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Geopolitical surprises and macroeconomic shocks: A tale of two events



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Geopolitical Surprises and Macroeconomic Shocks: A Tale of Two Events^{*}

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May 12, 2025

Abstract

We investigate the macroeconomic effects of two recent major geopolitical events on the euro area economy, namely, the outbreak of the Israel-Hamas war and the Russian invasion of Ukraine. To take into account the heterogeneity of geopolitical events, we do not seek to identify a homogeneous geopolitical shock on which to base our causal inference, but construct event-specific combinations of jointly identified macroeconomic shocks instead. To this end, we employ a non-Gaussian structural vector autoregressive model that is statistically identified but also makes use of zero- and sign restrictions and illustrate how different sources of identifying information complement each other. Our results show that adverse geopolitical events may have either inflationary or deflationary effects on indirectly affected economies and that context dependence is required from the monetary authorities when assessing the importance of geopolitical shocks to achieving their price stability objectives.

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1 Introduction

The global geopolitical environment has become increasingly turbulent in recent years. This is especially true for the euro area, which has been particularly affected by the war in Ukraine and is not geographically distant from the Middle Eastern geopolitical tensions either. Geopolitics has also entered the political discourse as a factor with potentially serious consequences for inflation and economic stability. However, geopolitical shocks and their economic consequences on indirectly affected economies are not yet particularly well understood in the economic literature.

This paper seeks to provide empirical evidence and new tools that contribute to a better understanding of such shocks and their economic consequences. In particular, we develop an empirical estimation procedure that takes into account the heterogeneity of geopolitical shocks, and we show that the effects of adverse geopolitical events on indirectly affected economies may be either inflationary or deflationary, depending on the specifics of the event. We also argue that this calls for context dependence from the monetary authorities when assessing the importance of geopolitical shocks to achieving their price stability objectives.

Traditionally, geopolitical shocks have been interpreted as political surprises that serve as catalysts for supply shocks. For instance, a surprising conflict in an oil producing nation puts pressure on the supply of oil, pushes up energy prices, and puts upward pressure on inflation. However, Caldara and Iacoviello (2022), among others, have recently emphasized the importance of also deflationary macroeconomic effects of events that increase geopolitical uncertainty. That is, in transmission of geopolitical shocks to the global economy there seem to be both supply and demand channels at play.

However, homogeneity of geopolitical shocks is not a plausible assumption since the relative importance of different channels varies from one geopolitical surprise to another. In other words, the macroeconomic consequences of any geopolitical event are more or less unique to that particular event. Thus, to properly understand the economic consequences of different geopolitical surprises, *all* the channels through which the transmission happens need to be studied on a case by case basis. This constitutes a crucial starting point for our analysis. To this end, we do not only pursue the identification of a homogeneous geopolitical shock (as in the recent literature; see, e.g., Caldara and Iacoviello 2022; Caldara et al.

2024; Brignone, Gambetti, and Ricci 2024), but map the geopolitical events of interest to different combinations of jointly identified macroeconomic shocks. This effectively allows for the relative magnitudes and even the signs of impulse responses to differ between different geopolitical surprises.

Simultaneous identification of all the relevant macroeconomic shocks without unrealistic identifying assumptions calls for making use of recent advances in the literature on statistically identified structural vector autoregressive (SVAR) models. While non-Gaussianity of the shocks of interest is technically enough for identification of all the shocks (see, e.g., Lanne, Meitz, and Saikkonen 2017), we also make use of some relatively indisputable zeroand sign restrictions. Combining different sources of identifying information not only allows for stronger identification and more precise inference (as the estimates are conditioned on more information), but it also helps in labeling the shocks. With only a handful of zeroand sign restrictions we are able to give interpretation to most of the shocks a priori, which greatly alleviates any challenges related to ex post labeling of the statistically identified shocks. The identification of the shocks is discussed more thoroughly in Section 3, but most importantly, we argue that traditional identifying restrictions (e.g., zero- and sign restrictions) and statistical identification should be viewed as complementary approaches to the identification of macroeconomic shocks with SVAR models, *not* as substitutes.

Our empirical analysis is based on a Bayesian SVAR model with non-Gaussian innovations. The model is of monthly frequency and constitutes of five variables and five shocks. Importantly, to gauge the effects of geopolitical shocks on the euro area economy in full, we include real gross domestic product (GDP) in our model. This obviously poses a methodological challenge, as we want to preserve the monthly specification of our model, but the GDP is observed only at quarterly frequency. In our treatment of mixed frequency variables we follow Anttonen, Jokiluoma, and Luoto (2025) who illustrate how in a Bayesian setting quarterly variables can be included in a monthly model by simply integrating over all the unobserved monthly values conditional on them summing up to the observed quarterly values within each quarter. This is discussed in Section 2.3.

The contribution of our paper is two-fold. First, we show that adverse geopolitical surprises may have either deflationary or inflationary macroeconomic consequences, the direction of the effect on inflation depending on what kind of macroeconomic shocks can be attributed to these events. We specifically focus on two recent geopolitical surprises through the lens of our model and find that the Russian invasion of Ukraine had an inflationary effect on euro area consumer prices, whereas the outbreak of the Israel-Hamas war had the opposite (deflationary) effect. Yet in both of these cases, the effect on euro area GDP was clearly contractionary.

Second, our contribution is of a methodological nature. We show that statistically identified non-Gaussian SVAR models can be easily extended to allow for zero- and sign restrictions on the contemporaneous effects of the shocks and how this alleviates challenges related to ex post labeling of statistically identified shocks *and* strengthens the identification of the shocks. To our knowledge, the previous literature has not considered *complementing* statistical identifying information with zero- and sign restrictions to achieve stronger identification, but has mostly treated statistically identified SVAR models as purely substitutive to more traditional SVAR models.¹ In contrast to the previous literature, we argue that statistical identifying information is best interpreted as complementary to traditional identifying restrictions.

We also illustrate how the interpretation of heterogeneous shocks as combinations of homogeneous shocks goes beyond the topic of geopolitical events and can be applied to, for instance, supply shocks under varying degrees of price elasticity of demand (see Section 4.2).

The rest of the paper is structured as follows. In Section 2 we describe our data and discuss the structure and estimation of our model. In Section 3 we discuss the identification of the shocks and in Section 4 we go through our empirical investigation. Finally, Section 5 concludes.

¹Anttonen, Lanne, and Luoto (2024b) can be considered an exception. In that paper, a sign restriction on a statistically identified impulse response to a monetary policy shock is imposed by discarding posterior draws that do not comply with the restriction. Sign restrictions have also been considered for labeling of statistically identified shocks in the previous literature (see, e.g., Lanne and Luoto 2020).

2 Data and Estimation

In our empirical analysis, we consider a typical *n*-variate structural vector autoregressive (SVAR) model of order p^2 ,

$$y_t = a + A_1 y_{t-1} + \dots + A_p y_{t-p} + B\varepsilon_t,$$
(1)

where y_t is a vector of time series of interest, a is an intercept term, $A_1, ..., A_p$ are $n \times n$ coefficient matrices, and the $n \times n$ nonsingular matrix B summarizes the contemporaneous structural relations between the variables and the vector of shocks $\varepsilon_t = (\varepsilon_{1t}, ..., \varepsilon_{nt})'$ consisting of independent non-Gaussian components.³

2.1 Data

As the number of shocks equals the number of variables in our model (n), the number of time series included in the model also determines the number of shocks we can, or in our case *need* to, identify. We want to include enough time series, and hence information, in our model to identify all the relevant channels through which geopolitical surprises transmit to the euro area economy, but on the other hand, we want to keep the dimension of the model relatively low to preserve the interpretability of our model and to be able to give an economic interpretation to all the shocks in our model.

Table 1 summarizes the time series we include in our model. Since we are primarily interested in the effects of geopolitical surprises on euro area prices and production, we include the euro area harmonized index of consumer prices (HICP) and gross domestic product (GDP) in our model. We also include the euro area industrial production index (IP) for two reasons. First, its inclusion may improve our understanding of the consequences of geopolitical events, as the responses to geopolitical surprises might be (and are, as we shall see) quite different between IP and GDP. Second, the inclusion of IP is more or less necessary

²We set p = 6.

³The independence assumption can be relaxed to allow for common stochastic volatility and dependent volatility processes in general. This is because statistical identification of non-Gaussian SVARs can also be established under mean independence (see, e.g., Keweloh 2023). However, to keep things simple, we assume the shocks independent in our analysis for now.

Name	Description	Freq.	Log.	SA
HICP	Euro Area, HICP, All-Items, Index	М	х	х
IP	Euro Area Industrial Production Index, ECB	М	Х	х
GDP	Euro Area Total GDP, Chain-Linked Volumes	Q	Х	х
GPR	Global Geopolitical Risk Index of Caldara and	М		
	Iacoviello (2022)			
Oil	ICE Brent Crude, 3rd Position, Close, USD,	М		
	Monthly Average			

Table 1: Summary of the time series included in our model. Last three columns report whether the series are monthly or quarterly frequency (Freq.), whether they are defined in levels or in log-levels (Log.) and if they are seasonally adjusted (SA).

because it strongly correlates with GDP and therefore makes our estimates of monthly GDP figures much more precise (recall that GDP is only quarterly observed). The way in which we incorporate mixed frequency data in our model is discussed in Section 2.3 below.

We also include two global variables that are relevant to the topic of geopolitics. First, we include the global geopolitical risk index (GPR) of Caldara and Iacoviello (2022). GPR index has recently been used in numerous studies on the macroeconomic effects of geopolitical shocks (see, e.g., Caldara and Iacoviello 2022; Caldara et al. 2024; Brignone, Gambetti, and Ricci 2024; Pinchetti 2024) and has sparked a surge in quantitative studies on the effects of geopolitical shocks and geopolitical uncertainty in general.

However, quantitative studies using the index of Caldara and Iacoviello (2022) have almost exclusively ignored the heterogeneity of geopolitical events and focused only on the supposedly homogeneous effects of geopolitical shocks.⁴ In our analysis, we leverage the index of Caldara and Iacoviello (2022) to identify a homogeneous geopolitical shock similar to the previous literature, but we do not assume this to be the only (or even primary) channel through which adverse geopolitical surprises transmit to the euro area economy. We continue the discussion on the identification of the shocks in Section 3.

Finally, as comovements in oil prices and geopolitical risk are certainly possible, we include oil prices to disentangle the effects of exogenous changes in the price of oil from those associated with geopolitical surprises. All time series span from January 1995 to

 $^{^{4}}$ One of the few exceptions is Pinchetti (2024). In that paper, the consequences of different classes of geopolitical risk shocks for inflation and economic activity are investigated with the focus on the role of energy markets.

March 2024 and the number of monthly observations per series is 351.

2.2 Estimation

We estimate our model by sampling from the posterior distribution of parameters in θ . Following Anttonen, Lanne, and Luoto (2024a; 2024b), an expression proportional to the posterior distribution of parameters is easily obtained by multiplying the likelihood function by the prior density $p(\theta)$, and is given by

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)} \propto p(\theta) \underbrace{|\det(B)|^{-T} \prod_{i=1}^{n} \prod_{t=1}^{T} f_i(\varepsilon_{it}(\theta|y);\gamma)}_{likelihood}},$$
(2)

where $f_i(.)$ is the point density function of the *i*th shock, of which shape depends on parameters in γ . We follow Anttonen, Lanne, and Luoto (2024a) and assume the mutually independent shocks to each follow a skewed *t*-distribution. This nests the typically assumed normal distribution as its special case and is therefore a generalization of the more restrictive Gaussian model. The parameter vector γ is of dimension 2n (one skewness and one degree-of-freedom parameter per shock) and the vector of all parameters reads as $\theta = (vec(A_1)', ..., vec(A_p)', vec(B)', \gamma', ...)'.$

Zero restrictions on the contemporaneous effects of the shocks (to be discussed in Section 3) can be easily imposed by defining the *vec* operator above so that only the non-restricted components of B are included in θ and the restricted components are simply set to zero in B for each evaluation of (2). Sign restrictions are just as easy to implement and can be imposed simply by setting priors with limited support on some of the parameters of $p(\theta)$.

We do not impose any other priors on B and we use a standard Minnesota prior on the autoregressive parameters, $A_1, ..., A_p$. The strength of the prior is estimated hierarchically as in Anttonen, Lanne, and Luoto (2024a) and akin to the approach of Giannone, Lenza, and Primiceri (2015). We follow Anttonen, Lanne, and Luoto (2024a) also in how we set our relatively non-informative priors on γ (see Figure 1). For posterior sampling, we use the No-U-Turn Sampler (NUTS) of Gelman and Hoffman (2014) (as implemented in Carpenter et al. 2017), again, following Anttonen, Lanne, and Luoto (2024a).⁵

⁵Estimation, i.e. sampling four MCMC chains of sufficient length in parallel, took around 20 minutes on

2.3 Mixed Frequency Data

We can easily make use of the quarterly GDP series in our monthly model by treating the unobserved monthly values similarly to any other random variable or parameters in the model. To this end, we follow Anttonen, Jokiluoma, and Luoto (2025) and append the unobserved monthly values to the parameter vector θ . The distribution of the unobserved values is then sampled jointly with the posterior distribution of all the model parameters. This amounts to integrating over all the uncertainty concerning the monthly values and makes use of all the information in the structure of the model and in dependencies between the model variables and the unobserved monthly values of GDP.

The key to the approach of Anttonen, Jokiluoma, and Luoto (2025) lies in how the unobserved monthly values are made consistent with the observed quarterly values, because this allows the information in the observed values to be used efficiently. This happens by restricting the unobserved monthly values of GDP to sum up to the observed quarterly values within each quarter. In practice, this happens by sampling from the posterior distribution in terms of $a_1^q, a_2^q \in (0, 1)$, for each quarter q, instead of using the unobserved monthly values directly and by making use of the so-called stick breaking algorithm (see, e.g., Carpenter et al., 2017).⁶ For a more thorough discussion of the approach, we refer the interested reader to Anttonen, Jokiluoma, and Luoto (2025).

This way of incorporating mixed frequency data into our model allows us to study the effects of geopolitical surprises on the quarterly observed GDP in the context of our monthly model without any compromises. No additional assumptions are required for the identification and estimation of the model, all the information in the monthly observed variables can be efficiently made use of (as opposed to a model with quarterly aggregation of all the variables), and the analysis need not be limited to monthly indicators of production (e.g., industrial production index) instead of GDP.

a laptop with Apple M3 Pro chip (including warm-up) and the maximum \hat{R} convergence diagnostic value (see, e.g., Gelman et al., 2013) with respect to any parameter was 1.02.

⁶Let us denote the observed quarterly value for quarter q by y_q and the unobserved monthly values within that quarter by y_1^q, y_2^q, y_3^q . Then, using the stick breaking algorithm, the observed quarterly value y_q and the sampled parameters $a_1^q, a_2^q \in (0, 1)$ map to the unobserved monthly values as $y_1^q = a_1^q y_q, y_2^q = a_2^q (y_q - y_1^q)$ and $y_3^q = y_q - y_1^q - y_2^q$, which implies $y_q = y_1^q + y_2^q + y_3^q$.

3 Identification of Structural Shocks

The identification of shocks in an SVAR model can be equivalently expressed as the identification of the parameter matrix of contemporaneous effects (see B in Equation 1). In the so-called traditional SVAR literature, from Sims (1980) to this day, only information up to second moments of the data (i.e., up to variance and covariance structures) is made use of, which does not allow for identification of B without numerous a priori identifying restrictions. Statistical identification, however, refers to the utilization of information in the data beyond the first and second moments and consequently allows for identification of structural shocks without a priori identifying restrictions. However, such information is only available if the shocks feature non-Gaussian characteristics (i.e., if they do not follow a normal distribution), to which end specifically non-Gaussian SVAR models are considered statistically identified.

Figure 1 draws the marginal posterior intervals for the parameters that control the distribution of the shocks in our model. A normally distributed shock would feature zero skewness and a high value of the degree-of-freedom parameter.⁷ This is clearly not the case for any of the shocks in our model, which all feature significant excess kurtosis and some of which are considerably skewed as well.⁸ Hence, all the shocks in our model are clearly non-Gaussian.

The identification of non-Gaussian shocks in an SVAR model is easily established if the shocks are assumed to be independent (see, e.g., Lanne, Meitz, and Saikkonen 2017). In the context of likelihood-based inference, the assumption of shock independence is typically required for the construction of the likelihood function in any case, which means that for statistical identification of structural shocks, no more assumptions are required than for traditional SVAR models.⁹

The non-Gaussianity of the structural shocks in our model (see Figure 1) is therefore enough to establish the joint identification of all the shocks, regardless of any additional a

⁷To be exact, for a normally distributed shock the degree-of-freedom parameter would approach infinity. However, for practical purposes, a *t*-distribution with a degree-of-freedom parameter close to 30 can already be considered normal enough for there to be no identifying information in the data.

⁸The skewness parameter in Figure 1 has a support from -1 to 1 and corresponds to the parameter λ in Theodossiou (1998, 2018).

⁹Statistical identification of structural shocks can be established even if the independence assumption is relaxed to allow for, say, dependent shock volatility processes. For an identification result under mean independence, see, e.g., Keweloh (2023).



Figure 1: 68% and 90% posterior and prior intervals for the parameters controlling the skewness (left) and kurtosis (right; degree-of-freedom parameter) of the shocks following skewed *t*distributions.

priori restrictions to the model. The joint identification of all the shocks, without implausible identifying restrictions, is essential for us to be able to study all the channels through which the transmission of geopolitical surprises to the euro area economy happens. However, structural interpretation (i.e., labeling) of the statistically identified shocks is still required for our analysis.

3.1 Shock Labeling

Statistically identified shocks represent the most probable sources of exogenous variation in the data given the model assumptions. Moreover, in the context of Bayesian inference, a sample of sufficient size from the posterior distribution of model parameters not only represents the most probable values, but covers *all* the plausible values for the shocks and their effects on model variables, conditional on the assumptions, of course. However, as such they are merely statistical signals without any structural (or economic) interpretation.

To attain structural interpretation of the shocks, we need to associate each source of exogenous variation (i.e., identified shock) with a structural concept. The most obvious examples of such concepts are supply and demand shocks, which unarguably have certain effects on prices and production. Traditionally (i.e., in the case of no statistical identification) the same restrictions (e.g., zero- and sign restrictions) are imposed to give shocks their structural interpretation *and* to extract the sources of exogenous variation from the data. However, problematically, the number of restrictions required for the identification of Gaussian (i.e., not statistically identified) shocks often far exceeds the number of indisputable (or even plausible) restrictions implied by the structural concepts of interest. The overimposition of identifying restrictions obviously makes the labeling of the shocks a non-issue, but puts any results obtained under suspicion as well.

The literature on statistically identified SVAR models tends to take the opposite approach and seeks to identify shocks in the absence of any a priori restrictions or information beyond the data (see, e.g., Lanne, Meitz, and Saikkonen 2017; Gouriéroux, Monfort, and Renne 2017; Lanne and Luoto 2021; Keweloh 2021; Lewis 2021; Brunnermeier et al. 2021). This leads to the need for ex post labeling of all the shocks by means of inspecting the resulting impulse response functions, for example. However, this extreme might not be ideal either since if we have (even relatively) indisputable information available for labeling purposes, we might as well use it for more precise inference and potentially avoid the issue of ex post labeling altogether. To quote Uhlig (2017): "If you know it, impose it! If you do not know it, do not impose it!".

To this end, we impose zero- and sign restrictions on the contemporaneous effects of the shocks (see Table 2). Importantly, due to statistical identification, none of these restrictions is necessary for the shocks to be identified. Hence, we are free to impose only what we "know". On the other hand, the restrictions fix the ordering of the shocks with respect to the restrictions given. Hence, we can give a priori labels for most of the shocks in our model, although the labels need to be confirmed ex post.

First, to identify aggregate supply and demand shocks that drive much of the changes in consumer prices (HICP) and production (IP, GDP), we impose very standard sign restrictions on the first and second shocks. We assume the first to be a supply shock that has an effect of an opposite sign on prices and production, whereas the second shock is assumed to be a demand shock with an effect of the same sign on prices and production. Since we have two variables related to production (IP, GDP), we are also left with a third shock to label. This is presumably a shock that explains the unexpected changes in the more volatile IP

	Shocks					
Variables	Supply	Demand	IP Demand	Geopol.	Oil	
HICP	+	+				
IP	-	+				
GDP	-	+				
GPR	0	0	0	+	0	
Oil					+	

Table 2: Restrictions on the contemporaneous effects of the shocks used for identification and labeling, i.e. sign- and zero restrictions on the components of the parameter matrix B.

not reflected in GDP. However, we have no structural concept to associate this shock with a priori, so we leave it unrestricted (expect for the lone zero restriction to be shortly discussed) and label it only ex post. We discuss the ex post labeling of this shock in the next subsection (3.2 IP Demand Shock).

Second, we assume the unexpected changes in geopolitical risk index (GPR) to be exogenous to all the other variation in our model. In other words, we assume the fourth shock in our model to be the only shock with nonzero effect on GPR. We impose this by using zero restrictions. Caldara and Iacoviello (2022) too discuss the exogeneity of the GPR in a similar context, the rationale being that the measure of geopolitical risk should not be driven by macroeconomic shocks, but by exogenous geopolitical surprises.¹⁰ For now, we label the fourth shock simply as a GPR shock. The discussion on the exact interpretation of this shock is adjourned to Section 3.3.

Finally, the last shock needs to account for all the exogenous changes in the price of oil. These include factors relating to the supply of oil, but also to demand to the extent that these are not correlated with the euro area macroeconomic developments. The zero restriction on its impact on the GPR is important, since adverse geopolitical events are sometimes associated with oil supply disruptions, and the restriction helps us to better disentangle the effects arising from geopolitical surprises from those caused by other factors affecting the price of oil.

Figure 2 shows the estimated impulse responses of all the variables to all the shocks in the model over 36 months following the initial shock. It is easy to confirm that the responses

 $^{^{10}}$ We tested the exogeneity assumption by re-estimating our model without the zero restrictions and the results supported the assumption.



Figure 2: 68% and 90% point-wise posterior intervals for the impulse responses of all the variables (rows) to all the shocks (columns/colors) for horizons up to 36 months. The magnitude of each shock is one standard deviation.

to the first two shocks match our a priori labels (supply shock and demand shock) very well. The responses to the exogenous oil price shock are also mostly characteristic of a contractionary oil supply shock, as expected. In the following two subsections, we discuss the labeling and interpretation of the remaining two shocks, as well as the impulse responses to those shocks in detail.

3.2 IP Demand Shock

The third column of Figure 2 shows the estimated impulse response functions of the third shock in our model. The shock seems to have a clear positive effect on HICP and IP, while



Figure 3: Posterior mean of the historical decomposition of euro area inflation into shocks in our model from 2007 to the beginning of 2024. The trend includes the effect of initial conditions and a small approximation error that arises from the use of logarithmic differences instead of percentage changes in the computation of the decomposition.

the effects on any other variables are close to zero and/or inconclusive. As the shock induces a simultaneous increase (or decrease) in prices and production, it has most likely something to do with demand. Moreover, the shock appears to have a significant short-term effect specifically on industrial production, while the effect on GDP remains small. To this end, we label the shock as an "industrial production specific demand shock" or in short, an "IP demand shock".

What is interesting about this shock is that, based on standardized impulse responses in Figure 2, it appears to be the most important driver of unexpected changes in inflation in the short term (or at least as important as the supply shock). Figure 3 shows the historical decomposition of inflation into shocks in our model, which gives a better idea of the relative importance of the IP demand shock in explaining different inflation episodes.

Forecast error variance decompositions (FEVD) are another common way to assess the relative importance of shocks in the context of SVAR models. However, variance decompositions can be misleading if the tails of the shock distributions are significantly thicker than those of a Gaussian and especially if the thickness of the tails differs between the distributions of the shocks and/or variables in the model. For instance, the FEVD in Figure 4 exaggerates the importance of the IP demand shock in explaining the unexpected changes in

HICP due to the very low estimate for the degree-of-freedom parameter of this shock (i.e., thick tails; see Figure 1). This is an issue that, to our knowledge, has not been acknowledged in the earlier literature.¹¹

The importance of the IP demand shock can be motivated by the fact that it represents a *sectoral element* in our model, which is in line with the common narrative of the recent post-pandemic inflation bout. According to the narrative, inflation began to accelerate when pandemic-related reallocation shocks were followed by supply chain bottlenecks and the eventual energy crisis in Europe, which was further inflated by the Russian invasion of Ukraine. Ferrante, Graves, and Iacoviello (2023), among others, show how the pandemic led to an unprecedented, albeit temporary, shift from consumption of services to consumption of goods, but that the supply of goods was constrained by the reallocation costs, which consequently added up to inflationary pressures. In addition, inflation was amplified by the relatively flexible pricing of goods relative to services. All this implies that a demand reallocation shock, potentially captured by the IP demand shock in our model, might explain a large part of the accelerated inflation in the aftermath of the pandemic.

There are several other studies as well that stress the importance of sectoral shocks for inflation and business cycle dynamics. For instance, Atalay (2017) suggests that industryspecific shocks are more important than previously thought and even concludes that sectoral shocks are the main drivers behind GDP fluctuations. This view is also supported by De Graeve and Schneider (2023) who argue that sectoral shocks are distinct from aggregate shocks, but better capture business cycle fluctuations. There is also some evidence that sectoral model characteristics may enhance the identification of aggregate shocks, as shown by Amir-Ahmadi and Drautzburg (2021) and Matthes and Schwartzman (2025), who apply heterogeneity restrictions to this effect.

Overall, what we have labeled as the "IP demand shock" in our model and the fact that we have two distinct demand shocks operating in different frequency domains seem important features of the model in order to capture all the relevant aspects of the euro area inflation dynamics. Most importantly, the identification of the IP demand shock in our model is

¹¹To elaborate, forecast error variance decompositions are by no means incorrect under any form of non-Gaussianity under the assumption of finite variance of the shocks. They can, however, be misleading and may not be representative of anything of use or interest. Our suggestion is to stick with the historical shock decompositions instead.



Figure 4: Posterior means for the forecast error variance decompositions (FEVD) of HICP and IP. The colored area is proportional to the share of squared unexpected movements on average in a given variable explained by the shock (color). Note that as variance decompositions are essentially measures of *squared* contributions, they understate the importance of the shocks of which contribution is relatively small and on the other hand exaggerate the importance of the shocks with the most excess kurtosis.

purely data driven, and its analysis offers interesting insights into the euro area inflation dynamics, as we shall see in Section 4.2.

3.3 GPR Shock

The fourth shock in our model by definition accounts for all the unexpected changes in the GPR index (see Subsection 3.1 above), those changes reflecting geopolitical surprises. However, none of the geopolitical surprises is quite like the other, so the GPR shock can only capture the average effect of those surprises. In other words, geopolitical events and their macroeconomic consequences are highly heterogeneous, and the identification of a *homogeneous* GPR shock necessarily falls short in the causal analysis of *heterogeneous* geopolitical surprises. This, we argue, is a major shortcoming in much of the recent literature that builds on the GPR index of Caldara and Iacoviello (2022) (e.g., Caldara et al. 2024 and Brignone, Gambetti, and Ricci 2024).

The impulse responses to homogeneous GPR shocks are obviously not without their



Figure 5: Global Geopolitical Risk (GPR) Index of Caldara and Iacoviello (2022) and exogenous shocks to the index according to our model (posterior mean). The shocks have been scaled for illustrative purposes.

interpretation, but we need to be explicit about that interpretation: they correspond to *average effects* of geopolitical events of certain magnitude (as measured by the GPR index) on the model variables. The average effects can obviously be of interest, but given the highly heterogeneous nature of geopolitical surprises, they are of no use in trying to assess the causal effect of any particular event. For example, according to the fourth column in Figure 2, an adverse geopolitical surprise that induces an increase of around 25 index points in GPR pushes euro area real GDP down by around 0.05% in the short term. Although interesting in itself, this is, however, not necessarily a very good estimate of the effect of any particular event on GDP, as we shall see in Section 4.

Figure 5 shows the GPR index of Caldara and Iacoviello (2022) from 1995 to the beginning of 2024. The spikes in the index correspond to major geopolitical surprises.¹² To serve as an example of heterogeneity of geopolitical events, the invasion of Iraq in 2003 and the invasion of Ukraine in 2022 induced spikes of a very similar magnitude in the GPR, but unarguably had very different kinds of macroeconomic consequences. Such heterogeneity needs to be taken into account if we are to make estimates of the economic consequences of

¹²Note that as there are only positive spikes in the index, the positive skewness of the shock that drives the unexpected changes in the index must itself be high (see Figure 1), which if made use of should allow for very strong statistical identification and precise estimation of the effects of the shock (see, e.g., Anttonen, Lanne, and Luoto 2024a, 2024b). It is not clear whether assuming a highly skewed shock symmetric, as in much of the literature that assumes Gaussian shocks, induces a significant bias in the estimates, but it certainly leaves valuable identifying information unexploited.

any particular geopolitical surprise.

As we illustrate in the next section, the same argument applies when we compare the Russian invasion with the latter outbreak of the Israel-Hamas war. Some geopolitical surprises transmit to the euro area economy (or to other economies) mainly through demand-related channels (most importantly through the uncertainty channel), whereas other geopolitical surprises have strong supply side effects.

The interpretation of the fourth shock in our model as the average effect of geopolitical surprises is essential for our analysis. It means that, in the context of our model, the causal effect not explained by the average response (i.e., not explained by the response to the fourth shock) must be transmitted to the euro area economy through other macroeconomic shocks. For instance, if a particular adverse geopolitical surprise has a greater effect on euro area economic uncertainty than events of that magnitude (as measured by the GPR index) do on average, this uncertainty must, according to our interpretation, manifest itself as a negative demand shock.¹³ Similar reasoning obviously applies to supply side effects as well.

As mentioned, on average, adverse geopolitical surprises seem to push down euro area production (see the fourth column in Figure 2). However, the average inflation response (HICP) seems small and is close to zero. This should *not* be interpreted as geopolitical surprises being inconsequential for euro area inflation, but as supply- and demand-related transmission channels balancing each other out *on average*. The net effect of any particular event on inflation depends on the relative strengths of the opposing forces on inflation, which themselves depend on the specifics of the event of interest. This explains how inflation can react very differently to different geopolitical surprises and why an increase in the GPR index itself cannot be associated with either a clear positive or negative response in euro area inflation.

In the next section, we illustrate how our model allows us to retrospectively assess the importance of different transmission channels through which adverse geopolitical surprises have affected the euro area economy. This subsequently allows us to produce plausible counterfactuals to estimate the causal effects of any particular geopolitical surprise on euro

¹³Note that this does not violate the assumed (mean) independence of the shocks (required for identification), since the effect on economic uncertainty can also be weaker than on average, which would manifest itself as a positive demand shock, and the expectation for the demand shock conditional on the homogeneous GPR shock remains zero.

area inflation and real GDP.

4 Macroeconomic Effects of Geopolitical Surprises

In this section, we assess the consequences of geopolitical surprises on euro area inflation and real GDP by focusing specifically on the recent outbreak of the Israel-Hamas war in October 2023 and the Russian invasion of Ukraine in February-March 2022. We make use of our model laid out in the previous sections by mapping the structurally identified shocks to the events of interest, which allows for the construction of counterfactuals in the absence of these events and for causal estimates of the consequences of the same events.

As already mentioned in the introduction, the macroeconomic consequences of geopolitical shocks on indirectly affected economies have not been extensively studied in the economic literature. Notable exceptions include Federle et al. (2024) and Caldara et al. (2024). According to former, wars lead to significant declines in output and increases in inflation for countries that are geographically close to the war site, irrespective of their participation in the war. On the other hand Caldara et al. (2024) focus on inflation and find that global geopolitical risks increase inflation, with inflationary effects more than offsetting the deflationary effects.

However, the main results in both Federle et al. (2024) and Caldara et al. (2024) concern the *average effects* of wars and geopolitical risk, respectively, and do not account for heterogeneity in time (e.g. historical regimes), geography, and geopolitical events themselves. Caldara et al. (2024) do study the cross-country heterogeneity and different sub-samples and find significant heterogeneity in the average responses of inflation to geopolitical risk. In particular, they find the inflation response to geopolitical risk to be close to zero in a significant proportion of the countries studied (see Figure 8 in Caldara et al. 2024), which is in line with our results for the average inflation response in the euro area (see Section 3.3).

We argue, however, that given the great heterogeneity of geopolitical events and their macroeconomic effects, from the point of view of policy relevance, the historical averages are not very useful. Instead, providing policymakers with specific estimates of the effects (and contributing factors) of particular geopolitical events on a given economy would better equip them for informed policy decisions. For example, from the perspective of the monetary policy decision-making at the European Central Bank, the knowledge of historical inflation response to geopolitical conflicts *on average* (across countries, in time, and between events) might not be all that useful in practice. With this in mind, our aim is to provide tools for the analysis of macroeconomic consequences of particular events in the context of particular economies.

Finally, before diving into a detailed analysis of our geopolitical events of interest, we need to emphasize the fact that, in addition to the immediate macroeconomic effects induced by the initial surprise, adverse geopolitical events may also have complex and long-lasting effects that cannot plausibly be all captured by an empirical model as general as used in our approach. That is, our approach is not directly comparable to those of Federle et al. (2024) and Abadie and Gardeazabal (2003), among others, which try to capture the total long-term cost of wars and conflicts. Instead, what we are interested in are the macroeconomic effects of adverse geopolitical *surprises* on euro area inflation and real GDP, how the effects differ between the events, and why and under what circumstances do they differ? For such questions, we believe, our approach strikes a fine balance between parsimony and precision.

4.1 Israel-Hamas War

We first investigate the effects of the outbreak of the Israel-Hamas war in October 2023 in the context of the euro area economy. This event is of particular interest not only because of its recency, but also because it serves as an example of a deflationary geopolitical surprise. According to our results, the geopolitical upheaval of October 2023 put significant downward pressure on euro area demand and temporarily cut euro area GDP by as much as 0.5 %. However, the events of October 2023 did not seem to have any effect on euro area supply. Thus, the net effect on inflation was deflationary, which is at odds with the predominant narrative of inflationary geopolitical risks.

Figure 6 shows our estimates (posterior means) for the signs and relative magnitudes of different structural shocks in and around October 2023. The shocks plausibly associated with the outbreak of the war are bolded and used to construct the counterfactuals (to be elaborated on). Most notably, there was a large positive GPR shock in October 2023.



Figure 6: Posterior means for the structural shocks around the outbreak of the Israel-Hamas war in October 2023 (the gray area covers one month following the outbreak). The shocks associated with the outbreak and set to zero in our counterfactual are bolded. Shocks have been rescaled for illustrative purposes and the magnitudes are not comparable between the shocks. Bars to the right correspond to positive values (cf. responses in Figure 2). Note that scaling by standard deviation would not make for comparable shock magnitudes under differing degrees of excess kurtosis.

Moreover, both demand shocks in our model were clearly negative during the very same month. We obviously cannot be certain that these shocks are due to our geopolitical event of interest, but the timing, magnitudes, and signs of the shocks strongly suggest that we can rather plausibly associate these shocks with the event.¹⁴ In particular, we are not aware of anything else happening in October 2023, that could explain negative demand shocks of this magnitude. Of course, a certain degree of expert judgment is necessarily required, but our approach allows us to be very explicit about all the assumptions we make.

On the other hand, there does not seem to be anything out of the ordinary in the supply and oil price shock series that could be linked to the geopolitical upheaval of October 2023. If anything, the negative oil price shocks suggest that the oil supply could have picked up a little during and after the events of October 2023, although this could be due to a slowdown in global demand of oil as well.

Note that although we interpret several independent shocks to stem from the same geopolitical event, the shocks do remain mutually independent (as assumed) as long as the probability distribution of, say, the demand shock stays the same whether it is conditioned on the

¹⁴These shocks do of course most likely include other factors as well, but as we have no means of further decomposing the shocks and the expected value of the other factors can be argued to be zero, associating all of the shock with the event of interest represents our best estimate.

GPR shock or not. This means that we can make the interpretation of several independent shocks as different transmission channels for geopolitical shocks only if the probability distribution of every other shock remains the same conditional on the GPR shock. The role of the homogeneous GPR shock in our model is therefore to absorb the average effects of the heterogeneous geopolitical events, leaving the shocks (at least mean) independent¹⁵, even if they originate from the same source in a non-repeating manner.

The left panes of Figure 7 zoom in on the historical decomposition of euro area inflation and annual growth rate of GDP around the outbreak of the Israel-Hamas war in October 2023. The decompositions on the left show the contribution of every shock to both variables up to that moment, but because the effects are dynamic, they do not give a good idea of the timing, and hence the origin, of different shocks. For example, due to base effects¹⁶, the contribution of supply shocks to inflation turns negative around the time of the outbreak, but has nothing to do with the outbreak.

To this end, the panes on the right (Figure 7) show only the contribution of the shocks that we associate with the event (see Figure 6). Most importantly, these shocks can be used to construct a counterfactual that gives us an estimate of what would have been the path of these variables without the shocks, or in other words, without the event ever taking place. The dashed line represents this counterfactual. The upper right pane of Figure 7 shows that the deflationary effect of the outbreak is due to the negative IP demand shock. By inspection of Figure 7 only, the magnitude of the effect would appear to be small, but this is mostly an illusion created by the relatively broad scale of the y-axis. To this end, Figure 8 shows the impulse response of the euro area inflation to the outbreak. According to our results, euro area inflation decelerated by a few tenths of a percentage point due to the outbreak of the Israel-Hamas war in October 2023.

The outbreak of the war seems to have induced a downward pressure on euro area GDP as well. The lower right pane of Figure 7 shows how this is due to negative demand and

 $^{^{15}}$ Even though we assume full independence of the shocks in our likelihood function, the identification of the model only requires for the shocks to be *mean* independent. Identification of the model could therefore be established under conditionally heteroskedastic shocks with dependent volatilities as well. However, we leave the consideration of such model extensions for future work.

¹⁶By *base effects* we refer to changes in annual growth rates (including inflation) due to rolling reference observation a year before.

(a) Inflation



(b) Annual growth rate of real monthly GDP



Figure 7: Left: Historical decomposition of euro area inflation and real GDP (cf. Figure 3). Right: Counterfactual that assumes the outbreak of the Israel-Hamas war in October 2023 never took place and the effects of the shocks contributing to the difference between the counterfactual and the observed value. The difference is the causal estimate for the effect of the outbreak. The gray vertical area covers one month following the outbreak and all values are posterior means.

GPR shocks associated with the event. Both of these shocks can be interpreted to act mainly as a transmission channel for the increased economic uncertainty associated with the event. More specifically, the negative contribution of the demand shocks in addition to that of the GPR shock can be interpreted as evidence of the uncertainty effects in the euro area being greater than for geopolitical events of similar magnitude (as measured by the GPR index) on average. According to our estimates, the annual growth rate of euro area real GDP decelerated by around 0.5 percentage points due to the outbreak of the Israel-Hamas war in



Figure 8: Posterior mean (dashed line) and point-wise posterior intervals (68%/90%) for the impulse response of euro area inflation to the outbreak of the Israel-Hamas war in October 2023.

October 2023.

4.2 Russian Invasion of Ukraine

From the perspective of the euro area economy, the Russian invasion of Ukraine in February 2022 was a very different geopolitical surprise from that of the outbreak of the Israel-Hamas war in October 2023. This obviously holds for the magnitude of the surprise, but for other characteristics as well. Whereas the events of October 2023 affected the euro area economy exclusively via the uncertainty channel, putting downward pressure on demand, the invasion of Ukraine led to significant supply chain disruptions and further accelerated the already surging energy inflation.¹⁷

Construction of the mapping from macroeconomic shocks to our event of interest is slightly more difficult for the invasion of Ukraine in February 2022 than for the events of October 2023. First, the initial invasion took place near the end of February and is therefore not reflected in the macroeconomic time series until March. However, Figure 9 shows that the GPR shocks started ramping up already in February, to which end we have chosen to associate the GPR shocks of both February and March with the invasion. There was also a huge inflationary supply shock in March that can be very plausibly associated with the invasion.

 $^{^{17}\}mathrm{Euro}$ area energy inflation was 28.8 % already in January 2022. It peaked at 44.3 % in March 2022.

With demand shocks, however, things become slightly more difficult to reconcile. Previous literature has suggested that much of the euro area inflation surge of 2022 was due to positive demand shocks that most probably had nothing to do with the invasion, but more so with post-pandemic recovery and expansionary fiscal policies (see, e.g., Giannone and Primiceri 2024 and Ascari et al. 2024). Our estimates are consistent with the previous literature and we find mainly positive demand shocks throughout the beginning of 2022, during which the invasion took place as well (see Figure 9). This makes it difficult to untangle the effects of the invasion on euro area demand from other forces simultaneously affecting it. We could assume that none of the demand shocks is associated with the invasion, since the response to the GPR shock already captures the average effect of an adverse geopolitical event of this magnitude on demand, making it a reasonable best guess.



Figure 9: Posterior means for the structural shocks around the Russian invasion of Ukraine in February 2022 (the gray area covers one month following the invasion). The shocks associated with the invasion and set to zero in our counterfactual are bolded. Shocks have been rescaled for illustrative purposes and the magnitudes are not comparable between the shocks. Bars to the right correspond to positive values (cf. responses in Figure 2). Note that scaling by standard deviation would not make for comparable shock magnitudes under differing degrees of excess kurtosis.

However, we find a very distinct *positive* IP Demand shock timed exactly at the time of the invasion (see Figure 9).¹⁸ Since to our knowledge, there were no other potential sources of demand shocks of this magnitude affecting the economy in March 2022, we must conclude that this shock is very plausibly due to the invasion. Although positivity of the demand shock might seem counterintuitive at first, it makes perfect sense under correct interpre-

¹⁸There are only three shocks in our sample of 345 IP Demand shocks for which the absolute value of the posterior mean exceeds that of March 2022.

tation. Recall that under heterogeneity of macroeconomic phenomena impulse responses to individual shocks represent *average* responses. On average, a negative supply shock of the magnitude observed in March 2022 would put serious downward pressure on industrial production. However, the volume of industrial production in the euro area did not decrease much in March 2022.¹⁹ According to our model, this must be explained by a positive IP demand shock.

The economic interpretation is clear. If the price elasticity of demand varies from one supply shock to the next, then an impulse response to a homogeneous supply shock only explains the average response to a supply shock. This is exactly analogous to the case of heterogeneous geopolitical events discussed earlier, and the same basic principles apply to identification of any shocks in general. The identified IP demand shock of March 2022 can only be interpreted in the context of other shocks simultaneously hitting the economy, and impulse responses to an individual shock can only be interpreted as average responses to such a shock. Importantly, as discussed, none of this breaks the orthogonality or mean independence assumption typically required for the identification of structural shocks with SVAR models. It only means that one has to be careful with the interpretation of such shocks, and homogeneous model implied shocks must not be confused with heterogeneous concepts of interest. This is one of the main arguments of this paper.

To return to our empirical application, our results thus suggest that the negative supply shock associated with the Russian invasion of Ukraine in 2022 had a relatively large effect on euro area inflation due to low price elasticity of demand. Although our focus is only on the geopolitical events of February 2022 and their effects on inflation, our results do support the view that the inflation surge of 2022 in general was at least partly explained by firms being able to transfer much of the higher production costs to consumers. Our results also illustrate why it might be difficult to answer to what extent the inflation surge was due to demand forces and to what extent it was due to disruptions in supply (cf. Giannone and Primiceri 2024). It all depends on whether we interpret the exceptionally low price elasticity of demand during that episode as a positive demand force or as a part of the response to supply disruptions.

 $^{^{19}}$ The monthly decrease of seasonally adjusted euro area industrial production index in March 2022 was merely 0.6 % and the level of February was already surpassed in May.

(a) Inflation



(b) Annual growth rate of real monthly GDP



Figure 10: Left: Historical decomposition of euro area inflation and real GDP (cf. Figure 3). Right: Counterfactual that assumes the Russian invasion of Ukraine in 2022 never took place and the effects of the shocks contributing to the difference between the counterfactual and the observed value. The difference is the causal estimate for the effect of the invasion. The gray vertical area covers one month following the invasion and all values are posterior means.

Finally, Figure 10 shows the counterfactuals for euro area inflation and annual growth rate of GDP that assume that the Russian invasion of Ukraine in February 2022 never took place. According to our estimates, inflation would have peaked around 8 % as opposed to 10.6 % observed in October 2022. Interestingly, this is close to the inflation observed in the United States²⁰ of which economy was much less affected by the geopolitical events of 2022. The upper right pane of Figure 10 also shows how less than half of the inflation response can

 $^{^{20}\}mathrm{US}$ CPI inflation peaked at 9.1 % in July 2022 and US PCE inflation peaked at 7.2 % in June 2022.

be explained by the negative supply shock alone (blue bars) and that the rest is explained by the positive IP demand shock.

As previously discussed, the interpretation of this is that inflation would have accelerated much less in response to the supply disruptions caused by the invasion if it were not for the unusually low price elasticity of demand. This interpretation is also supported by the fact that the increase in inflation during that time was most pronounced in items attributable to basic needs, such as energy and food.

Although the negative effects of supply disruptions on euro area production were limited by the low price elasticity of demand, the increase in uncertainty did push down the euro area GDP throughout 2022 (see the negative contribution of GPR shocks in the bottom right pane of Figure 10). According to our estimates, almost 1 % of the euro area real GDP was lost in 2022 due to the Russian invasion of Ukraine in February 2022.

5 Conclusion

Our empirical investigation into the effects of two recent major geopolitical surprises on euro area GDP and inflation well demonstrates the need to take into account the heterogeneous nature of geopolitical events in empirical queries on their causal effects. We show that both the outbreak of the Israel-Hamas war and the Russian invasion of Ukraine decreased the euro area GDP, but due to a difference in the relative importance of supply and demand related transmission channels, only the latter (Russian invasion of Ukraine) had an inflationary effect on consumer prices, whereas for the former (outbreak of the Israel-Hamas war) the effect was deflationary.

We also show how joint identification of multiple macroeconomic shocks is required for causal inference on the macroeconomic effects of heterogeneous geopolitical surprises and illustrate how statistically identified SVAR models are well suited for such a purpose. We also illustrate how traditional identifying restrictions and statistical identifying information can complement each other. Making use of both, instead of choosing between, strengthens identification and helps in labeling the statistically identified shocks, making the joint identification of multiple shocks more convenient. As geopolitical surprises and their effects are heterogeneous and the net effect on inflation can be either inflationary or deflationary, depending on the context, context dependence is also required from the monetary authorities when assessing the importance of geopolitical shocks to achieving their price stability objectives. Although our empirical investigation only makes an illustration of these arguments in the context of the euro area economy, the same arguments can be generalized to other economies as well.

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