho(\theta|\gamma)\, d\theta. \tag{5}$$

The ML is the density of the data as function of γ, which is obtained after integrating out θ. In the case of VAR (or SVAR) model relying on conjugate priors, the ML is fortunately available in close form, which allows the conduction of formal and theoretically grounded inference on the hyperparameters.

4.2 Bayesian SVAR with Sign and Zero restrictions

Learning from the results of the recursively identified Bayesian SVAR use to analyze the impact of geopolitical risk and commodity price shocks in the global economy, we introduce further identifying restrictions to study their effect in the Euro Area. The region is a unique case with a median trade openess[14] of 72% between 1990 and 2022, making it the most open economy among large counterparts during that period[15], and clearly more open than the US (25%), the UK (53%), Japan (26%), India (40%) or Brazil (25%). Thus, the region has a presumably higher exposure to external shocks

We combine the Minnesota prior specification outlined previously in subsection 4.1, and the *sign and zero restrictions* approach to identification proposed by Rubio-Ramirez et al. (2010) and Arias et al. (2018). More precisely, at the Euro Area level, a geopolitical shock is characterized by an increase in (global) geopolitical risk, an unknown effect in commodity prices, no impact on the interest rate, and a decrease in GDP, business confidence and consumer confidence. A commodity price shock is characterized by a positive increase on commodity prices, a negative impact on Euro Area GDP, no impact on geopolitical risk, and unknown impact on the remaining variables. We also introduce minimal, uncontroversial restrictions to identify further shocks, including a

[14] The sum of exports and imports of goods and services measured as a share of gross domestic product; retrieved from the World Bank Development Indicators.

[15] Such statement holds even if we look at the two largest Euro Area economies, Germany (71%) and France (55%), individually.

monetary policy one, but our main focus lies in the effects of geopolitical and commodity price shocks. All the restrictions hold for contemporaneous relationships only (i.e., at the time of the shock).

$$\begin{pmatrix} u_t^{GPR} \\ u_t^{COMM} \\ u_t^{InterestEA} \\ u_t^{GDPEA} \\ u_t^{BusinessEA} \\ u_t^{ConsumerEA} \end{pmatrix} = \begin{bmatrix} + & 0 & 0 & * & * & * \\ * & + & * & * & * & * \\ 0 & * & + & * & * & * \\ - & - & - & + & + & * \\ - & * & * & * & + & * \\ - & * & * & * & * & + \end{bmatrix} \begin{pmatrix} w_t^{\text{Geopolitical shock}} \\ w_t^{\text{Commodity price shock}} \\ w_t^{\text{Monetary policy shock}} \\ w_t^{\text{Domestic demand shock}} \\ w_t^{\text{Business confidence shock}} \\ w_t^{\text{Consumer confidence shock}} \end{pmatrix} \tag{6}$$

where a plus sign $(+)$ indicates a positive impact, a minus sign $(-)$ indicates a negative impact, a zero (0) implies no impact, and an asterisk $(*)$ indicates a unrestricted parameter.

4.3 State-Dependent Local Projections

The methodology of local projections (LPs), initially proposed by Jordà (2005), has gained significant popularity over the past two decades in many fields of economics as an alternative for computing impulse responses through direct regressions (see Jordà and Taylor, 2025 for a review). Choosing LPs over VAR-based approaches is a matter of preference and there is a vibrant debate between the defendants of each alternative (e.g., Plagborg-Møller and Wolf, 2021, Montiel Olea et al., 2025, Baumeister, 2025). Similarly, the estimation state-dependent impulse responses is subject debate, with Auerbach and Gorodnichenko (2013) as seminal proponents of a (*regime-* or) *state-dependent* LPs framework which became prominent in the study of non-linear effects over the last decade (e.g., Ramey and Zubairy, 2018, Tillmann, 2020, Ahmed et al., 2024, among others). Unlike the competing smooth-transition VAR approach (e.g., see the ST-VAR in Auerbach and Gorodnichenko, 2012), state-dependent LPs do not assume that the economy remains in the current stays in the current state over the horizon in which the impulse responses are calculated. Such assumption has made the ST-VAR subject to criticism, for instance, in contexts where the real duration of a state in the economy is shorter than the horizon impulse responses[16].

Motivated by their flexibility, computational simplicity, and popularity in the literature, we choose state-dependent LPs to explore how the dynamic effects geopolitical risk and commodity price shocks differ depending on the level of geopolitical risk. As a starting point, Jordà (2005) proposed to estimate OLS regressions for each horizon $h = 0, 1, 2, ..., H-1$:

[16] In turn, state-dependent local projections have also been thoroughly criticized by Gonçalves et al. (2024) for their limited ability to recover the conditional responses to shocks under different assumptions about the state change and depending on the size of the shock itself. However, the states we define in this study are exogenous to the state of the economy and therefore overcome their main critique

$$y_{t+h} = a^h + B_1^h y_{t-1} + \ldots + B_p^h y_{t-p} + u_{t+h'}^h \tag{7}$$

letting a^h be a vector of constants, B_i^h the paremeter matrices for lag p and forecast horizon h, and u_{t+h}^h the autocorrelated and heteroskedastic disturbances[17]. Local projections is then the name for the collection of regressions arising from the last equation.

Structural impulse responses can be estimated as $\hat{IR}(t, h, d_i) = \hat{B}_1^h d_i$ where the $d_i = B_0^{-1}$. The structural shock matrix d_i must be identified from a linear VAR (through recursive identification in our case[18]) and thus becomes clear that local projections face the same identification challenge as the SVAR approach. Moreover, we use 4 lags for the underlying SVAR used to identify d_i, and 2 lags for the non linear model.

State variation is introduced in the spirit of Auerbach and Gorodnichenko (2013) and Ramey and Zubairy (2018) through a logistic function:

$$F(\zeta_t) = \frac{e^{(-g\zeta_t)}}{\left(1 + e^{(-g\zeta_t)}\right)}, \tag{8}$$

where ζ_t is a switching variable, and $g > 0$ is parameter selected by the econometrician. A low value of g makes the regime-switching smoother (e.g., 1), whereas higher values (e.g., 5) results in a quicker switch. Auerbach and Gorodnichenko (2012, 2013) set $g = 1.5$ so that the economy spends about 20% of the time in a recessionary regime, consistent with the fraction of recessionary periods in the US. Since periods of elevated geopolitical risk are not cyclical and are also less frequent than recessions, we set $g = 1.0$[19]. Additionally, although there are various alternatives to specify ζ_t, we use the standardized cyclical component of geopolitical risk in log scale as our transition variable, derived from the Hodrick-Prescott filter with a smoothing parameter of 1600 (see Ravn and Uhlig, 2002), which resembles the approach of Auerbach and Gorodnichenko (2013). Geopolitical risk is then only filtered to obtain the transition variable, but remains unfiltered in the vector of variables used in the estimation. Such vector has the same ordering of variables specified in subsection 4.1.

The observations of two regimes (R1: High geopolitical risk; R2: Low geopolitical risk) are obtained by multiplying the endogenous variables by the values of the transition function at $t-1$:

[17] For this reason, the author proposed to estimate robust Newey-West standard errors.

[18] A potential shortcoming of combining state variation with a recursive identification is that, although model coefficients (and therefore impulse responses) transition smoothly, d_i is held constant across the two states. However, a similar strategy has been pursued by Ahmed and Cassou (2016), Ahmed et al. (2024), and also in the initial estimations by Auerbach and Gorodnichenko (2017).

[19] In our case, however, choosing different values from 1 to 3 does not result in fundamentally different impulse responses.

$$
\begin{aligned}
R1 &= y_{t-l} \cdot (1 - F(\zeta_{t-1})) \\
R2 &= y_{t-l} \cdot (F(\zeta_{t-1})),
\end{aligned} \tag{9}
$$

where $l = 1, ..., p$. Hence, plugging equation 9 into 7 yields:

$$
\begin{aligned}
y_{t+h} = a^h + B^h_{1,R1}(y_{t-1} \cdot (1 - F(\zeta_{t-1}))) + \ldots + B^h_{p,R1}(y_{t-p} \cdot (1 - F(\zeta_{t-1}))) + \\
B^h_{1,R2}(y_{t-1} \cdot F(\zeta_{t-1})) + \ldots + B^h_{p,R2}(y_{t-p} \cdot F(\zeta_{t-1})) + u^h_{t+h'}
\end{aligned} \tag{10}
$$

In Figure 3, it becomes evident that the standardized cyclical component of geopolitical risk and geopolitical risk itself (in log scale) move closely during the whole period under consideration. Moreover, our choice of $g = 1.0$ in the transition function allows for a quick transition between states, where values of close to zero in $F(\zeta_t)$ indicate a period of high geopolitical risk. For example, $F(\zeta_t)$ remains very close to zero around the Gulf War in the early 1990s, the 9/11 attack and the following Iraq war in the early 2000s, and the Russian aggression war on Ukraine in 2022.

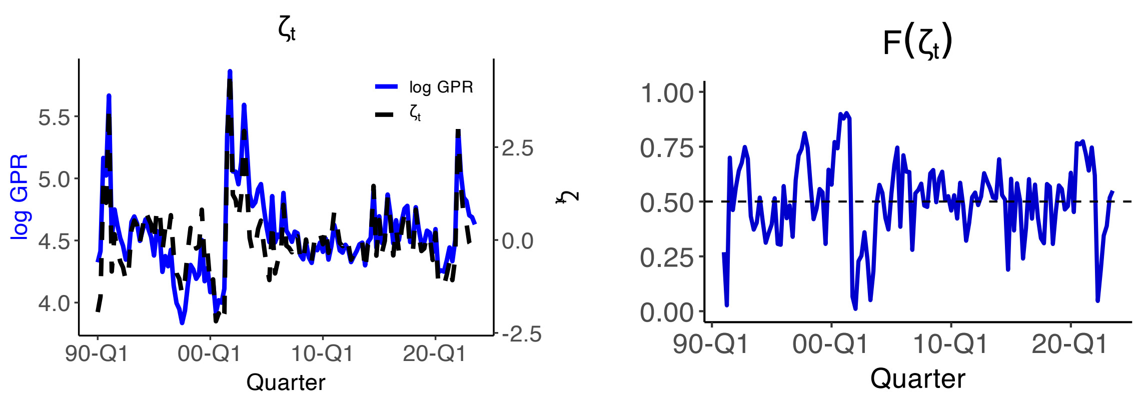

Figure 3: Transition variable (ζ_t) and transition function ($F(\zeta_t)$) over the period of analysis.

In Appendix C, we conduct an additional robustness check in which states are defined through a dummy variable that takes the value of 1 whenever the geopolitical risk variable (in log scale) is equal or higher than its 75% percentile, and 0 otherwise. Such alternative approach does not require the use of the Hodrick-Prescott filter or a logistic function.

5 Geopolitical Risk and Commodity Price Shocks

5.1 Recursively-Identified Bayesian SVAR: Impact on the Global Economy

The responses to shocks in geopolitical risk and in real commodity prices, respectively, are shown in Figure 4. Regarding geopolitical risk shocks, our results are qualitatively similar to those obtained by Caldara and Iacoviello (2022), Bondarenko et al. (2024), and more recently, Brignone et al. (2025). A one-sd. innovation in GPR results in a short-lived increase in the VIX, followed by a pronounced decline. The response of economic activity in both G7 and commodity-dependent countries is negative and long lasting, although larger in the latter group. The impact on real commodities prices is also negative throughout the horizon, potentially reflecting the lower global aggregate demand which originates from the geopolitical risk shock, and contrary to standard belief that geopolitical events directly increase commodity prices. In this particular regard, Caldara and Iacoviello (2022) and Brignone et al. (2025) obtained similar findings, but the latter authors found that the response of commodity prices can depend on the choice of the GPR index over its components. Moreover, the impact of a GPR shock also produces a delayed and modest increase in the US monetary policy rate.

It should be noted that Bondarenko et al. (2024) found that using geopolitical risk series constructed with local-language sources, instead of the English-based index by Caldara and Iacoviello (2022) used in this paper, resulted into overall larger responses of macroeconomic variables to geopolitical risk shocks. However, local-language sources can be more difficult to access and to analyze, and consequently, the authors produced local-language geopolitical risk series for a few selected countries only.

Regarding real commodity price shocks, a one-sd. innovation in COMM results in an increase in geopolitical risk, nevertheless, we show this response only for completeness, as the dynamics of geopolitical events cannot be entirely explained by commodity prices. The response of the VIX is largely positive over 12 quarters, indicating increased financial risk perceptions potentially due to the financial market narrative that higher oil prices correlate with US recessions. On the other hand, the impact of a commodity price shock is negative and long-lasting for G7 countries, and largely positive but for commodity-dependent ones. The differentiated effect across countries matches the results of Fernández et al. (2023), and the many country-specific studies in the oil price shocks literature. Further, the impact on the US monetary policy rate is negative over the whole horizon.

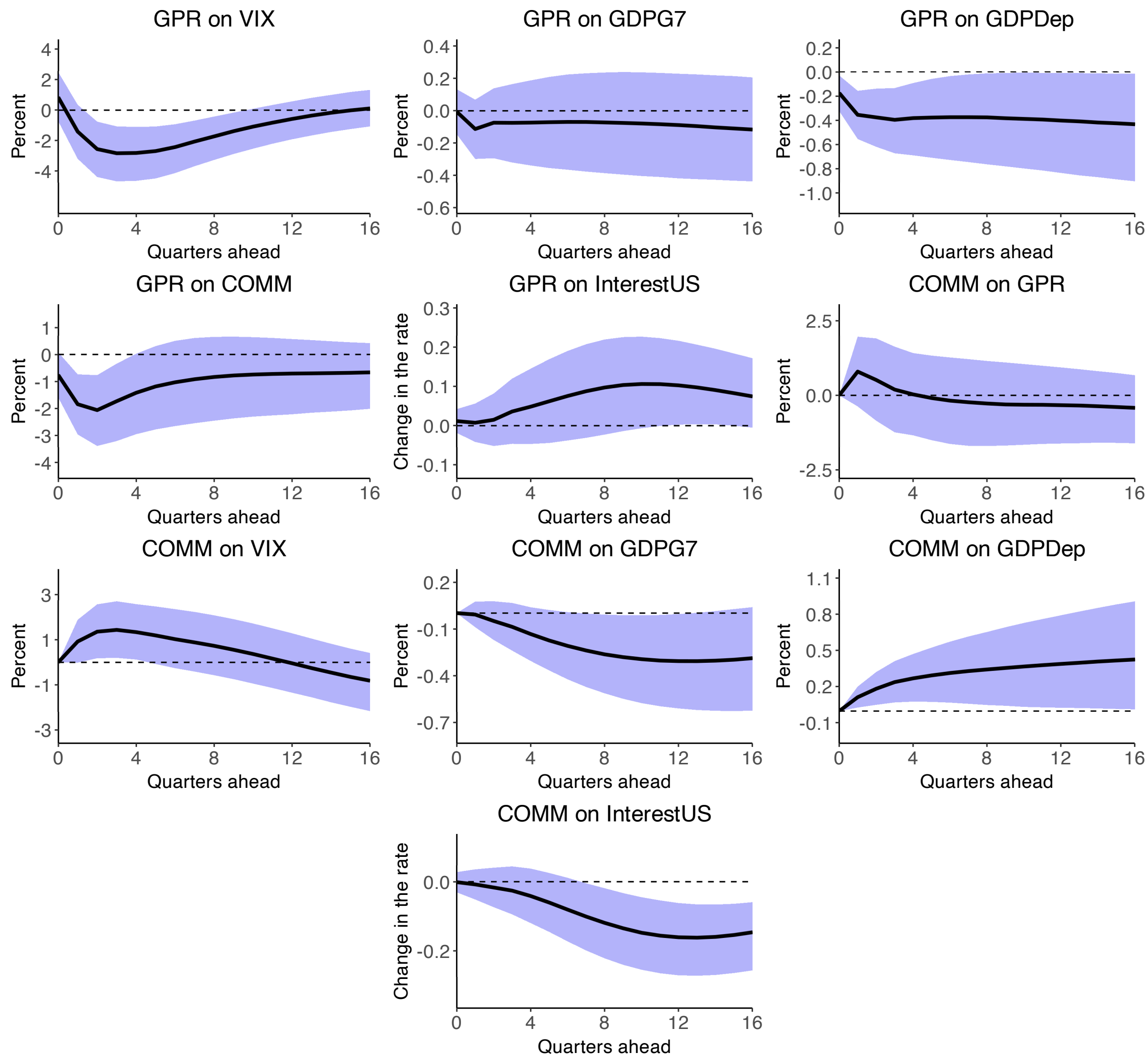

Figure 4: Median impulse responses to a one-sd. shock Geopolitical Risk and in Real Commodity Prices. Note: Shaded areas denote 68% credible sets.

We acknowledge that many credible sets of the median responses (roughly analogous to error bands in the frequentist tradition) in Figure 4 overlap the zero-line, which in turn posits questions about the statistical significance of the results. Yet, we stress that this is a common empirical outcome not only in recent studies on geopolitical risk shocks (e.g., Caldara and Iacoviello, 2022, Bondarenko et al., 2024, Brignone et al., 2025, Alonso-Alvarez et al., 2025), but also in many contributions within the broader literature of commodity price shocks (e.g., Kilian, 2009, Baumeister and Peersman, 2013, Baumeister and Hamilton, 2019, Fernández et al., 2023, Güntner et al., 2024). In line with earlier contributions, we keep the discussion in terms of economic significance.

5.2 Sign and Zero Restrictions: Impact on the Euro Area

As mentioned in Section 4.2, the Euro Area the most open economy among large counterparts and therefore it is presumably highly exposed to external shocks (for instance, via terms-of-trade shocks as in Fernández et al., 2017 and Schmitt-Grohé and Uribe, 2018). Following the revival of geopolitical tensions that came up with the Russian aggression war in Ukraine, the effects of energy price shocks in the region have become an important subject of study. For instance, the work of Casoli et al. (2024) addresses the effect on Euro Area inflation, and Güntner et al. (2024) explored the effect on Germany's output. The work of Bondarenko et al. (2024) also sheds light on the effect of geopolitical risk shocks on the German economy.

The results we present in table 1 outline the shocks that explain output, business confidence and consumer confidence in the Euro Area. Starting with output, we find that 16% of its variance is explained by its own, while geopolitical risk and commodity price shocks account for 20% and 17% of its variance, respectively. About 31% percent of the output variance is jointly explained by economic (business and consumer) confidence, which reflects the role of animal spirits. Lastly, about 16% of the variance is explained by the monetary policy shock. With regard to business confidence, geopolitical risk and commodity price shocks explain 18% and 17% of the variance, respectively, while the monetary policy shock explains 15% of the variance. On the other hand, regarding consumer confidence, geopolitical risk and commodity price shocks shocks account for 21% and 16% of the variance, respectively, with monetary policy shocks accounting for 16%.

The implications of these results are twofold. First, a large share of the variance of output does not the depend on the monetary policy shock, which suggests that relying on a single macroeconomic policy tool (i.e., the interest rate of the ECB) can be insufficient to cope with the adverse effects of a geopolitical risk or a commodity price shock. Second, these two external shocks jointly explain a significant share of the confidence among economic agents.

Table 1: Share of variance explained by shocks (mean of posterior draws) after 16 quarters.

Shock	**Output**	**Business Confidence**	**Consumer Confidence**
Geopolitical	0.20	0.18	0.21
Commodity Price	0.17	0.17	0.16
Monetary	0.16	0.15	0.16
Domestic Demand	0.16	0.17	0.15
Business Confidence	0.16	0.18	0.16
Consumer Confidence	0.15	0.16	0.15

5.3 State-Dependent Local Projections: Does the Level of Geopolitical Risk Matter?

Setting the geopolitical risk as a transition variable (see figure 3) allows us to explore whether our main shocks of interest produce differentiated results depending on the level of geopolitical risk. We show the state-dependent local projections in Figures 5 and 6. It should be noted that impulse responses estimated through state-dependent local projections look more jagged or less smooth than those generated with the SVAR framework. This is a general characteristic of local projections which has been documented by Plagborg-Møller and Wolf (2021) and Montiel Olea et al. (2025) for the linear case, and in Ahmed et al. (2024) for the nonlinear one.

In periods of high geopolitical risk, a one-sd. shock in geopolitical risk produces a brief increase followed by a pronounced decline in economic activity in both G7 and commodity-dependent countries, and a decline in real commodity prices. On the other hand, in periods of low geopolitical risk, the response to the shock is largely negative for G7 countries, and rather positive for commodity-dependent ones after some quarters, in line with a large and prolonged increase in real commodity prices. The VIX and the US monetary policy rate respond to the shock more or less equally negatively in both regimes. The economic intuition behind these results is that in an environment of low geopolitical tensions, a geopolitical shock comes as a surprise in commodity markets and leads to a substantial price increase that predominantly benefits commodity-dependent countries. Conversely, there is no surprise in an environment of high geopolitical tension, where a GPR shock is predominantly contractionary for both country groups, and for real commodity prices as a result of lower economic activity. In this respect, there is evidence in the behavioral economics literature (e.g., Tversky and Kahneman, 1992, Bordalo et al., 2012, Dessaint and Matray, 2017) suggesting that businessmen and investors may either react to geopolitical risk events heuristically and pay less attention to them in a context of prolonged geopolitical tension so that a certain degree of complacency arises, as acknowledged recently by the International Monetary Fund (2025).

Concerning real commodity price shocks, the responses considerably more jagged across both states of geopolitical risk, making their interpretation more challenging. Following a one-s.d. shock, the response of economic activity in G7 economies is positive in the high geopolitical risk state, and negative in the low one, but short lived in both cases. Conversely, commodity-dependent economies respond positively only in the high geopolitical risk state. The responses of the VIX and the US interest rate also have a different sign depending on the state.

The main implication of these results is that transitions between low and high levels of geopolitical risk are important for the size and sign of responses of economic activity to geopolitical shocks, but relatively less relevant for the responses to a commodity price shock.

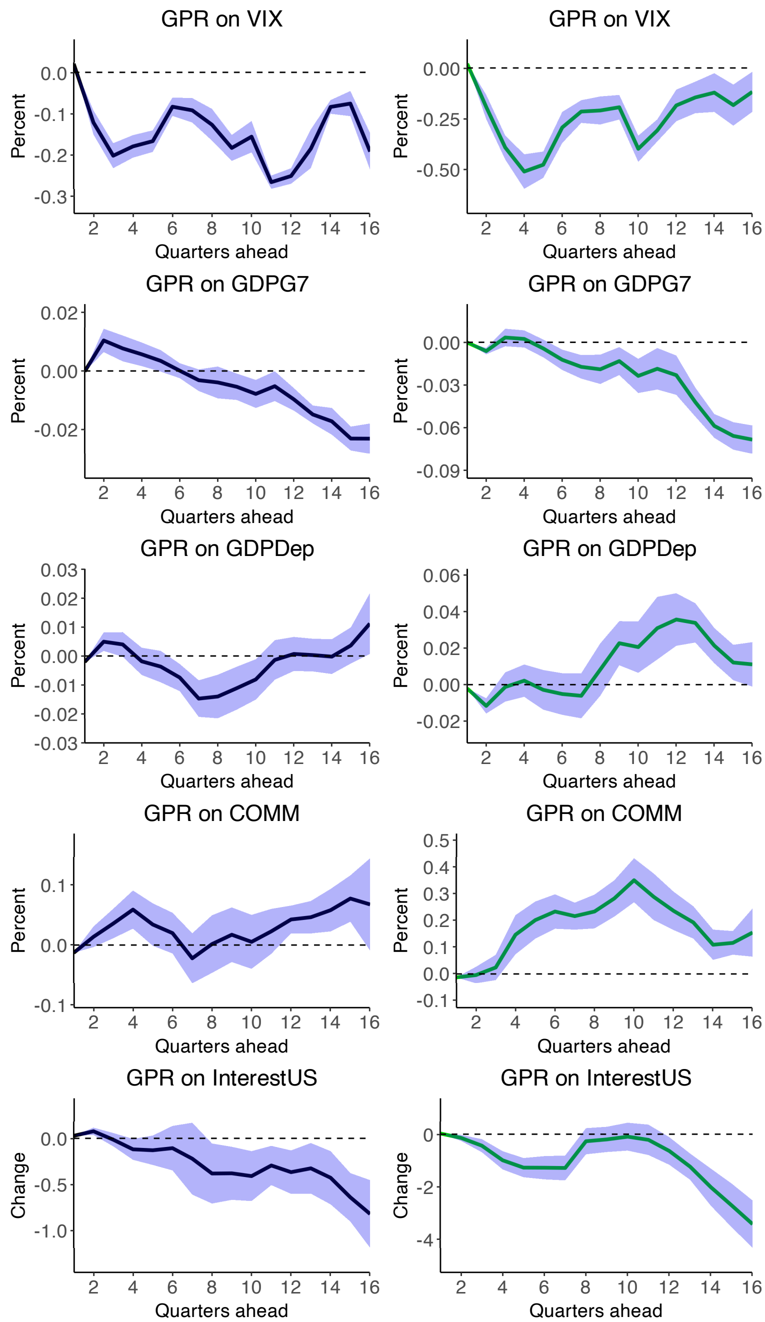

Figure 5: LP-based responses to a one-sd. shock in Geopolitical Risk during high (black line) and low (light brown line) geopolitical risk states. Note: Shaded areas denote 68% error bands.

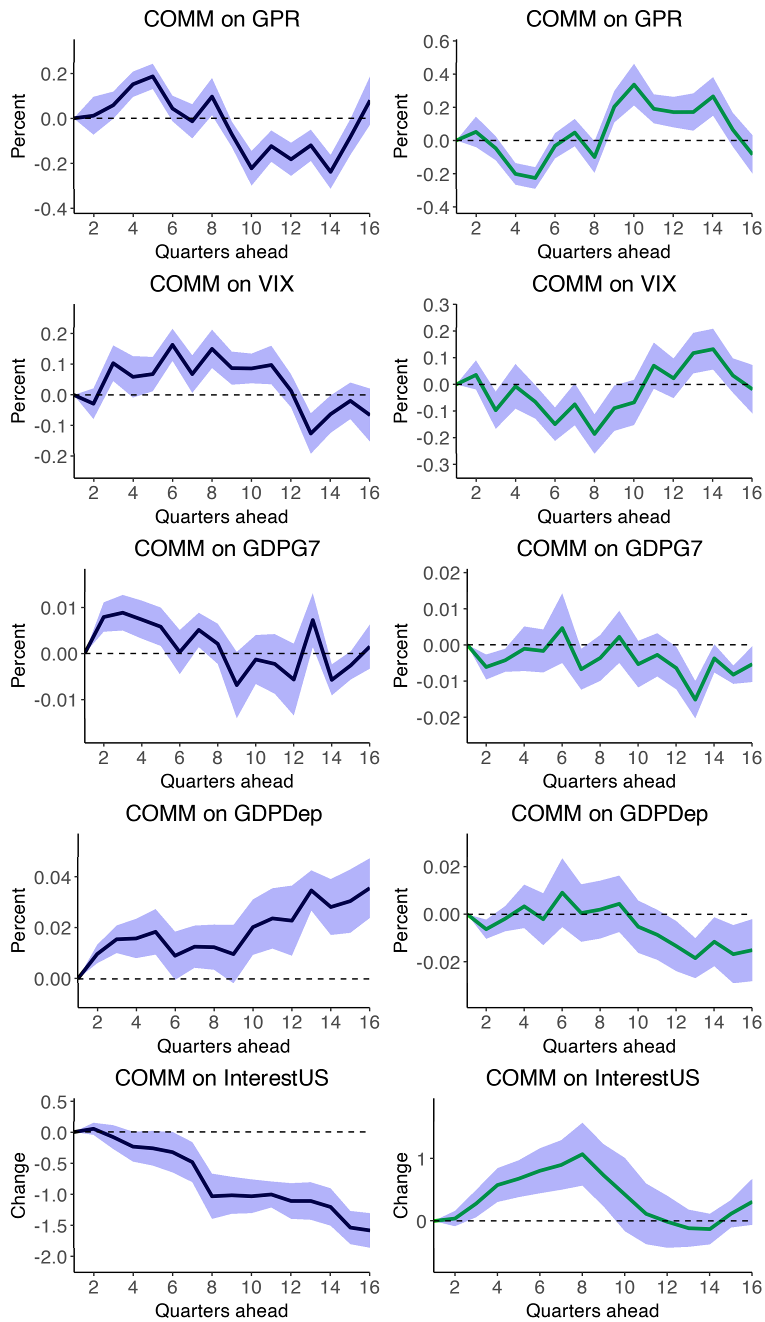

Figure 6: LP-based responses to a one-sd. shock in Real Commodity Prices during high (black line) and low (light brown line) geopolitical risk states. Note: Shaded areas denote 68% error bands.

6 Concluding Remarks

The geopolitical events of recent years have fostered the emergence of a rich research (and policy) agenda at the intersection of geopolitics, commodity markets, and macroeconomic activity. Through a set of methodologies, we aimed at characterizing how this interaction operates at the global (G7 and commodity-dependent economies) and Euro Area level. Our study builds upon various strands of empirical and international macroeconomics, and we contribute to this literature by showing that the impact of these two external shocks is heterogeneous across country types.

First, a recursively-identified SVAR suggested that a geopolitical risk shock produces a decline in economic activity in both G7 and commodity-dependent countries, and in commodity prices as a result of lower economic activity. However, a commodity price shock is largely contractionary for G7 countries and modestly expansionary for commodity-dependent ones. Second, learning from this results, we introduce a set of sign and zero restrictions to identify a SVAR model for the Euro Area (the most open economy among large counterparts) and find that geopolitical risk and commodity price shocks are important up to the extent that the economy cannot be solely stabilized through the use of an interest rate as the single macroeconomic policy tool. These results motivate the inclusion of geopolitical risk and commodity prices in baseline open-economy macroeconomic models. Third, state-dependent local projections indicate that the level of geopolitical risk matters for both the sign and size of the response to a geopolitical risk shock, while the responses more are more erratic in both regimes. More specifically, when geopolitical risk is low, a geopolitical risk shock is contractionary for G7 countries but largely expansionary for commodity-dependent countries as a result of a commodity price increase. Nevertheless, in times of high geopolitical risk, economic activity responds negatively in both country groups following a geopolitical risk shock. Lastly, we provide an additional frequency domain analysis in Appendix B which shows that the interaction between geopolitical risk, commodity prices, and economic activity is not clearly visible through the lens of a frequency domain Granger causality test.

A Sample and Data Sources

The series listed in Section 3 were retrieved from various sources. The geopolitical risk (**GPR**) was sourced from Caldara and Iacoviello (2022), while the commodity price index (**COMM**) is the result of deflating the commodity price index based on 2010 nominal US Dollars, retrieved from the World Bank, with the seasonally adjusted consumer price index for all urban consumers in the US, retrieved the St. Louis Federal Reserve. Both variables were transformed to their natural logarithm.

GDP series for G7 (**GDPG7**) and commodity dependent (**GDPDep**) countries were computed as a GDP-weighted average of seasonally adjusted log real GDP series, originally retrieved from the 2023 vintage of the GVAR Database compiled by Mohaddes and Raissi (2024). The weights for the average were fixed over the whole sample using GDP figures in 2023 (in constant 2015 US Dollars, retrieved from the World Bank). The weights of **GDPG7** are: USA (55%), Japan (11%), Germany (9%), UK (8%), France (7%), Italy (5%), Canada (4%). On the other hand, the weights of **GDPDep** are: Brazil (49%), Saudi Arabia (20%), Argentina (15%), South Africa (9%), Chile (7%). Countries were allocated to the two subsamples based on the definition proposed by the UNCTAD (2023). Additionally, the GDP series for the Euro Area (**GDPEA**) is based on the seasonally adjusted real GDP for the 19 countries, in millions of chained 2010 Euros, and retrieved from the St. Louis Fed. GDPEA was transformed to its natural logarithm, while the resulting GDPG7 and GDPDep series were not.

The interest rate for the US (**InterestUS**), taken here as the global interest rate, was compiled by splicing the effective federal funds rate (retrieved from the St. Louis Federal Reserve) in the periods of 1990 Q1-2008 Q2 and 2022 Q3-2023 Q3, and the Shadow Rate for the US (Wu and Xia, 2016) for the period 2008 Q1-2022 Q2. Likewise, the interest rate for the Euro Area (**InterestEA**) was compiled by splicing the ECB monetary policy rate (retrieved from the Bank of International Settlements) in the periods 1999 Q1-2008 Q2 and 2022 Q3-2023 Q3, and the Shadow Rate for the Euro Area (Wu and Xia, 2016) for the period 2008 Q1-2022 Q2.

The CBOE VIX index (**VIX**) was retrieved from the St. Louis Federal Reserve, and transformed to its natural logarithm. The business (**BusinessEA**) and consumer (**ConfidenceEA**) confidence indices for the Euro Area, amplitude-adjusted, were retrieved from the OECD and transformed to their natural logarithms.

B Frequency-Domain Granger Causality

Breitung and Candelon (2006) proposed a test of Granger-causality[20] in the frequency domain which is based on a set of linear restrictions the parameters of a (possibly cointegrated) VAR model which represent the series well. Following the exposition of Strohsal et al. (2019), consider the concrete case of a two dimensional VAR model of order p with a vector of variables $y_t = (c_t, d_t)'$, resulting in $y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t$. In this case, $A_i, i = 1, 2, ..., p$ are (2×2) coefficient matrices that can be estimated efficiently and consistently by OLS, and $U_t = (u_c, u_d)'$ is a 2D error vector which is a asummed to be white noise with $E(U_t) = 0$ and positive definite (2×2) variance-covariance matrix $E(U_t U_t') = \Sigma_U$.

[20] Granger (1969) formalized the concept of statistical causality in a regression context. In short, a time series c_t is said to Granger-cause another time series d_t, if past values of c_t (i.e., c_{t-1}, c_{t-2}, ...) are helpful in predicting the current value of d_t. Although this concept of causality in the time domain has been around for decades, the development of its frequency domain counterpart is more recent.

Departing from the MA(∞) representation $y_t = (I - A_1 L - ... - A_p L^p)^{-1} U_t$, it is possible to derive the (2×2) spectral matrix:

$$F_y(\lambda) = \left(I - A_1 e^{-i\lambda} - .... - A_p e^{-ip\lambda}\right)^{-1} \frac{\Sigma_u}{2\pi} \left(I - A_1 e^{-i\lambda} - .... - A_p e^{-ip\lambda}\right)^{-1'} \tag{11}$$

with $0 \leq \lambda \leq \pi$ and $\left(I - A_1 e^{-i\lambda} - .... - A_p e^{-ip\lambda}\right)^{-1'}$ denoting the complex conjugate. $F_y(\lambda)$ includes the real value spectra $f_{cc}(\lambda)$ and $f_{dd}(\lambda)$, as well as the complex value cross spectra $f_{cd}(\lambda)$ and $f_{dc}(\lambda) = f_{cd}(\lambda)$:

$$F_y(\lambda) = \begin{pmatrix} f_{cc}(\lambda) & f_{cd}(\lambda) \\ f_{dc}(\lambda) & f_{dd}(\lambda) \end{pmatrix}. \tag{12}$$

The real valued spectra are orthogonal decompositions of the variances of c and d in cyclical components. Thus, the spectral densities contain information about the variance contributions of cycles at different frequencies.

On the other hand, the complex valued cross spectra indicate the strength of the relation between c and d. The square coherency is given by

$$K_{cd}^2(\lambda) = \frac{|f_{cd}(\lambda)|^2}{f_{cc}(\lambda) f_{dd}(\lambda)} = K_{dc}^2(\lambda) \tag{13}$$

with $0 \leq K_{cd}^2(\lambda) \leq 1$. This measure is analogous to the coefficient of determination (R^2) for a linear relation between the cycles of c and d at a given frequency λ. Nonetheless, in contrast to the R^2 of a linear regression, the coherency is in this case invariant to different linear transformation applied to the series under consideration. This has two main implications: first, the coherency does not change when going from the relation in levels to the relation in first differences, and second, it does not change either when regressing c on d or d on c.

Defining the (2×2) matrix $B(L) = (I - A_1 L - ... - A_p L^p)^{-1} P$, with $PP' = \Sigma_U$ and P as lower triangular regular matrix, the individual spectral densities of c and d can be written as:

$$f_{cc}(\lambda) = \frac{1}{2\pi} \left(|B_{cc}\left(e^{-i\lambda}\right)|^2 + |B_{cd}\left(e^{-1\lambda}\right)|^2\right) \tag{14}$$

Based on on the measure of individual spectral densities, Breitung and Candelon (2006) proposed a test for Granger-causality at different frequencies using the statistic:

$$M_{d\to c}(\lambda) = \ln\left(\frac{|B_{cd}\left(e^{-i\lambda}\right)|^2}{|B_{cc}\left(e^{-i\lambda}\right)|^2}\right) \tag{15}$$

When d_t ("cause" variable) does not Granger-cause c_t ("effect" variable) at frequency λ, it holds that $M_{d \to c}(\lambda) = 0$ if $|B_{cd}\left(e^{-i\lambda}\right)|^2 = 0$. The higher the value of the test statistic, the stronger the impact of d on c. We use 4 lags for the test.

This test can be extended to include additional series as conditional variables, or to allow for a more detailed null hypothesis by testing causality and delay within a frequency band (as in Breitung and Schreiber, 2018), but we rely on its bivariate version, as the relationship between the series is explored in a multivariate framework in other sections of the paper.

We show the results of the (non-)causality test proposed by Breitung and Candelon (2006) in Figure 7, which displays the critical value at 5% and the test statistics at frequencies $w \in [0.0, 3.0]$, corresponding to a wavelength of $2\pi/w$ quarters. Thus, lower frequency values indicate a longer wavelength. Our main finding is that the specified null hypothesis of non-causality from a given *cause variable* to a given *effect variable* cannot be rejected in most cases. There are, however, some interesting exceptions. Namely, real commodity prices cause: GDP in commodity-dependent economies at frequencies below 1.0 (6 quarters or more) and above 2.5 (3 quarters of less), and the US monetary policy rate at frequencies below 0.4 (16 quarters or more) and above 2.5 (3 quarters or less). Hence, commodity prices affect economic activity only in commodity-dependent countries in both the short and long run. Conversely, the null hypothesis of non-causality could not be rejected for geopolitical risk (as a cause variable) at any frequency.

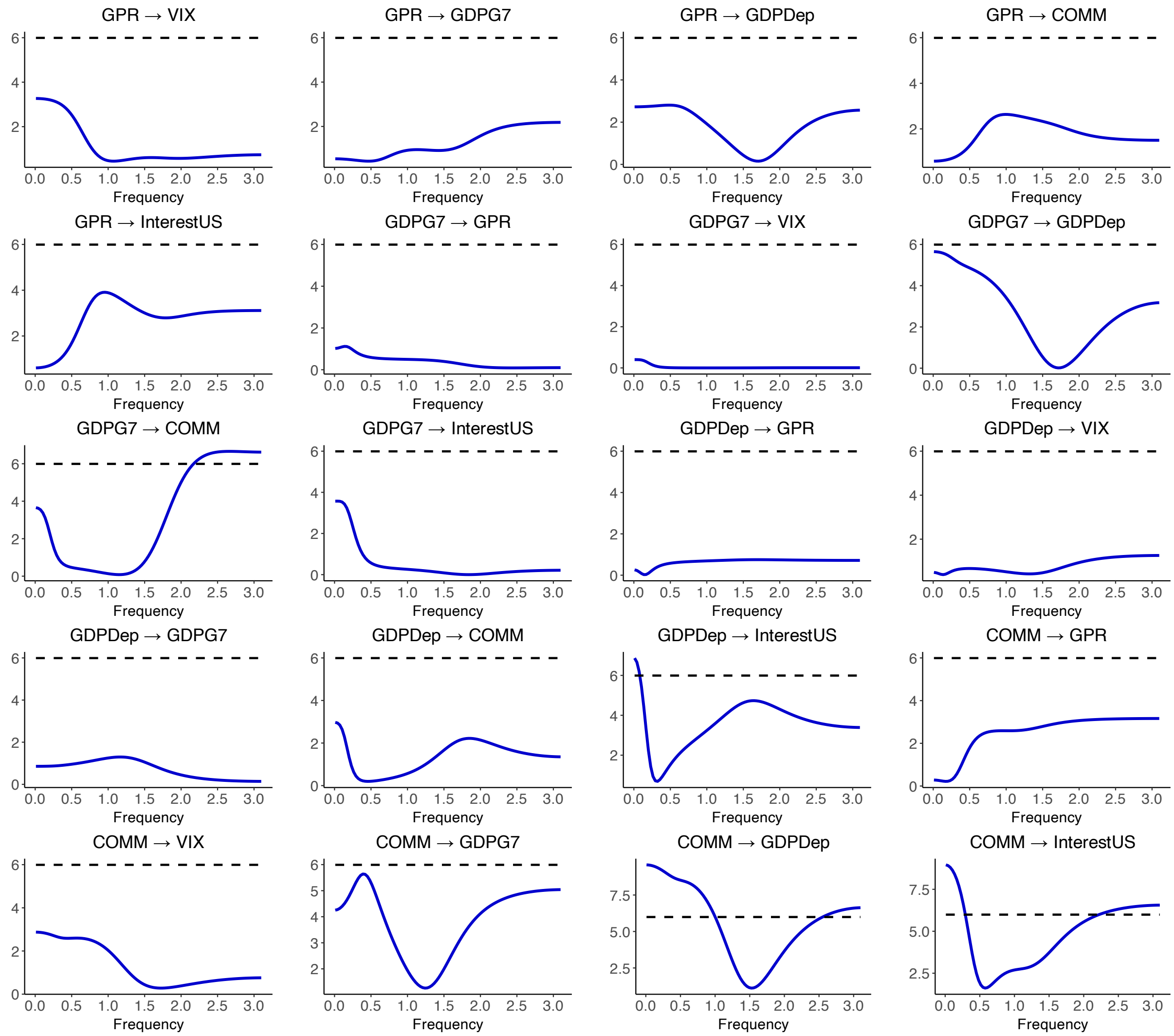

Figure 7: Breitung-Candelon Test of (Non-)Causality in the Frequency Domain. Note: Solid lines are test statistics, dashed lines are critical values.

C Robustness Checks

C.1 SVAR models estimated on a Pre-Covid-19 Sample

With regard to the recursively-identified SVAR model for the global economy, when running the model on a sample ending in 2019 Q4, the responses to a commodity price shock are qualitatively similar in all cases to those presented in subsection 5.1. Nevertheless, the size and duration of the negative responses of economic activity to a geopolitical risk shock, in both country groups, is slightly smaller. In this regard, excluding the period between 2020 Q1 and 2023 Q3 from the sample seems to result in the loss of relevant information regarding geopolitical risk shocks, but does not result in fundamentally different responses.

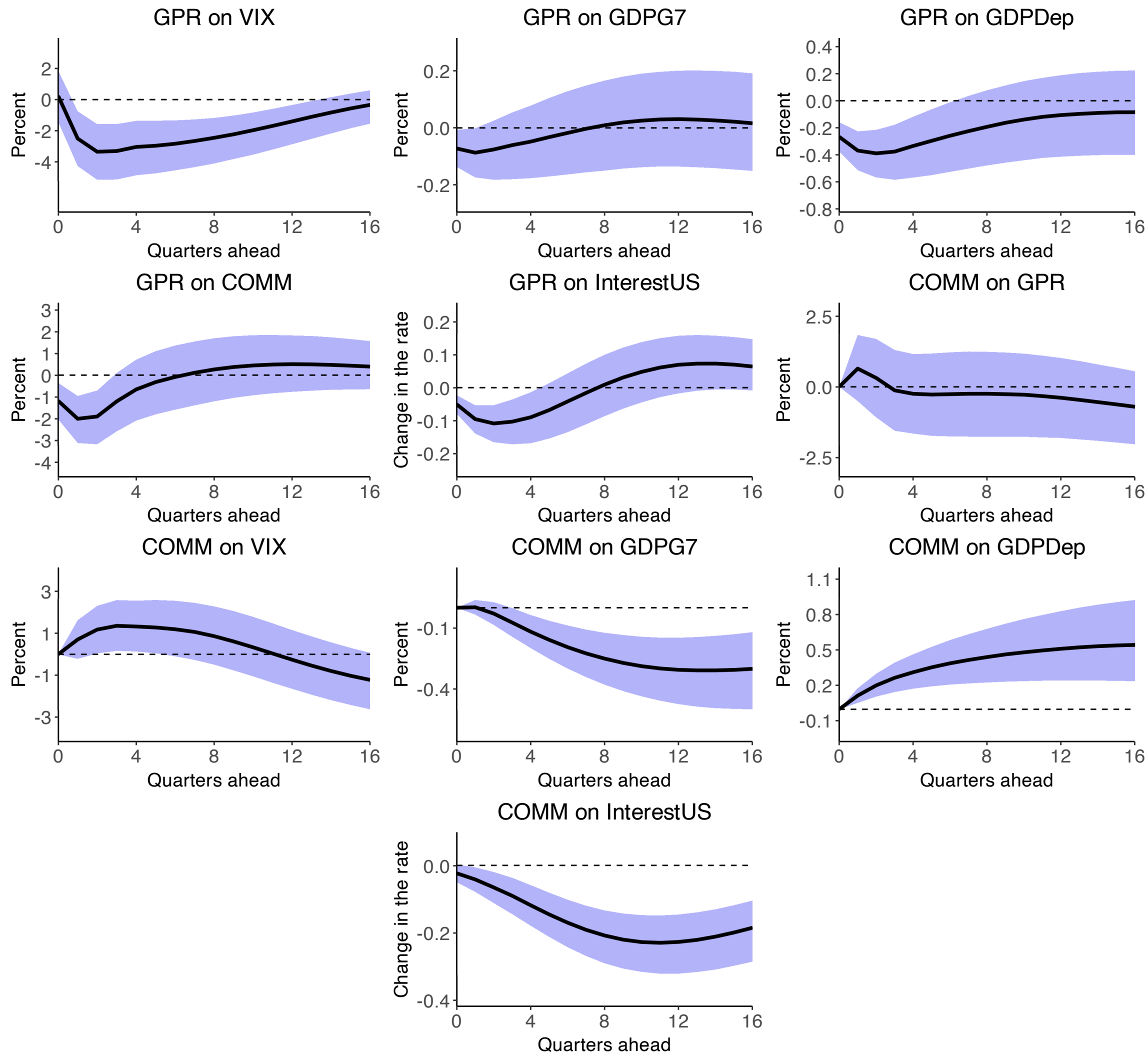

Figure 8: Global Sample Robustness Check. Median impulse responses to a one-sd. shock Geopolitical Risk (first row) and in Real Commodity Prices (second row). Note: Shaded areas denote 68% credible sets.

With respect to the SVAR model with sign and zero restrictions for the Euro Area, using a similar sample ending in 2019 Q4, results in geopolitical risk shocks explaining a similar share of variance of output (20%) and business confidence (15%), but a lower share of the consumer confidence variance (18%), compared to the results in section 5.2. However, these findings are not fundamentally different. Similarly, the share of variance explained explained by commodity price shocks is quite similar to the baseline results too. The results hold even if the period period between 2020 Q1 and 2023 Q3 is excluded.

Table 2: European Sample Robustness Check. Share of variance explained by shocks (mean of posterior draws) after 16 quarters.

Shock	Output	Business Confidence	Consumer Confidence
Geopolitical	0.20	0.15	0.18
Commodity Price	0.18	0.17	0.17
Monetary	0.15	0.17	0.17
Domestic Demand	0.16	0.17	0.16
Business Confidence	0.16	0.18	0.17
Consumer Confidence	0.15	0.15	0.15

C.2 State-Dependent Local Pojections estimated on a Pre-Covid-19 Sample

Concerning the non-linear local projections for the global economy, the results below indicate that, when using a sample that ends in 2019 Q4, the responses of economic activity in G7 and commodity-dependent countries are qualitatively similar to the ones presented in Section 5.3, following both shocks and in both regimes.

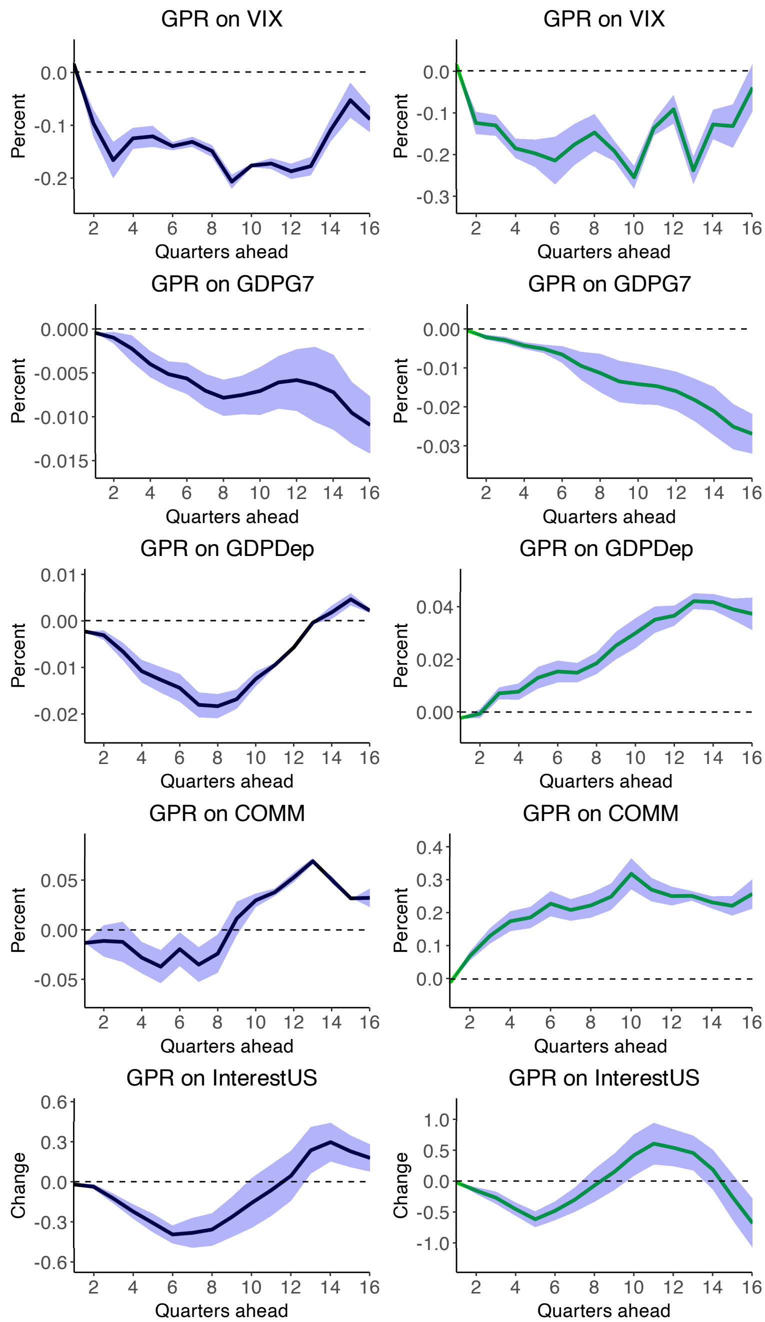

Figure 9: Global Sample Robustness Check. LP-based responses to a one-sd. shock in Geopolitical Risk during high (black line) and low (light brown line) geopolitical risk states. Note: Shaded areas denote 68% error bands.

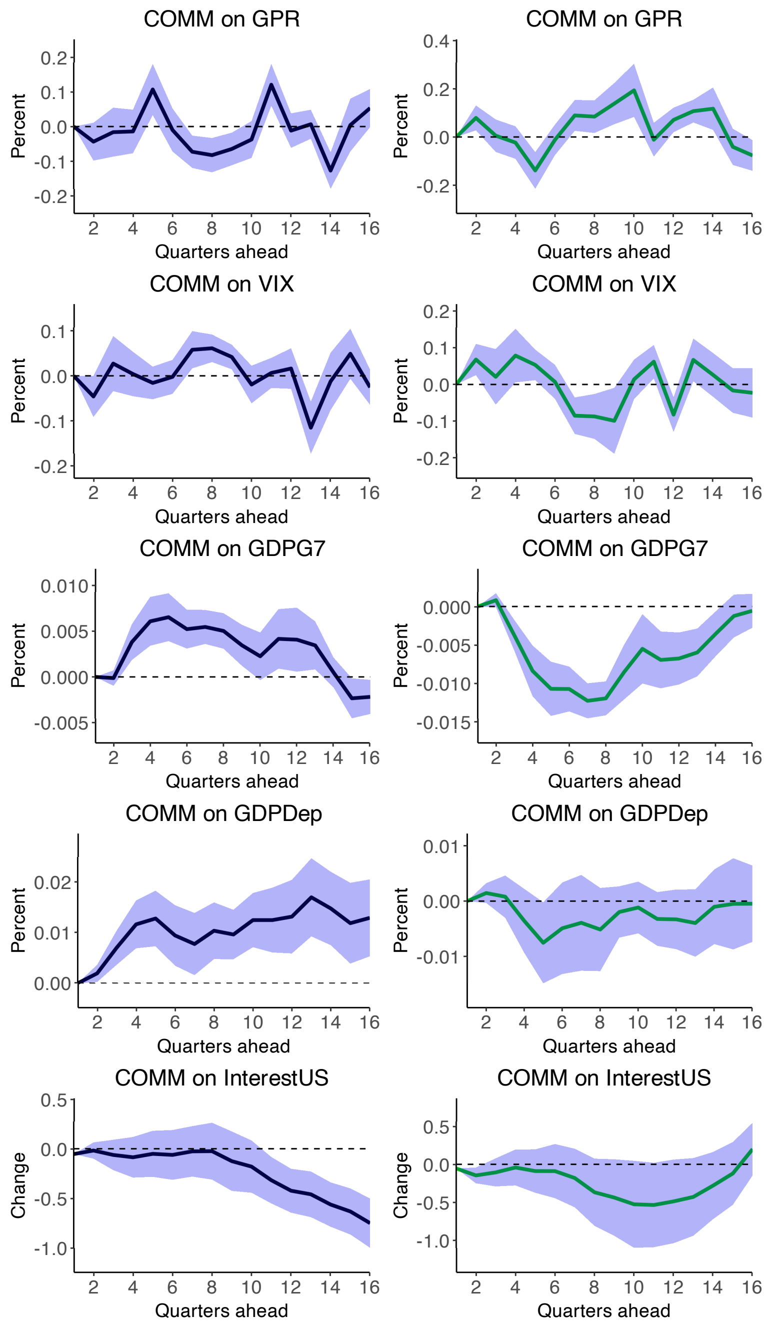

Figure 10: Global Sample Robustness Check. LP-based responses to a one-sd. shock in Real Commodity Prices during high (black line) and low (light brown line) geopolitical risk states. Note: Shaded areas denote 68% error bands.

C.3 State-Dependent Local Projections with a Dummy Transition Variable

As a second robustness check for the non-linear local projections, we use a dummy transition variable is set to be equal to 1 when geopolitical risk (in log scale) is higher or equal than its 75th percentile, and 0 otherwise. This approach does not require the use of the Hodrick-Prescott filter or a logistic function, and is related to the earlier work of Ahmed and Cassou (2016).

Following a geopolitical risk shocks, we obtain different signs for the response of economic activity in commodity-dependent countries in the high geopolitical risk regime, and in general, more puzzling responses in the low geopolitical risk regime. Thus, the results presented in Section 5.3 are sensitive to changes in the way state-variation is introduced. Nevertheless, our baseline approach is aligned with the relevant literature.

Following a commodity price shock, the responses are jagged and equally difficult to interpret as in the baseline specification.

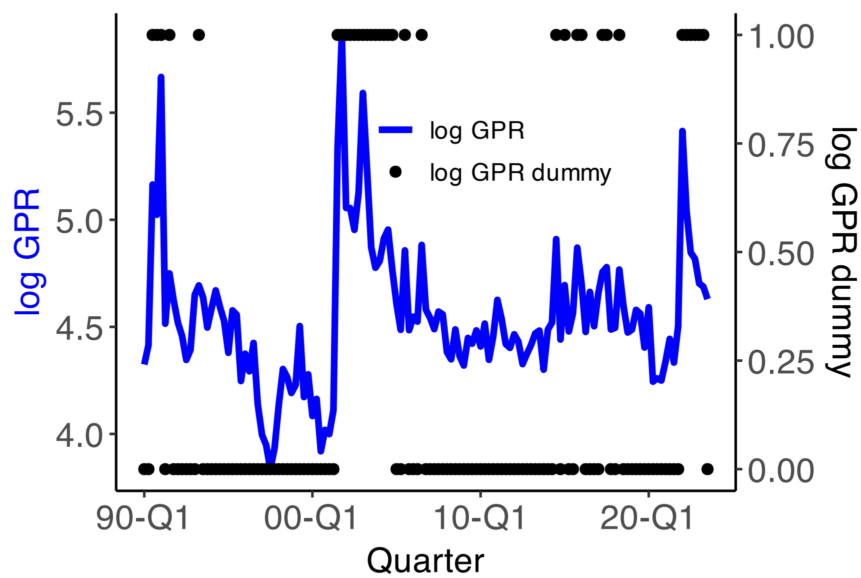

Figure 11: Transition variable over the period of analysis

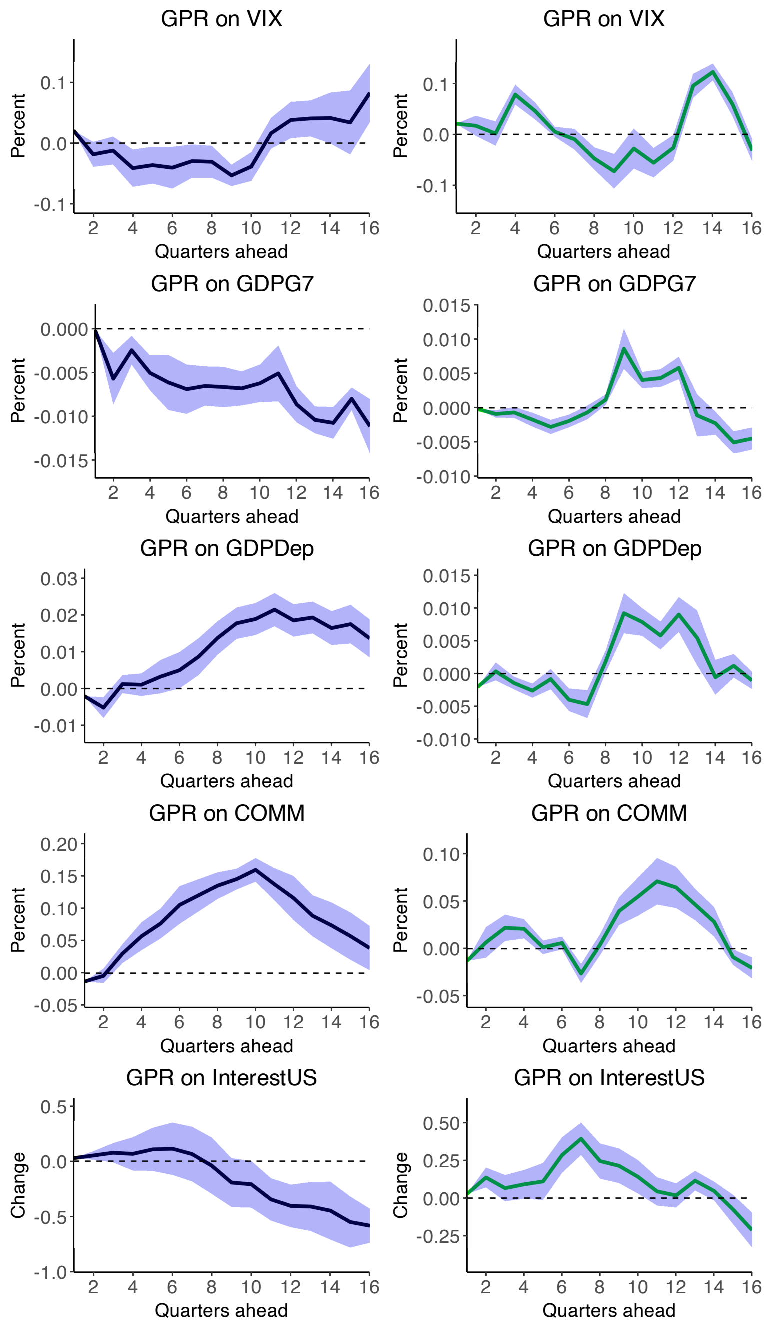

Figure 12: Global Sample Robustness Check. LP-based responses to a one-sd. shock in Geopolitical Risk during high (black line) and low (light brown line) geopolitical risk states. Note: Shaded areas denote 68% error bands.

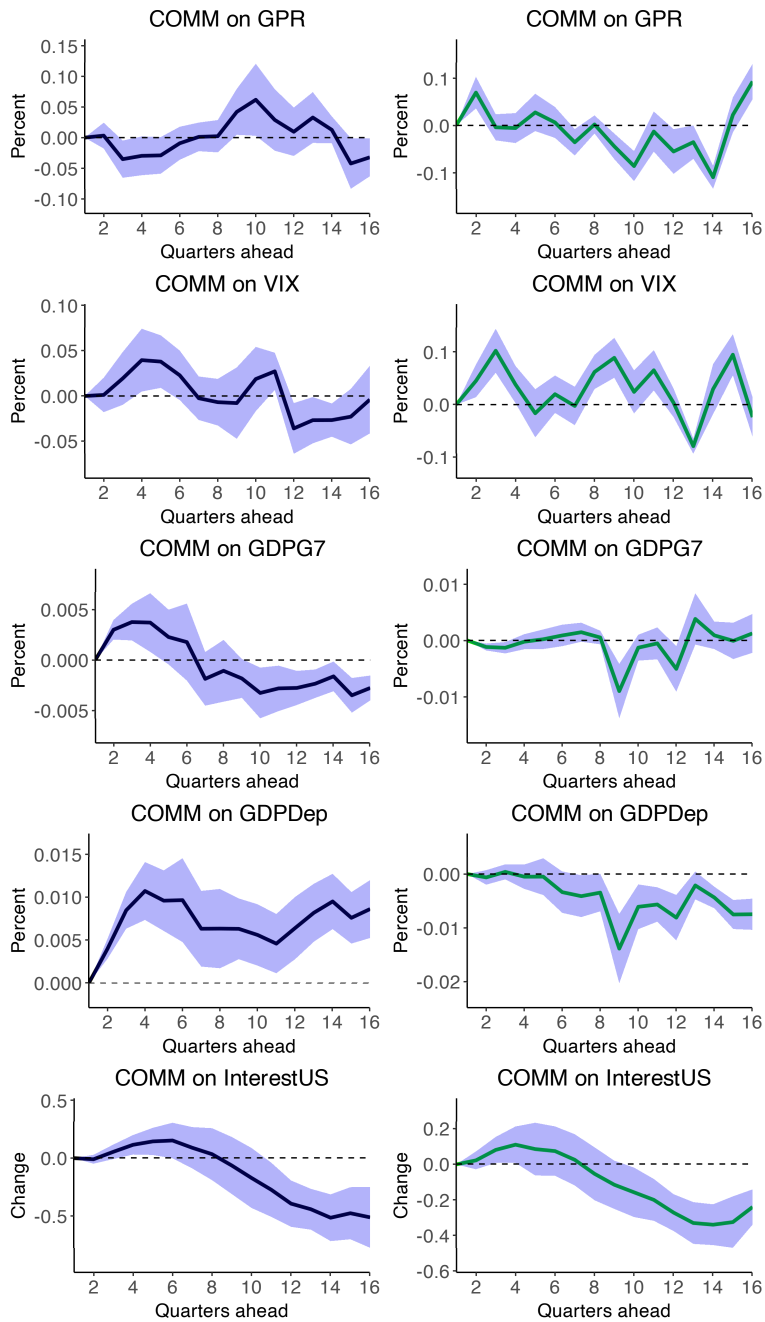

Figure 13: Global Sample Robustness Check. LP-based responses to a one-sd. shock in Real Commodity Prices during high (black line) and low (light brown) geopolitical risk states. Note: Shaded areas denote 68% error bands.

D Historical Commodity Prices

The figure below illustrates that the increase in commodity prices (and energy in particular) in 2022 was rather moderate when compared to similar episodes between 1947 and 2003. The largest increases in commodity prices took place in the 1970s and between the early 2000s and 2014.

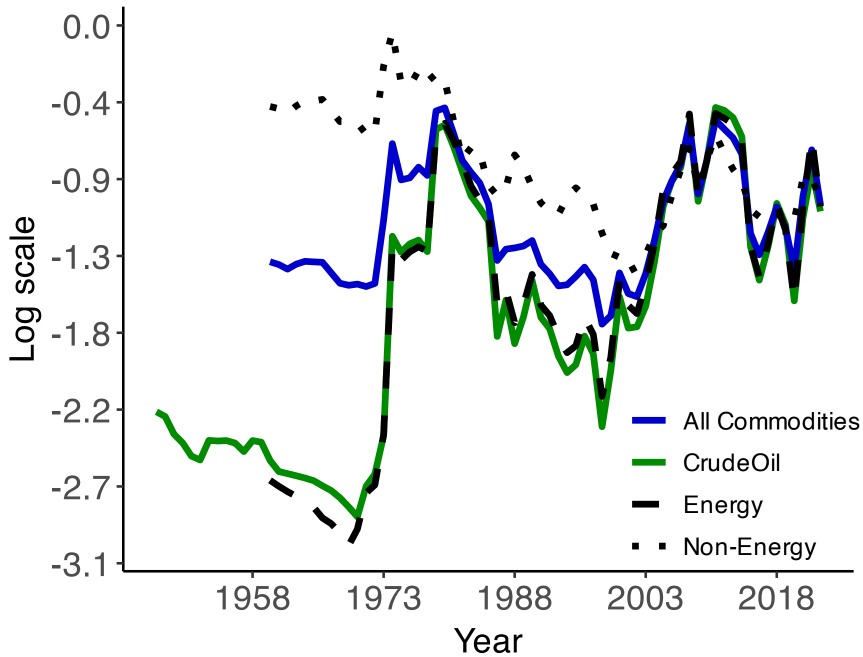

Figure 14: Yearly Average Commodity Prices from 1947 to 2023 (deflated by the US CPI). Note: All commodities, energy and non-energy series were retrieved from the World bank, and the price of crude oil was retrieved from the Statistical Review of Energy, by the Energy Institute.

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