Working Paper Series

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Geopolitical risk shocks: when the size matters

Abstract

In this paper, we investigate the presence of non-linearities in the transmission of geopolitical risk (GPR) shocks. Our methodology involves incorporating a non-linear function of the identified shock into a VARX model and examining its impulse response functions and historical decomposition. We find that the primary transmission channel of such shocks is associated with heightened uncertainty, which significantly escalates only with substantially large GPR shocks (i.e., above 4 standard deviations). This increase in uncertainty prompts precautionary saving behaviors, exerting a strong impact on consumption and reducing activity. The response of inflation is more subdued, reflecting both diminished demand and heightened uncertainty, which influence prices in opposing directions.

Non-technical Summary

In the aftermath of recent global events, such as Russian's attack on Ukraine and renewed conflicts in the Middle East, heightened geopolitical risk (GPR) has emerged as a focal point in academic and policymaking discourse. Existing literature underscores the consequential role of geopolitical risk shocks on economic activity and inflation (Caldara and Iacoviello, 2022; Caldara et al., 2022). However, understanding the transmission mechanisms of these shocks remains challenging due to their diverse nature, resulting in varying impacts and transmission channels throughout the economy.

Geopolitical risk shocks can influence the economy through two primary channels: the first channel yields direct and tangible impacts, akin to those of disaster events, such as wars impairing infrastructure or industrial capacity Barro and Ursúa (2012), but may also stimulate output through increased military spending Ramey (2011). Thus, these shocks may concurrently manifest as negative demand and supply shocks. The second channel operates by heightening volatility and uncertainty, leading to precautionary saving behaviors that defer consumption and investment.[1] Additionally, the magnitude of these shocks, serving as a proxy for their economic significance, may have significant implications. Minor shocks may have relatively inconsequential outcomes due to the localized nature of events and limited global repercussions, aligning with the notion that economies may not significantly deviate from their steady state following such shocks, justifying the use of linear methods for analysis. However, while predominant approaches to geopolitical risk studies typically adhere to linear frameworks, the literature on uncertainty (Caggiano et al., 2015, 2017b; Jackson et al., 2020; Chikhale, 2023), financial risk (Alessandri and Mumtaz, 2019; Candelon et al., 2021; Forni et al., 2023), and news shocks (Forni et al., 2024) advocates for delving into non-linearities and state-contingent effects for a more comprehensive understanding of shock transmission.[2]

In this paper, we address this gap in the literature by exploring the non-linearities associated with the magnitude of shocks producing sudden increases in geopolitical risk. Specifically, we follow a two-step strategy. First, building on the work of Caldara and Iacoviello (2022), who construct a measure of adverse geopolitical events and

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[1]See also ECB (2024) for a detailed discussion on the channels through which geopolitical risk can affect the economy.

[2]Non-linearities have been extensively studied also in the context of other shocks such monetary policy (Barnichon and Matthes, 2015; Debortoli et al., 2020; Ascari and Haber, 2021) or government spending such for example (Caggiano et al., 2017a; Mumtaz and Sunder-Plassmann, 2021).

risks, we estimate a GPR shock in a structural vector autoregressive (SVAR) model. Second, we follow the methodology proposed by Forni et al. (2023) who adopt a flexible way to estimate a vector moving average representation of the structural model containing the estimated shocks and their non-linear functions to retrieve the overall non-linear transmission mechanism. More precisely, in this paper we use the linear geopolitical risk shock estimated in the first step and its quadratic transformation.

Our findings indicate that incorporating non-linearities enhances our understanding of how geopolitical risk shocks are transmitted. Specifically, the non-linearity component significantly influences the response of variables to these shocks. Relying solely on linear models may lead to an underestimation of the overall impact. This conclusion is supported by both impulse response and historical decomposition analyses. The historical decomposition, in particular, highlights the crucial role of non-linear shocks in explaining the movements of real and nominal variables during major geopolitical events, such as the aftermath of 9/11, the Iraq War, and to some extent, Russia's invasion of Ukraine.

Moreover, accounting for non-linearities reveals a previously overlooked channel: large geopolitical shocks are associated with heightened uncertainty, which amplifies their overall impact by causing a significant decline in equity prices and private consumption. This channel becomes active only in the case of substantially large shocks (around four standard deviations) and remains generally muted with smaller shocks. These findings help explain why asymmetries in magnitude occur with large geopolitical shocks and clarify the interaction between these shocks and the more standard uncertainty channel.

Finally, we use the decomposition of geopolitical risk into Acts and Threats provided by Caldara and Iacoviello (2022) to get additional insights into the impact of heightened geopolitical risk on inflation. We find that the response of real oil prices, CPI, and activity to Acts shocks is negative, reflecting dampened aggregate demand, while Threats shocks lead to significant price increases, suggesting speculative demand and uncertainty impacts. Non-linearities, particularly in oil prices, are important only in the case of Threats shocks, providing additional evidence of their relation to second moments.

Apart from the aforementioned papers, our work is related to the literature on geopolitical risk. Pinchetti (2024) explores how geopolitical tensions affect energy markets, focusing on oil prices and supply dynamics. He proposes a way to disentangle geopolitical risk shocks acting through demand and those acting through the

supply of oil. Jalloul and Miescu (2023) examines how geopolitical risk influences the interconnectedness of G7 equity returns, particularly driven by perceived threats. Drobetz et al. (2021) investigates the effects of geopolitical risk on shipping freight rates, revealing its significant impact on global trade. Franconi (2024) demonstrates how monetary policy efficacy is influenced by geopolitical risk levels, affecting inflation and economic stability. Francis et al. (2019) identifies geopolitical uncertainty as a primary driver of international business cycle comovement. Nguyen and Thuy (2023) analyzes the association between geopolitical risk and bank loan costs, showcasing its influence on financial markets and lending practices.

1   Introduction

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The remainder of the paper proceeds as follows: Section 2 presents the methodology, Section 3 presents our empirical exercise, and Section 4 concludes.

2   Methodology

In this section, we present out econometric approach. The exposition follows closely Forni et al. (2023).

In the analysis, we make the assumption that the n-dimensional vector x_t, consisting of our variables of interest, follows a structural representation given by:

$$x_t = \nu + \beta(L)g(u_{z,t}) + B(L)u_t \tag{1}$$

Here, u_t is an n-dimensional vector of serially independent structural shocks with a zero mean and identity matrix covariance, $u_{z,t}$ represents the shock of interest, $g(u_{z,t})$ is a contemporaneous non-linear function of this shock, ν is a vector of constants and $B(L)$ is an $n \times n$ matrix of impulse response functions, and $\beta(L)$ is an n-dimensional vector of impulse response functions.

This representation 1 is considered a generalization of the standard Vector Moving Average (VMA) representation underlying Structural Vector Autoregressions (SVARs).

Further development of the model yields an equivalent representation under the assumption of invertibility of the linear term $B(L)u_t$:

$$D(L)x_t = \mu + D(L)\beta(L)g(u_{z,t}) + B_0 u_t \tag{2}$$

Where $D(L) = (I + B_1 B_0^{-1} L + B_2 B_0^{-1} L^2 + \ldots)^{-1} = I - \tilde{D}(L)$, $\mu = D(1)\nu$, and B_0 is a matrix of impulse response functions.

For simplicity, the assumption is made that no lags of $g(u_{z,t})$ enter equation 2,

leading to $D(L)\beta(L) = \beta_0$. The model can thus be rewritten as:

$$
\begin{aligned}
x_t &= \mu + \tilde{D}(L)x_t + \beta_0 g(u_{z,t}) + B_0 u_t \\
&= \mu + \tilde{D}(L)x_t + \beta_0 g(u_{z,t}) + \alpha_0 u_{z,t} + B_{-z,0} u_{-z,t}
\end{aligned}
\tag{3}
$$

Here, α_0 is the column of B_0 corresponding to the shock of interest, $B_{-z,0}$ is the matrix formed by the $n-1$ columns of B_0 excluding α_0, and $u_{-z,t}$ is the $(n-1)$-dimensional vector containing the remaining structural shocks other than $u_{z,t}$.

The linear SVAR is nested within this model, allowing for testing the significance of the non-linear term using standard methods.

Equations 2 and 3 reveal that the impulse response functions to $u_{z,t}$ and $g(u_{z,t})$ are $\alpha(L) = D(L)^{-1}\alpha_0$ and $\beta(L) = D(L)^{-1}\beta_0$, respectively. The total effect is non-linear and can be expressed as:

$$
IRF(u_{z,t} = u^*) = \alpha(L)u^* + \beta(L)g(u^*)
\tag{4}
$$

If non-linearity is deemed unimportant ($\beta(L) = 0$), the impulse response functions are identical to those of a linear SVAR. However, if non-linearity is significant, the propagation mechanisms of the shock considered differ.

Assuming $g(u_{z,t}) = u_{z,t}^2$ as in our baseline specification, the effect of the shock becomes:

$$
IRF(u_{z,t} = u^*) = \alpha(L)u^* + \beta(L)(u^*)^2
\tag{5}
$$

It is noteworthy that in equation 5, a non-linearity in terms of magnitude is observed, as a shock of double magnitude does not result in twice the effects.[5]

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[5]Furthermore, the coefficients $\beta(L)$ introduce an asymmetry between positive and negative shocks, leading to different effects depending on the sign of u^*. This is however a feature of the model not explored in the current analysis as geopolitical risk shocks, our shocks of interest are almost entirely negative (i.e. related to hightened risk). The model is also general enough to consider state dependencies. For instance, if the state variable d_t is introduced, the impulse response functions become:

$$
IRF(u_{z,t} = u^*) = \alpha(L)u^* + \beta(L)d_t u^* \quad (6)
$$

This accounts for different effects in different regimes ($d_t = 1$ or $d_t = 0$).

3 Empirical Application

Our empirical analysis focuses on the potential non-linear effects caused by geopolitical risk shocks following the methodology explained in section 2. Specifically, our approach is divided into two steps. In the first one, we identify the shock of interest from a SVAR model following a recursive algorithm as in Caldara and Iacoviello (2022). This practically translates into estimating the IRFs to the shock without explicitly accounting for the term $\beta(L)$ in equation (5). This step serves two primary purposes: a) it facilitates the estimation of the linear shock, which will be utilised in subsequent stages, and b) it provides a baseline for evaluating the impulse responses once we incorporate the non-linear component into the analysis.

In the second step, we estimate the effects of a geopolitical shock by also accounting for its non-linear transformation. We do this using a vector autoregression models with exogenous variables (VARX) where we include both the GPR shock u_t and its quadratic transformation $g(u_t)$ as exogenous variables. To be consistent with the first step, the VARX follows the same model specification of the SVAR used in the first part both in terms of sample, lag-order, and variables included. This procedure allows us to explicitly estimate both $\alpha(L)$ - namely, the responses to the linear shock - along with $\beta(L)$, which represents the responses to its quadratic transformation, and to retrieve the new responses to the GPR shock, thus offering a direct and easy comparison with the results obtained the linear SVAR.

3.1 Estimating Geopolitical Risk shocks

For the specification of the linear SVAR estimated in the initial stage, we utilise monthly U.S. data comprising the following variables: the Geopolitical Risk Index, the CBOE Volatility index (VIX), the S&P500 stock market index, Industrial Production, the Consumer Price Index (CPI), Real Consumption Expenditure, and the Federal Funds Rate.[6] We transform all real variables into log-levels, excluding the VIX and the interest rate, which enter the model in levels. The sample spans from January 1970 to December 2023.[7] Finally, we set the lag order equal to $p = 6$ following standard AIC and BIC tests.[8]

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[6]We complement the Fed Funds Rate with the measure of shadow rate proposed by Wu and Xia (2016) from 2000m1 to - 2023m6.

[7]Table B1 in Appendix A provides a detailed description of the data, including their sources and the applied transformations.

[8]Nevertheless, we conduct extensive robustness analysis by estimating the model using different lag lengths. The results remain robust across various lag orders, as detailed in Section 3.5.

We follow the methodology outlined in Caldara and Iacoviello (2022) and employ a recursive algorithm to estimate a geopolitical risk shock, with the GPR index designated as the first variable in our model — thereby assuming it to be the most exogenous variable.[9] Although the primary aim of the initial step is to estimate the shock of interest, we also present the IRFs associated with such shock. These IRFs serve as a valuable benchmark for elucidating our findings and, furthermore, constitute a necessary step to validate our subsequent analysis.

Figure 1 depicts the impulse response to a one standard deviation shock in geopolitical risk. The solid blue line represents the point estimate, while the shaded areas denote the 68% and 90% confidence intervals.[10] The x-axis denotes the months following the shock, spanning up to 36 months (3 years). The results closely resemble those reported in Caldara and Iacoviello (2022) and are consistent with findings presented in Caldara et al. (2022).[11]

A one standard deviation shock to geopolitical risk - corresponding to an increase of the geopolitical risk index by around 20 percent - has a non-significant and short-lived positive impact on uncertainty, as shown by a relatively muted response of the VIX, which declines after the initial increase and stays negative over the horizon considered. Industrial Production and Real Consumption both marginally decline initially, with the response of the latter being more short-lived than that of the former. Stock prices also decline at impact, though the overall effect is relatively contained in magnitude. The shock also exerts a positive effect on prices which increase on impact, but very mildly, before declining, while the Fed funds rate decreases modestly at impact but its response is rather insignificant. Overall, our results seem to confirm that (i) a geopolitical shock has an overall negative but rather marginal impact on the economy, that (ii) uncertainty does not appear to be a key transmission channel, as shown by the relatively muted response of the VIX and (iii) that the effect of the shock on prices is neither clearly positive nor negative .

Figure 2 illustrates the corresponding identified geopolitical risk shock in the top panel, alongside deviations of 1, 2, 4, and 8 standard deviations, while the bottom panel portrays its non-linear quadratic transformation. Several observations emerge from an initial visual inspection. Firstly, the shock displays notable positive surges,

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[9]Caldara and Iacoviello (2022) extensively discuss this choice. We direct the reader to their paper for a comprehensive justification of this approach.

[10]The confidence intervals are estimated via bootstrap technique following CITARE.

[11]It is noteworthy, however, that Caldara and Iacoviello (2022) estimate a model with quarterly data. Nonetheless, the responses from our monthly specification align with those obtained in the aforementioned study.

Figure 1. The Impact of Increased Geopolitical Risk
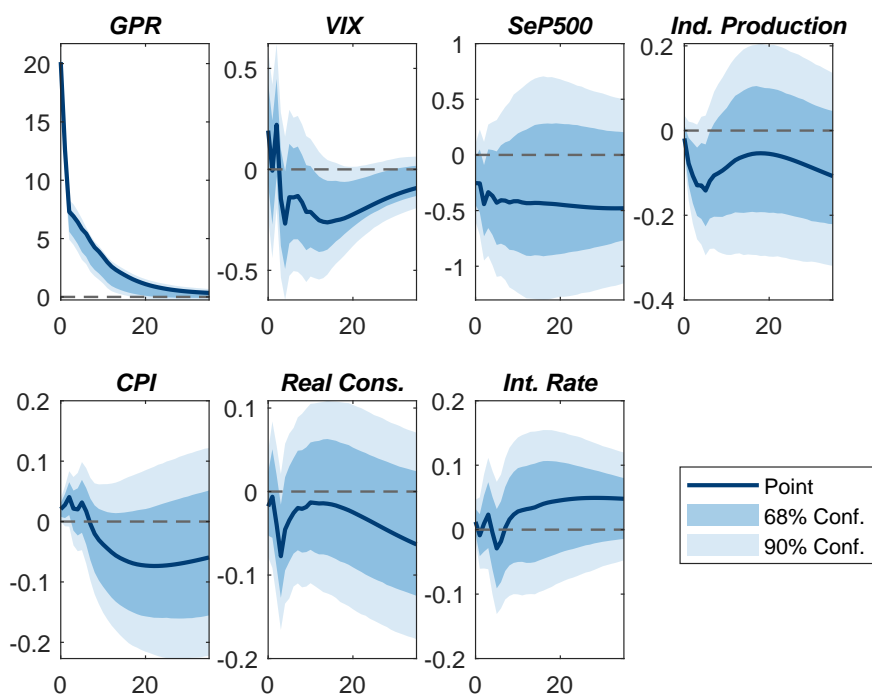
Notes: The solid blue line represents the point estimate, while the shaded bands the 68% and 90% confidence intervals estimated via bootstrap. All variables in percent, except for the FED shadow rate in percentage points and the VIX in points.

particularly on certain occasions. Across the analysed sample, the series surpasses two standard deviations in eighteen episodes. Among these occurrences, four instances stand out where the shock exceeds or equals four standard deviations: during the Yom Kippur War in 1973, amid the Gulf War in the early nineties, and during the periods encompassing 9/11 and the subsequent Iraq war. As anticipated, the shock demonstrates a pronounced spike during the 9/11 terrorist attacks, resulting in an 8 standard deviation increase in the geopolitical risk index.

In general, the shock exhibits a pronounced left-skewness, with only a few instances displaying non-significant negative values. This observation is unsurprising and is an intrinsic characteristic of the text-based index developed by Caldara and Iacoviello (2022), which predominantly detects increases in geopolitical risk. This one-sided nature is faithfully reflected in our estimated underlying shock and holds significance in our analysis and the selection of non-linearities examined in our study. Indeed, the literature typically concentrates on contrasting the varied impacts of positive and negative shocks on the economy once accounting for non-linearities, as exemplified Forni et al. (2023); Debortoli et al. (2020). However, the scarcity of sub-

stantial negative geopolitical risk shocks underscores the necessity to focus primarily on the non-linearities associated with the magnitude of the shock rather than its *direction.*

Figure 2. The Estimated Geopolitical Risk Shock and its square
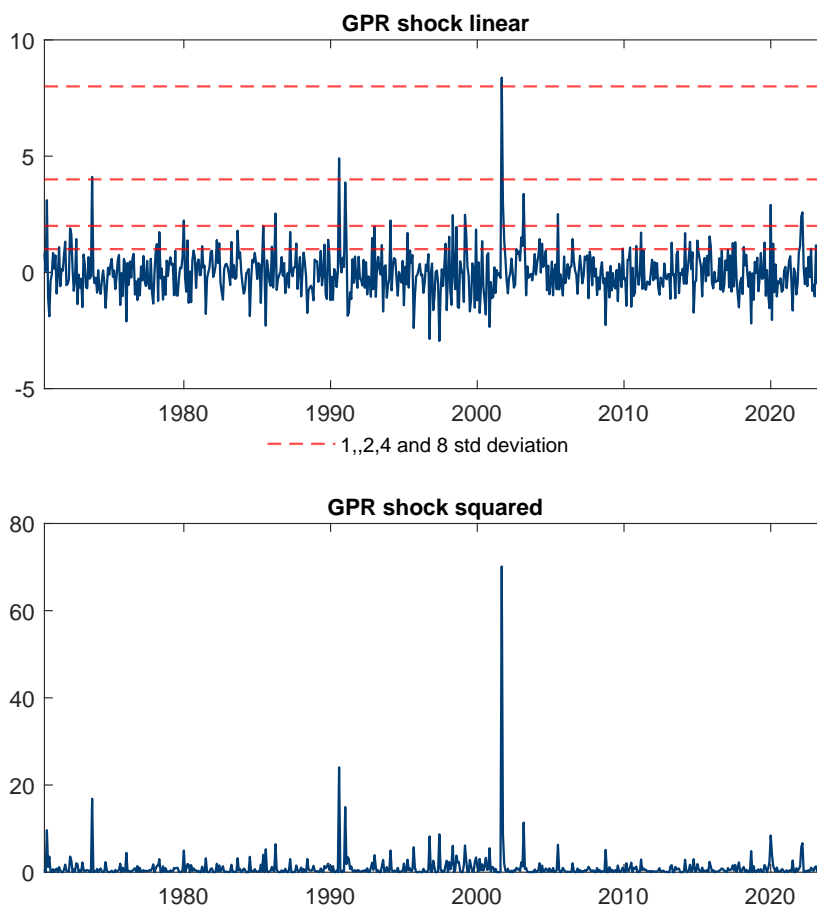
Notes: Geopolitical shock estimated in the linear model (top panel) along with its quadratic transformation (bottom panel). Positive values of the shock correspond to an increase in Geopolitical Risk. The red dashed lines in the top panel show 1, 2, 4 and 8 standard deviations respectively.

In the subsequent section, we extend our analysis to incorporate the non-linear quadratic transformation of the GPR shock. This expansion enables a comparison between the responses of the linear and non-linear shocks, providing insights into whether the overall results diverge from the IRFs estimated in the linear model.

3.2 Disentangling the role of non-linearities

Figure 3 shows the IRFs obtained using the non-linear model estimating following the two-step procedure described in Section 3. As evident from the first column to the left,

the responses to the linear shock are different compared to those presented in Figure 1. Across almost all variables, responses to the linear shock exhibit subdued impacts and are generally less statistically significant. Some variables, such as the VIX and Real Consumption, even display a reversal in response direction at impact compared to those depicted in Figure 1. Overall, the IRFs are not statistically significant at the 90% confidence interval.

Conversely, examining the IRFs to the non-linear shock presented in the second column to the right reveals a distinct scenario, with responses now predominantly significant across all variables. This observation indicates that $\beta(L) = 0$, thereby highlighting the significance of non-linearities arising from a geopolitical risk shock for the economy and their potential to *amplify* the shock's effects. Notably, the quadratic GPR shock elicits a significant and positive response of the VIX, suggesting the potential importance of the *standard* uncertainty channel in magnifying the impact of significant geopolitical shocks. Concurrently, industrial production and particularly real consumption exhibit notable negative responses at impact. These responses can be attributed to increased overall uncertainty prompting precautionary saving behaviour, thereby deferring consumption consistently with the literature on uncertainty.[12] Furthermore, equity prices also display significant negative reactions, potentially further impacting real consumption through the wealth effect. Finally, while the quadratic shock leads to an increase in the CPI, it also triggers a negative response in the policy rate. Although beyond the scope of this paper, the trade-off between prices and the policy rate's reaction may be explained by policymakers assigning greater weight to activity than inflation during such shocks. Nonetheless, further exploration of the impact on prices will be conducted in Section 3.6.

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[12]See for example Bernanke (1983), Kimball (1990), Bloom (2009), Bayer et al. (2015).

Figure 3. Impulse Response Functions of the VARX: Linear vs Quadratic GPR shock
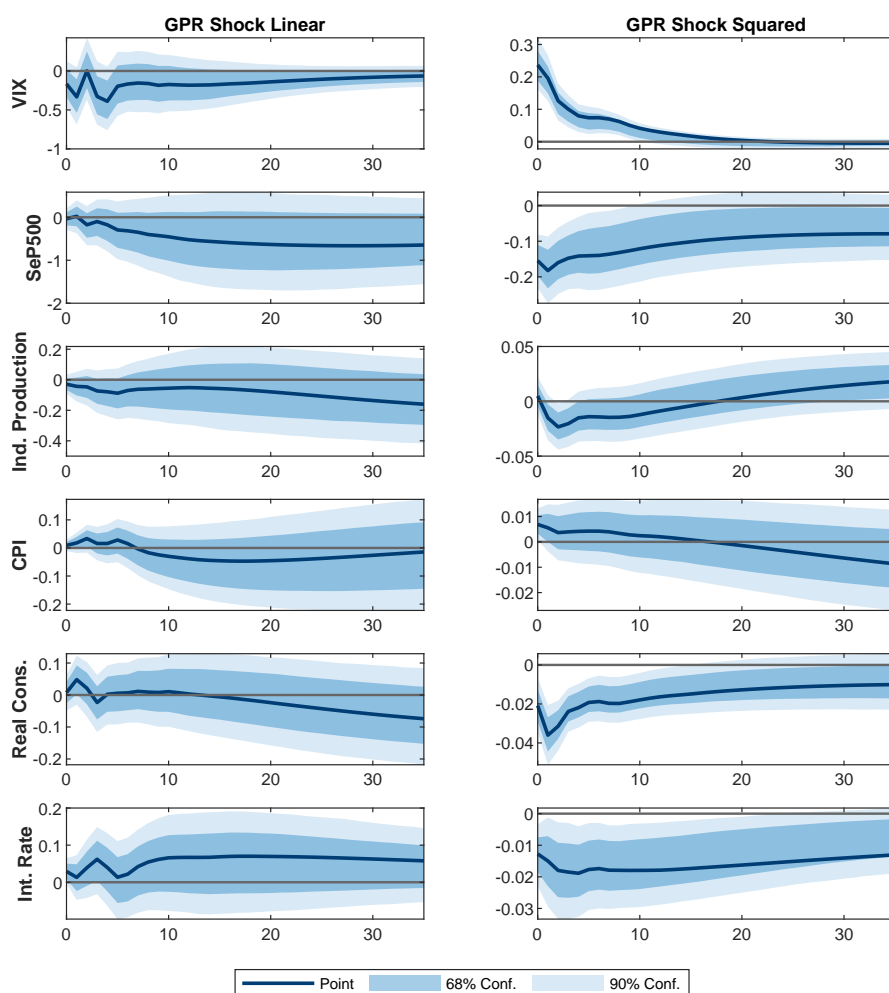
Notes: The solid blue line represents the point estimate, while the shaded bands the 68% and 90% confidence intervals estimated via bootstrap. The left column shows the responses to the linear shock, while the right column the responses to the non-linear shock.

3.3 When the size of the shock matters

Having established the significance of the non-linear component, i.e., $\beta(L)$, for the variables incorporated in our model, we proceed to investigate the overall impact of the geopolitical risk shock when accounting for both the linear and non-linear responses, as specified in equation (5). This entails aggregating the linear and quadratic components, i.e., the $\alpha(L)$ and $\beta(L)$ obtained in the second step, with the latter, as elucidated in Section 2, introducing potential asymmetries in the magnitude of the shock. Consequently, this may lead to distinct overall responses compared to those analysed previously in 3.1 as the magnitude increases.

Figure 4 presents the IRFs to a geopolitical shock, with a focus on the VIX, S&P 500, and Real consumption, pivotal variables for our analysis. Nevertheless, Figure B1 in Appendix B provides the results for all variables included in the model. We examine the responses to various sizes of the shock, guided by observations made in Figure 2. Specifically, we analyse how variables respond to shocks equal to two, four, and eight standard deviations, each depicted in a separate column.

The IRFs incorporating both linear and quadratic components are denoted by the blue solid line (point estimate), accompanied by the 68% and 90% confidence bands (shaded areas). Meanwhile, the *original* IRFs obtained in the first step, as depicted in Figure 1, are represented by the red dashed line. Both the *second-step* and *first-step* IRFs are rescaled according to the relative magnitude of the analysed shock, facilitating straightforward comparison and enabling identification of differences between the two steps.

We start our analysis with the two standard deviations shock (left-hand side column). Here, the responses obtained with the non-linear and linear models exhibit considerable similarity, with only equity prices and real consumption showing minor discrepancies — albeit not at impact and only from the second year. The responses of the remaining variables, as illustrated in Figure B1 in Appendix B, closely resemble those presented in Figure 1. This reaffirms that, with a relatively small shock, the transmission mechanism of a geopolitical risk shock remains largely unchanged compared to the analysis conducted in section 3.1. Thus, it can be well approximated by a linear model.

Nonetheless, with increasing magnitude, a distinct narrative unfolds. Focusing on the four standard deviations shock, depicted in the middle column, notable differences emerge in the responses of Real Consumption and S&P 500. The second-step IRFs indicate significantly larger responses both at impact and throughout the entire

analysed horizon. Specifically, equity prices now exhibit a decline of 3% at impact, compared to a decrease of 0.8% in the first-step SVAR. For Real Consumption, the decline implied by the non-linear model is approximately 0.5%, while the red dashed line depicts a decrease less than half that magnitude. Most notably, the VIX displays the most substantial discrepancy between the two models: the non-linear VARX suggests a significant increase at impact of 3 points, while in the non-linear SVAR, it registers only a marginal (and statistically insignificant) rise of less than 1 point.

As anticipated in section 3.2, these findings suggest two significant observations. Initially, when geopolitical shocks are of small magnitude, non-linearities do not exert a significant influence on shock transmission. However, as the shock increases, non-linearities assume greater importance, revealing a new channel through which the shock propagates. With increasing magnitude, the VIX *activates*, and the geopolitical shock propagates through a standard uncertainty channel. This prompts precautionary actions among agents and amplifies the shock's effects through a decline in the S&P500 and Real Consumption, both directly impacted by the wealth effect stemming from the decrease in equity prices.

Overall, the results emphasise the necessity of accounting for non-linearities to accurately assess the shock's impact on the economy. At the same time, this also highlights that the principal transmission channel for this shock appears to be via heightened uncertainty. This becomes particularly apparent when analysing the left-hand column, which depicts the responses to a shock of eight standard deviations. Here, the shock pushes the VIX up by 14 points in the two-step VARX, while decreasing equity prices by 10% and Real Consumption by nearly 2%. Conversely, without accounting for the non-linear component, the responses would be substantially smaller, and the shock would seem to have only a marginal impact on the economy. Furthermore, as illustrated in Figure B1, other variables now also exhibit notable differences: industrial production declines by around 2% compared to less than 1% implied by the first-step SVAR, while the policy rate decreases by around 1 percentage point in response to significantly weaker activity. Interestingly, prices increase at impact, albeit only marginally, and show no signs of non-linearities. We will delve further into the behaviour of prices in section 3.6.

3.4 Decomposition over selected historical events

Based on the evidence presented in previous sections, we now investigate whether the GPR shocks can account for (some of) the volatility observed in the variables under

Figure 4. Impulse Response Functions of the VARX summing the linear and the non-linear responses to a GPR shock
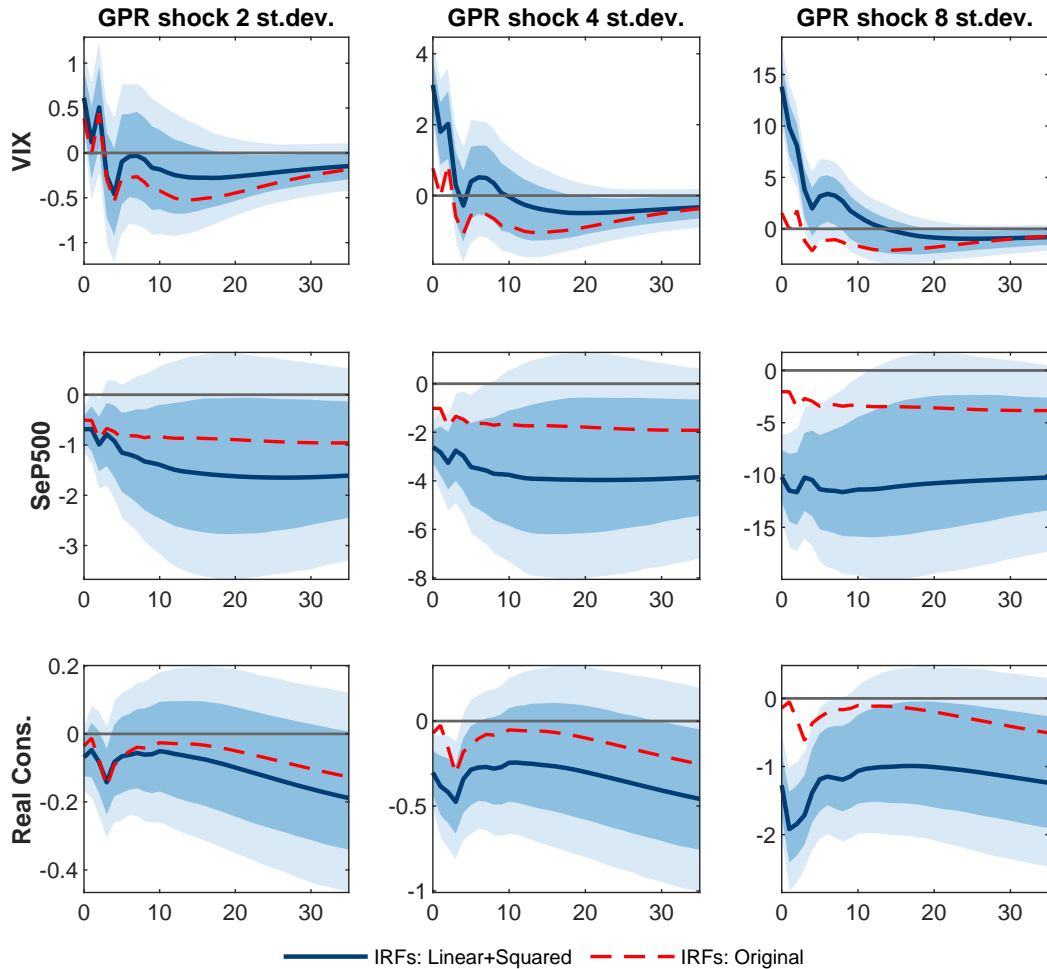
Notes: *The solid blue line represents the point estimate of the overall linear and non-linear responses estimated in the second step, while the shaded bands the 68% and 90% confidence intervals estimated via bootstrap. The dashed red line shows the responses of the first step SVAR. Each column depicts a different standard deviation of the shock.*

analysis. To achieve this, we decompose the variables into three components: the portion explained by the linear shock, the portion explained by the non-linear shock, and the residual.[13] This approach allows us to assess both the *overall* significance of the GPR shock in explaining fluctuations in the variables, as well as the *relative* importance of the linear and non-linear components.

Specifically, we examine the evolution of the variables during the 9/11 terrorist

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[13]The residual can be interpreted as a reduced-form component comprising a combination of all the remaining structural shocks.

attacks, the Gulf War, Russia's invasion of Ukraine and the Great Financial Crisis. The selection of these events is deliberate due to their heterogeneous nature and is informed by Figure 2; the first two events experienced a significant rise in geopolitical risk, leading to a substantial spike in the non-linear shock time series, while the third saw only a moderate increase in the shock, and the fourth should be unrelated to geopolitical dynamics.

Figure 5 presents the results. The S&P500, Real Consumption, Industrial Production, and CPI are depicted as the cumulative sum of the log-changes over the two years from the onset of the shock, while the VIX and the Fed funds rate are displayed as the cumulative sum (solid black line). The contribution of the linear shock is represented by the blue bars, while that of the non-linear shock is depicted by the red bars. Finally, the residual is shown in grey bars.

The geopolitical shock emerges as a significant driver in explaining the fluctuations observed in the variables during the 9/11 attacks and the Iraq invasion, as illustrated in the top-left panel. The combined effect of the two components accounts for almost all of the variability observed in the VIX and the Fed funds rate, and a substantial portion of the SP 500, Industrial Production, Real Consumption, and CPI. Further analysis of the individual components confirms our findings: non-linearities amplify the shock's effects through increased uncertainty, thereby influencing consumption, stock prices, and overall economic activity. Conversely, by considering only the linear component, the role of the shock in explaining industrial production and CPI would be substantially lower, while the remaining variables would remain largely unexplained. A similar pattern is observed in the Gulf War episode, as depicted in the top-right panel, where the geopolitical shock, particularly its quadratic component, explains a significant portion of the overall economic volatility.

Figure 5. Historical Decomposition over Specific Episodes with Different Level of Geopolitical Risk
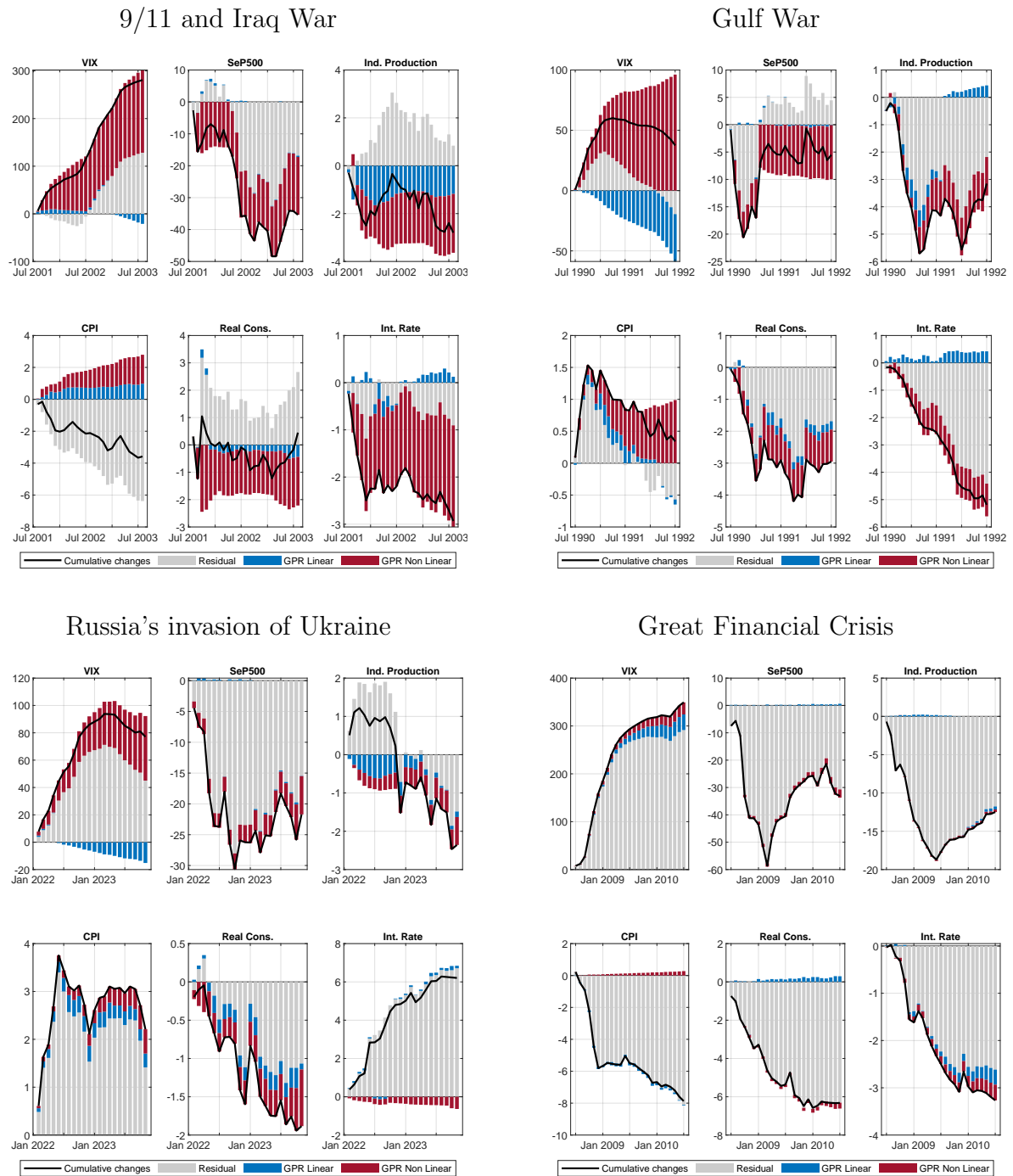
Notes: Historical Decomposition over four different episodes. The black line depicts the cumulated sum of the log-changes, except for the Fed fund rate and the VIX index reported as the cumulated sum of the level. The blue bars show the contribution from the linear shock, the red bars the one from the non-linear shock. The grey bars are the residuals.

The Russian invasion of Ukraine episode, shown in the bottom-left panel, shares similarities with the preceding two episodes analysed. Here, the contribution of the geopolitical shock is more subdued due to the comparatively lower escalation of geopolitical risk, with the residual shock that explains most of the fluctuations. This may suggest that other factors, such as a broader supply shock, predominantly drove the notable price increases and the subsequent decline in economic activity and financial markets valuations. Nevertheless, the geopolitical risk shock is still important in explaining a substantial part of the overall volatility of the variables.

In conclusion, these results corroborate what we described in section 3.2 and 3.3: the geopolitical risk shock is important in explaining variables' fluctuations in some specific historical episodes. Specifically, when large shocks occur, the non-linearities amplify the impact of the shock through an increase of the VIX, thus *switching on* the uncertainty channel. However, it is important to stress that the geopolitical risk shock is relatively unimportant for many other historical events. This is confirmed, for instance, by the bottom-right pane, which reports the decomposition around the great financial crisis. Here the geopolitical risk shock does not play any role in explaining the overall volatility of the variables, with the surge in the VIX that is not driven by any of the estimated geopolitical risk components.

3.5   Robustness

To validate our findings, we conducted several robustness checks. First, we change the number of lags in our VAR model, exploring specifications with eight, ten, and twelve lags. Second, we examine different sample periods to ensure the robustness of our results against sample selection biases. Third, we employ bayesian estimation methods and compare the results with those obtained using a frequentist approach. Specifically, we estimate the first step SVAR following the methodology proposed by Lenza and Primiceri (2022) to accommodate the COVID-19 period and the consequent change in the shock variance. Fourth, we estimated the model in differences rather than in levels. Detailed results of robustness checks one to four are provided in the Appendix B, all confirming our baseline findings.

Finally, we also check if our results on uncertainty are robust across alternative measures of uncertainty. To achieve this, we re-run the same exercise by using different uncertainty proxies instead of the VIX index, comparing the results across the different IRFs. More precisely, we consider (i) US Consumer's perceived expectations based on the Michigan consumer sentiment survey, which is a widely used

metric to gauge uncertainty used in the literature;[14] (ii) the US Composite Indicator of Systemic Stress (CISS) constructed by Kremer and Chavleishvili (2021) and (iii) the Global Economic policy uncertainty (GEPUI) index constructed by Baker et al. (2016). Consumer perception of uncertainty stems from responses collected in the Michigan consumer sentiment survey. This metric is formulated as the proportion of respondents indicating unfavorable timing for vehicle purchases due to uncertain future economic conditions. The US CISS index is constructed using fifteen indicators to gauge financial stress across various markets, encompassing money markets, bond markets, equity markets, and foreign exchange markets. Systemic stress is computed by assigning weights to each pair of indicators based on their time-varying correlation coefficient. This approach allows the CISS to assign greater significance to scenarios where stress pervades multiple market segments simultaneously, thereby capturing second-moment dynamics beyond stock market volatility and exhibiting greater persistence. Finally, the GEPUI is derived from newspaper coverage to capture policy-related economic uncertainty.

The correlation between these indicators and the VIX varies, ranging from 0.3 for the index derived from the consumer sentiment survey to 0.44 for the GEPUI, and reaching 0.8 for the CISS index.

Figure 6 illustrates the standardized response of each of the variables to a GPR shock in rows one through four, with the VIX displayed in the first row. The solid blue line shows point estimate of the non-linaer model, while the dotted red line shows the response of the uncertainty variables to a GPR shock identified with the linear model. Columns one through three depict the response for shocks of two, four, and eight standard deviations, respectively. All the considered uncertainty measures exhibit responses broadly aligned with the VIX. Notably, they all demonstrate non-linearities emerging as the size of the shock increases, exhibiting a roughly comparable increase in magnitude, ranging between 0.2 and 0.4 standard deviations for a 4-standard deviation shock, and between 1 and 2 standard deviations for an 8-standard deviation shock. This further confirms our results, and suggest that large geopolitical risk shocks transmit through the uncertainty channel.

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[14]See for example De Santis and Van der Veken (2022).

Figure 6. Robustness on uncertainty measures
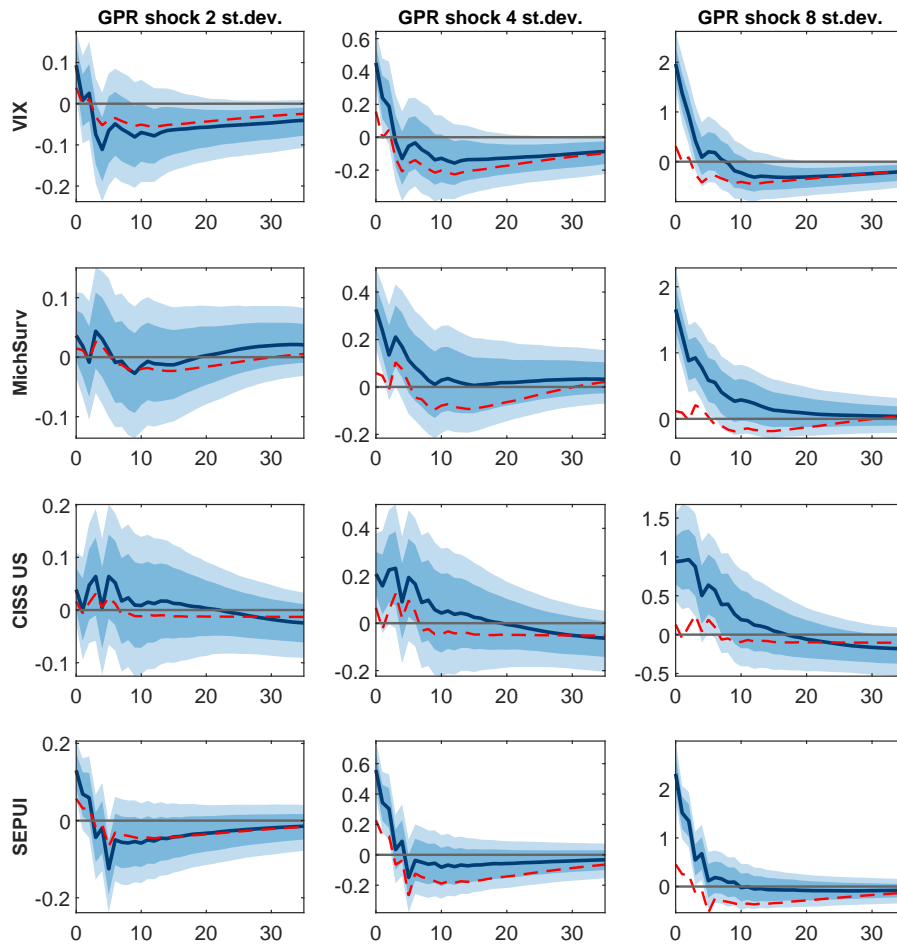
Notes: The solid blue line represents the point estimate of the overall linear and non-linear responses estimated in the second step, while the shaded bands the 68% and 90% confidence intervals estimated via bootstrap. The dashed red line shows the responses of the first step SVAR. Each column depicts a different standard deviation of the shock. Each row the responses of different measures of uncertainties. All the uncertainty measures are standardized.

3.6 Impact on prices: The role of Threats vs Acts

Our analysis has revealed a mild positive price reaction to GPR shocks, with limited asymmetries observed in response to variations in the shock magnitude. To delve deeper into the response of prices to geopolitical shocks, we utilize two different geopolitical risk indices proposed by Caldara and Iacoviello (2022), namely Geopolitical Threats (GPRT) and Geopolitical Acts (GPRA). As demonstrated by the authors, the generic geopolitical risk index can be disaggregated into these two components, where GPRT reflects spikes in response to the anticipation of future geopolitical threats, while GPRA represents the realization of such threats.

This approach allows us to discern which of the two components primarily drives the initial positive reaction of prices. Furthermore, we can gain insights into why their response is relatively subdued if we discover that GPRA and GPRT have contrasting effects on prices, potentially offsetting each other.[15]

Employing the same model specification and sample period as in previous sections, but with a crucial modification—incorporating both the GPRA and GPRT indices instead of the broader GPR index—we identify the two GPRA and GPRT shocks using a recursive algorithm, with Acts ordered before Threats to isolate acts that do not generate increased uncertainty, consistent with the approach adopted by Caldara and Iacoviello (2022). In the robustness section, we also explore an alternative ordering with GPRT preceding GPRA. Additionally, we augment our VAR with a series of real oil prices to better capture the transmission of shocks to prices.[16] Subsequently, we implement a two-step strategy akin to Section 3: first, we estimate an SVAR without accounting for possible non-linearities, retrieve the two shock series, and then estimate a VARX with the linear GPRA and GPRT shocks and their respective quadratic transformations.

Our focus here lies on the responses of CPI and real oil prices, while the remaining results can be found in Appendix ??. The left panel of Figure 7 illustrates the responses of these two variables to both a GPRA (depicted in red) and GPRT (depicted in blue) shock for the full-sample specification. Similar to previous sections, the dashed line represents responses obtained from the linear model (i.e., the first-step SVAR), while the solid line portrays responses of the overall shock, summing both the linear and non-linear components estimated in the VARX, along with the 68%

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[15]While Caldara and Iacoviello (2022) highlight heterogeneity in the transmission of shocks deriving from GPRA and GPRT, they do not explore how prices react to the two different components.

[16]The series used in the analysis is the price of Brent crude oil.
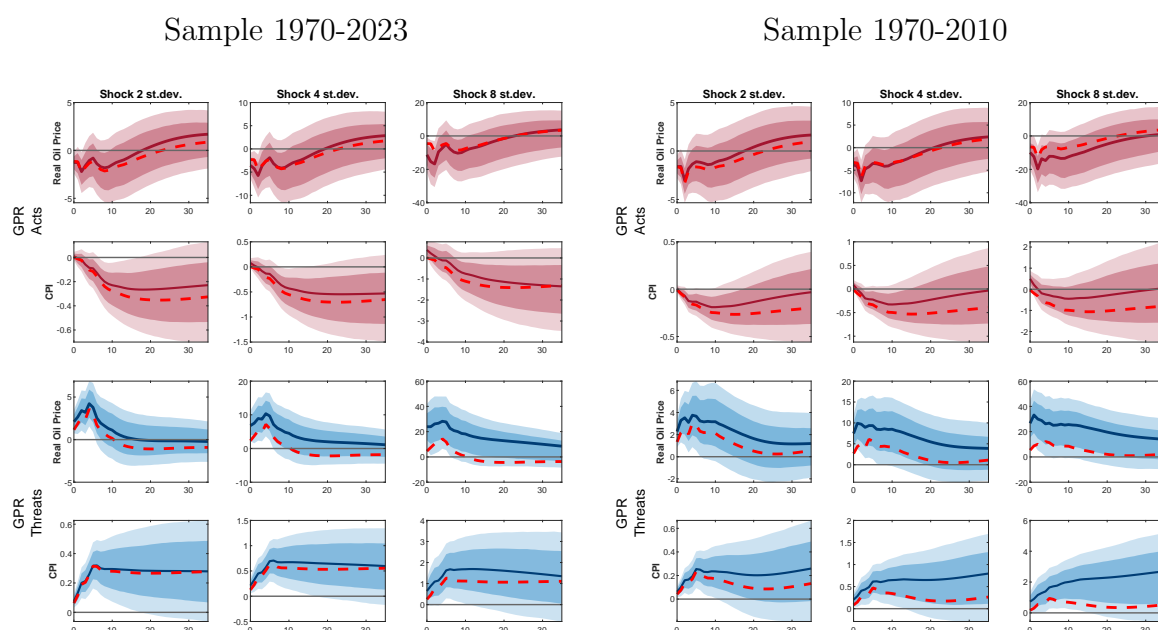
and 90% confidence intervals.

In response to a GPRA shock, both real oil prices and CPI decline. This is indicative of a shock that dampens aggregate demand, as also evident from industrial production which also decreases following the shock, as shown in Figure (C4). Conversely, a GPRT shock leads to a significant increase in both real oil prices and CPI. This observation suggests that threat shocks may share similarities with uncertainty shocks, prompting speculative demand for oil as markets anticipate potential future disruptions in oil supply, aligning with findings in the literature on oil prices (Kilian and Murphy, 2014; Juvenal and Petrella, 2015; Cross et al., 2022). Overall, we find that the two shocks have opposite effects on prices, potentially explaining the relatively muted response of CPI to a generic geopolitical risk shock.

Regarding non-linearities, we do not observe evidence of non-linearities for both real oil prices and CPI following a GPRA shock. The responses of the two variables increase linearly with the magnitude of the shock, as evidenced by the proximity of the solid line to the dashed line.[17] However, the scenario differs for responses following a GPRT shock, with real oil prices exhibiting significant non-linearities as the shock magnitude increases. This aligns with the interpretation described earlier: as the shock's size increases, uncertainty around the event amplifies, thereby intensifying the overall impact on real oil prices. This effect partially translates to inflation, with CPI exhibiting some non-linearities, albeit limited.

Finally, it's worth stressing that our estimation sample encompasses a period during which the US economy experienced a notable insulation from oil price shocks. Beginning in 2010, the US initiated a significant increase in oil production, resulting in its transition from a net importer to a net exporter. To account for this, we repeat the analysis by shortening the sample to exclude the last period. We re-estimate the responses of the variables to both GPRA and GPRT, spanning from 1970 to 2010. The outcomes, presented in the right panel of Figure 7, reveal compelling results: the variables continue to display an absence of non-linearities following a GPRA shock, while real oil prices exhibit significant non-linearities as the magnitude of the GPRT shock increases. However, this time, the amplifying effect extends to CPI, with prices showcasing notable disparities between the linear and non-linear models. This underscores the notion that GPRT shocks may instigate significant non-linearities in prices through the oil price channel, particularly impacting countries susceptible to oil price

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[17]If anything, as the size increases, CPI becomes less negative, suggesting that non-linearity may influence the direction of the response, as evident in Figure C2.

Figure 7. GPRA vs GPRT: Oil and Prices

Sample 1970-2023   Sample 1970-2010

Notes: The solid line represents the point estimate of the two-step VARX, with the respective 68% and 90% confidence intervals. The dashed red line shows the point estimate of the first step SVAR. Each column depicts a different standard deviation of the shock. The rows show the response of real oil price and CPI to a GPRA and GPRT shock respectively.

volatility.

4   Conclusion

Using an empirical model which allows us to consider non-linearities in the response to geopolitical risk shocks, our analysis sheds light on the intricate dynamics surrounding geopolitical risk shocks and their impact on the economy. Firstly, our investigation highlights the importance of considering both linear and non-linear components when assessing the effects of geopolitical risk shocks. While smaller shocks may not significantly trigger non-linearities, larger magnitude shocks tend to unveil pronounced non-linear effects, particularly through channels such as increased uncertainty and speculative behaviours. Secondly, we note that when non-linearities kick-in, uncertainty spikes in response to GPR shocks reverberating through equity prices and real consumption, suggesting that this is a crucial channel for the transmission of geopolitical risk shocks. This channel does not play a role when the size of GPR shocks is small. Thirdly, our exploration into the role of threat and act-based geopolitical risk indices reveals that threat shocks, akin to uncertainty shocks, incite speculative

demand for oil as markets anticipate potential future disruptions pushing oil prices and CPI up, while act shocks prompt significant negative price reactions, similarly to negative demand shocks.

Furthermore, our robustness checks underscore the resilience of our findings across various model specifications and sample periods, reaffirming the robustness of our conclusions.

Overall, our study contributes to the growing literature on the economic implications of geopolitical risk by offering nuanced insights into the transmission mechanisms and non-linear effects of such shocks. These findings hold significant implications for policymakers and market participants, emphasizing the importance of understanding the source of geopolitical shocks to better calibrate their policy response and safeguarding economic and financial stability.

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A   Appendix: Table

Appendix Table B1. Variables Used in the Analysis, Their Descriptions, Sources and Transformation

Variable	Description	Source	Transformation
GPR	Geopolitical Risk Index	Caldara and Iacoviello (2022)	log(x)*100
VIX	CBOE Volatility Index	Chicago Board Options Exchange	Levels
S&P500	S&P 500 Index, deflated by Consumer Price Index for All Urban Consumers	Standard & Poor's	log(x)*100
Ind. Production	Industrial Production Index	Federal Reserve Board	log(x)*100
CPI	Consumer Price Index for All Urban Consumers	Bureau of Labor Statistics	log(x)
Real Cons.	Real Consumption Expenditure	Bureau of Economic Analysis	log(x)*100
Int. Rate	Fed Funds Rate	Federal Reserve Board	Levels
Real oil price	West Texas Intermediate price of oil, divided by the Consumer Price Index for All Urban Consumers	Energy Information Admin and Chicago Mercantile Exchange	log(x)*100

Note: All variables sourced via Haver Analytics. The Federal Funds Rate has been augmented with the US Shadow Rate from Wu and Xia (2016).

B Appendix: Robustness and additional figures

Appendix Figure B1. Impulse Response Functions of the VARX using the linear and the non-linear GPR shock.
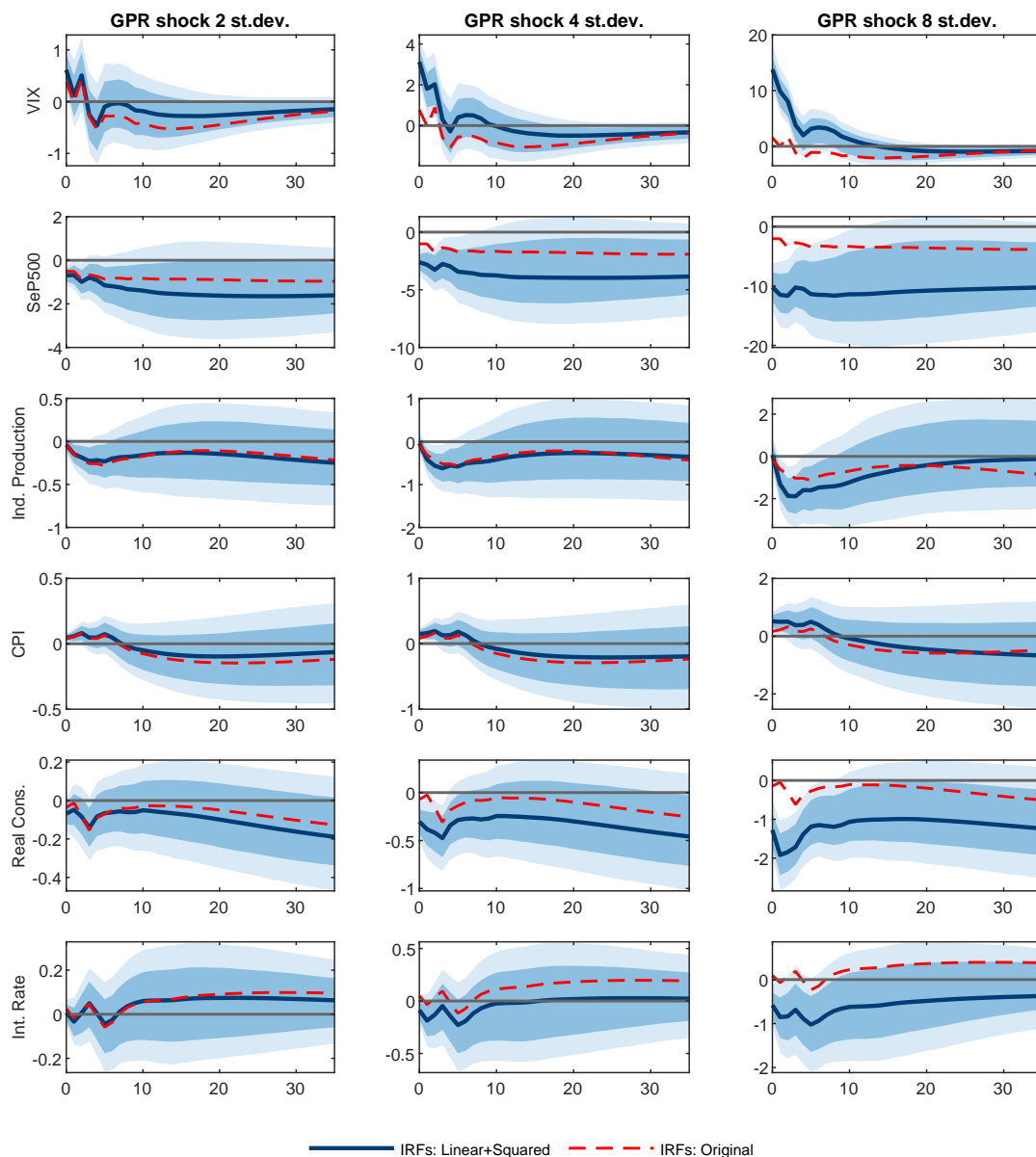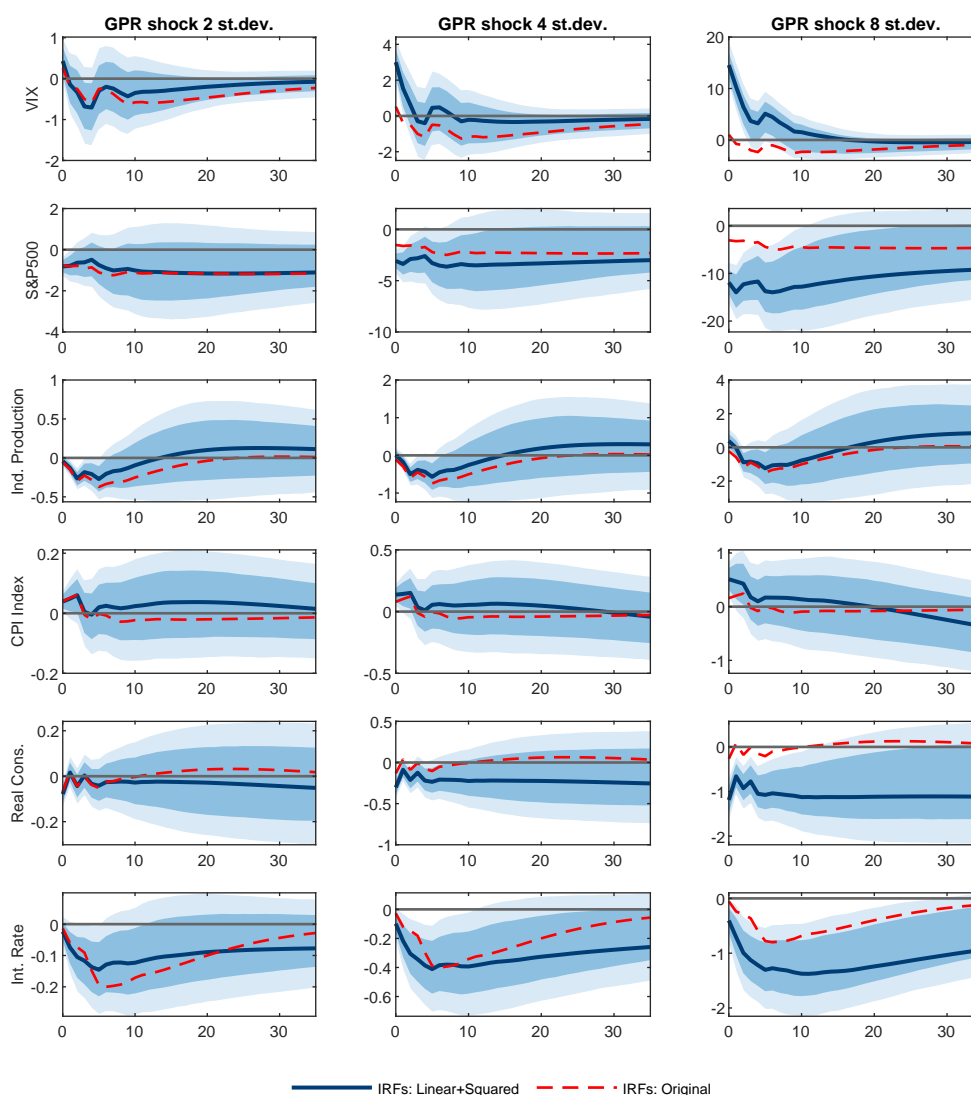

Notes: *Baseline specification with all the variables plotted together. The solid blue line represents the point estimate of the overall linear and non-linear responses estimated in the second step, while the shaded bands the 68% and 90% confidence intervals estimated via bootstrap. The dashed red line shows the responses of the first step SVAR. Each column depicts a different standard deviation of the shock.*

Appendix Figure B2. Robustness: p=8

IRFs: Linear+Squared — — — IRFs: Original
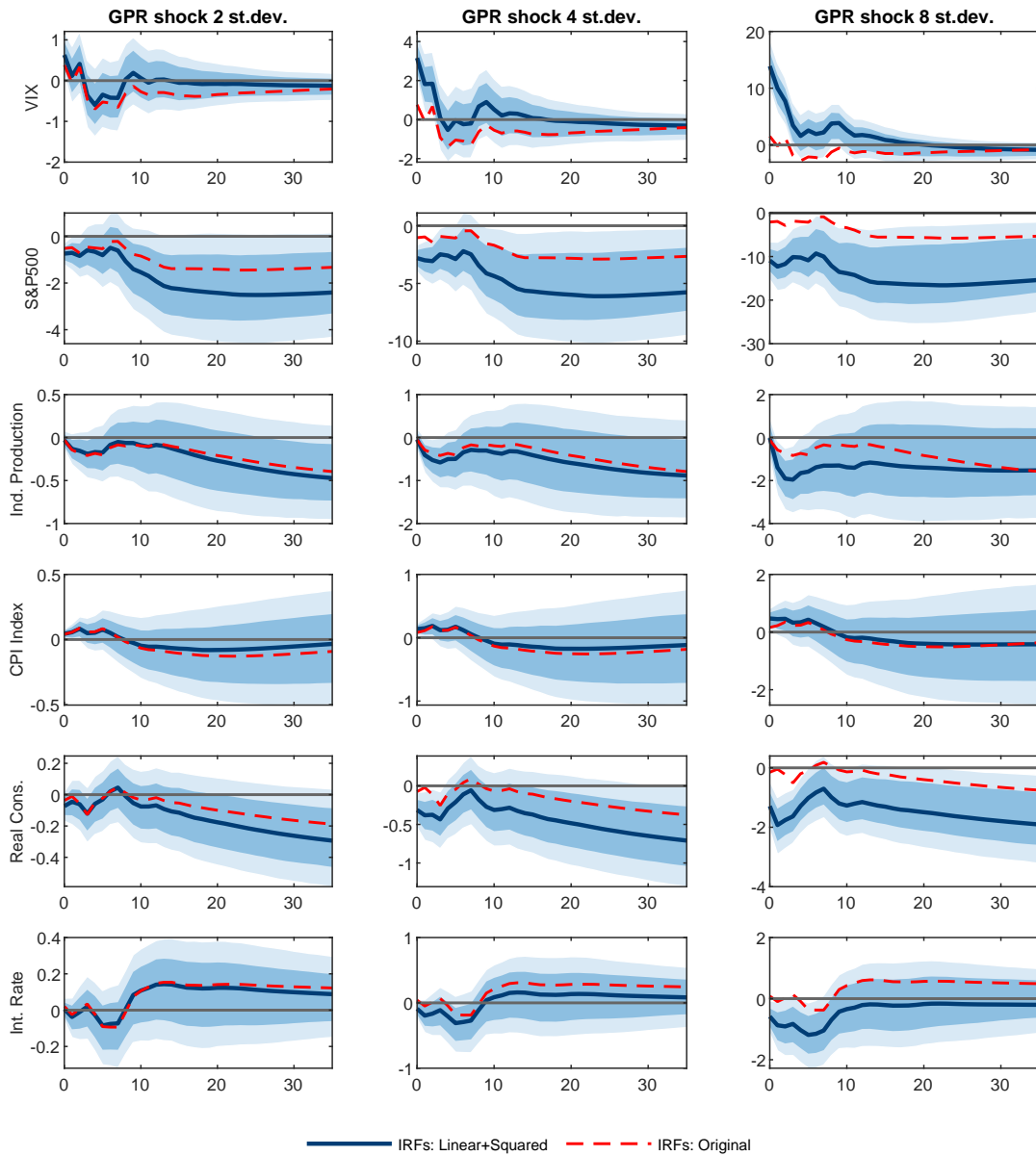
Notes: Robustness: p=8. The solid blue line represents the point estimate of the overall linear and non-linear responses estimated in the second step, while the shaded bands the 68% and 90% confidence intervals estimated via bootstrap. The dashed red line shows the responses of the first step SVAR. Each column depicts a different standard deviation of the shock.

Appendix Figure B3. Robustness: p=12
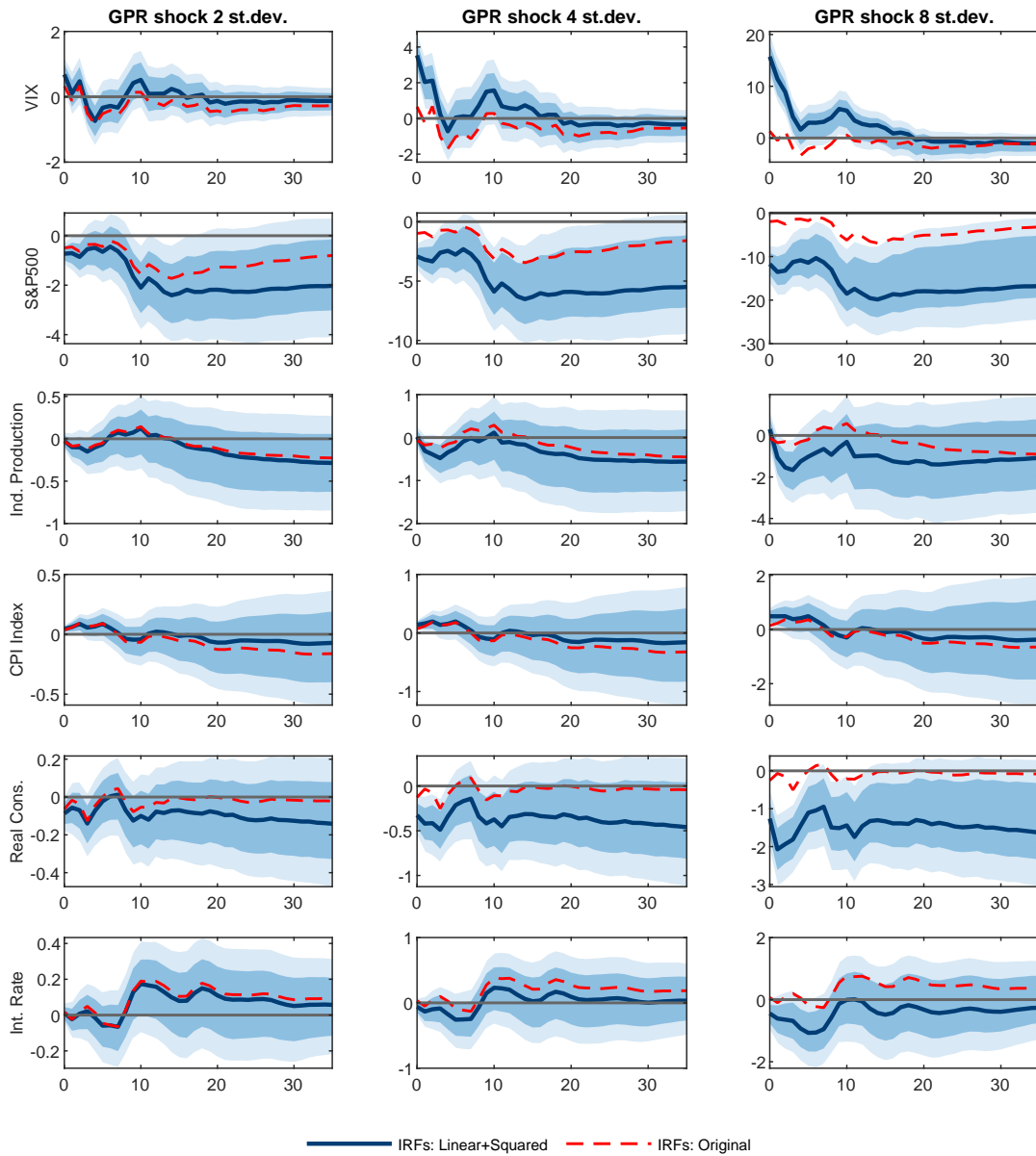
Notes: *Robustness: p=12. The solid blue line represents the point estimate of the overall linear and non-linear responses estimated in the second step, while the shaded bands the 68% and 90% confidence intervals estimated via bootstrap. The dashed red line shows the responses of the first step SVAR. Each column depicts a different standard deviation of the shock.*

Appendix Figure B4. Robustness: SVAR in difference

IRFs: Linear+Squared   IRFs: Original
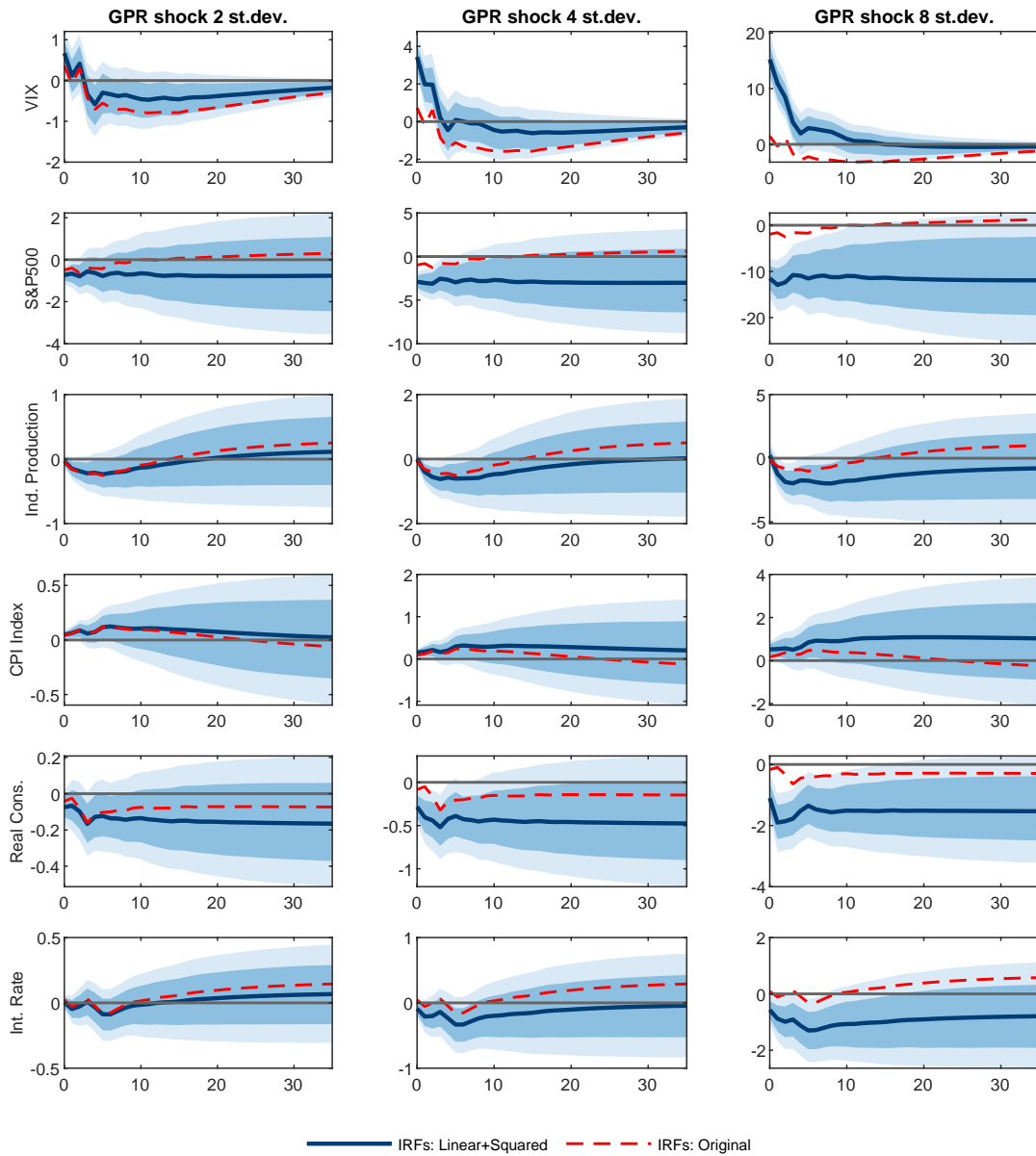
Notes: Robustness: SVAR in difference. The solid blue line represents the point estimate of the overall linear and non-linear responses estimated in the second step, while the shaded bands the 68% and 90% confidence intervals estimated via bootstrap. The dashed red line shows the responses of the first step SVAR. Each column depicts a different standard deviation of the shock.

Appendix Figure B5. Robustness: Caldara-Iacoviello Sample 1980-2019

IRFs: Linear+Squared   IRFs: Original

Notes:
Robustness: Sample 1980-2019 as the one used in the paper Caldara and Iacoviello (2022). The solid blue line represents the point estimate of the overall linear and non-linear responses estimated in the second step, while the shaded bands the 68% and 90% confidence intervals estimated via bootstrap. The dashed red line shows the responses of the first step SVAR. Each column depicts a different standard deviation of the shock.
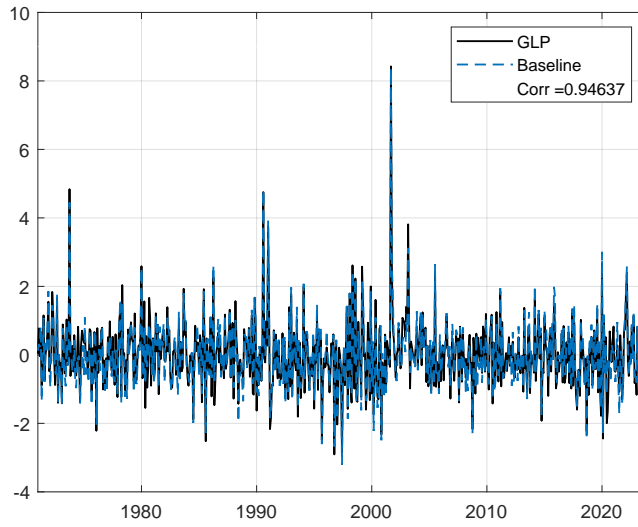
Appendix Figure B6. Caption
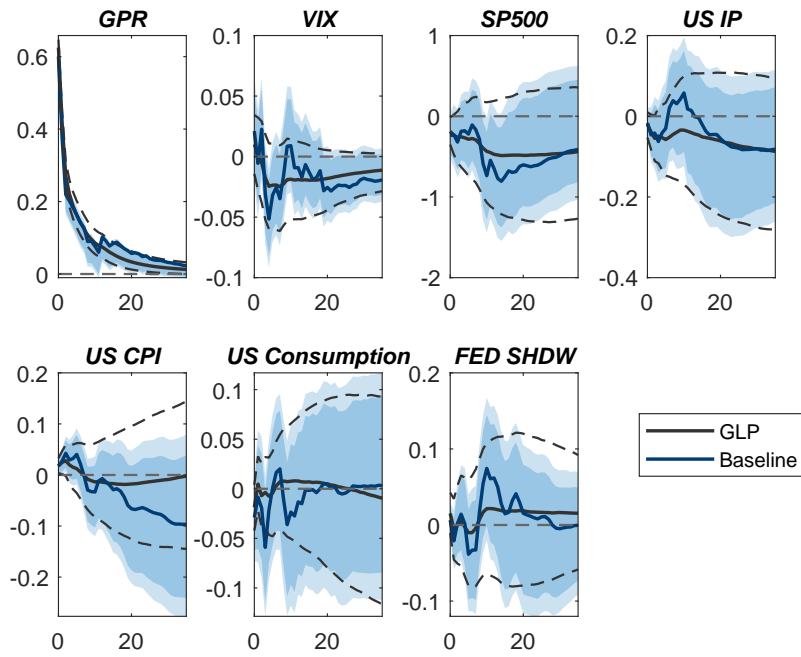
Appendix Figure B7. Caption

C   Appendix: GPRA vs GPRT

Appendix Figure C1. GPRA vs GPRT shocks
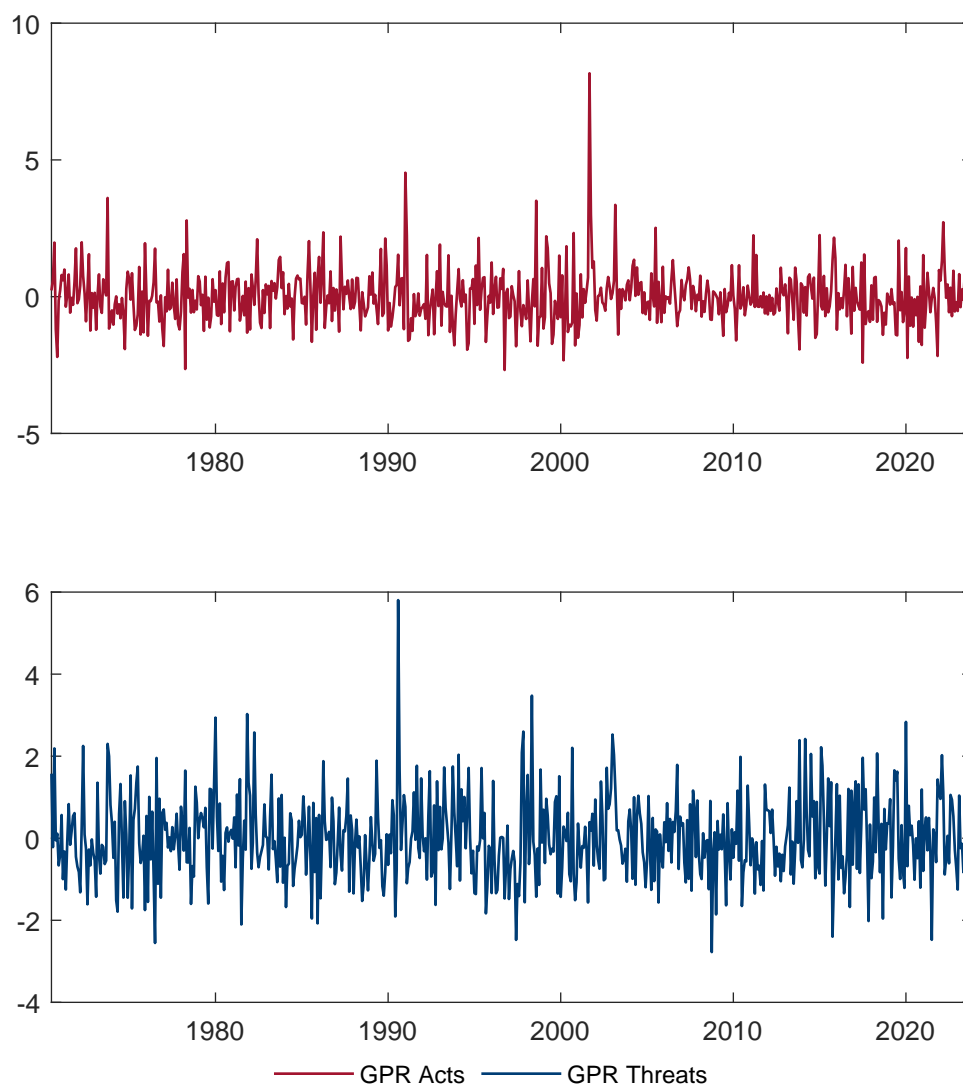
Appendix Figure C2. GPRA shock: Linear vs Non-Linear responses estimated from the VARX
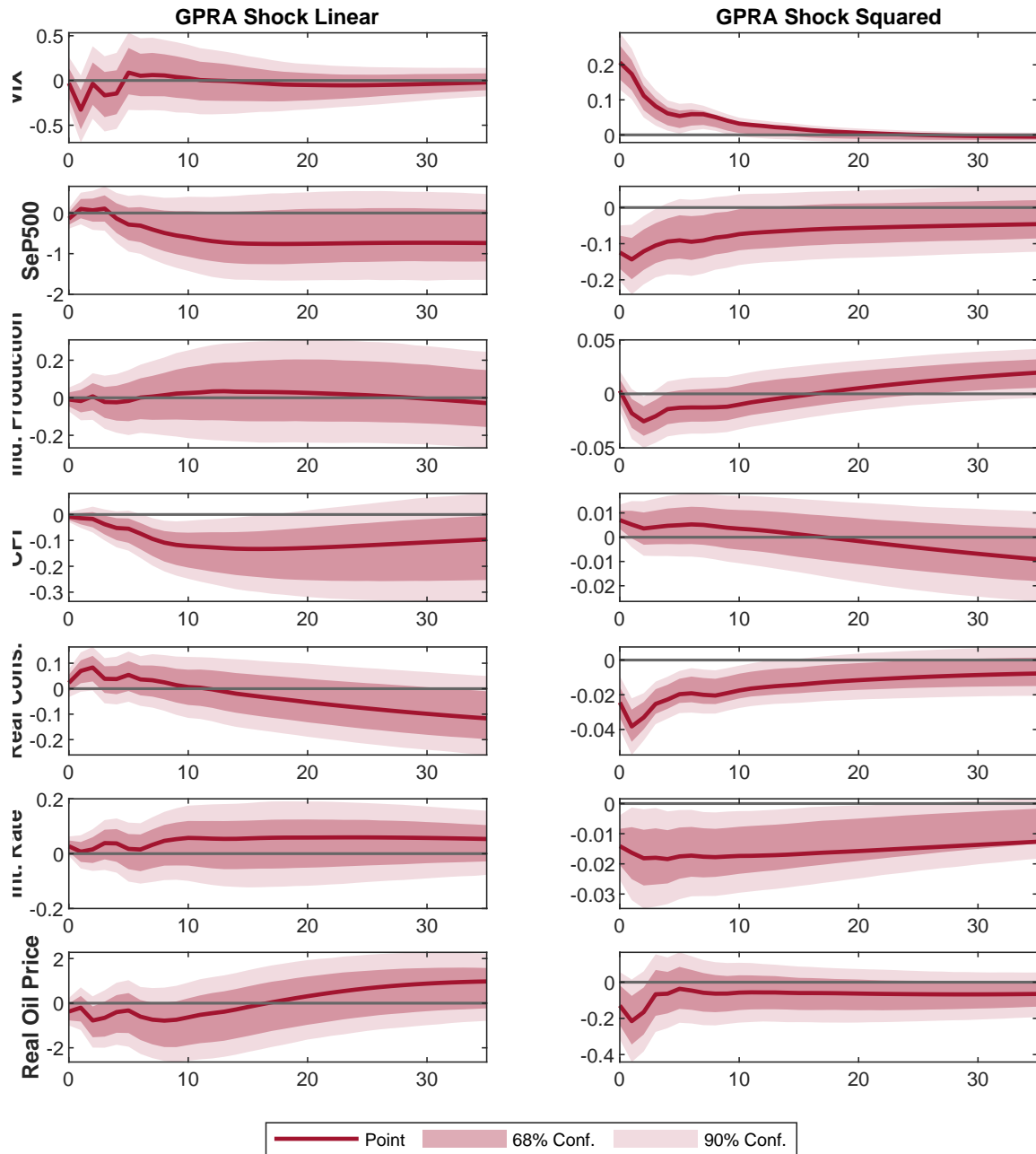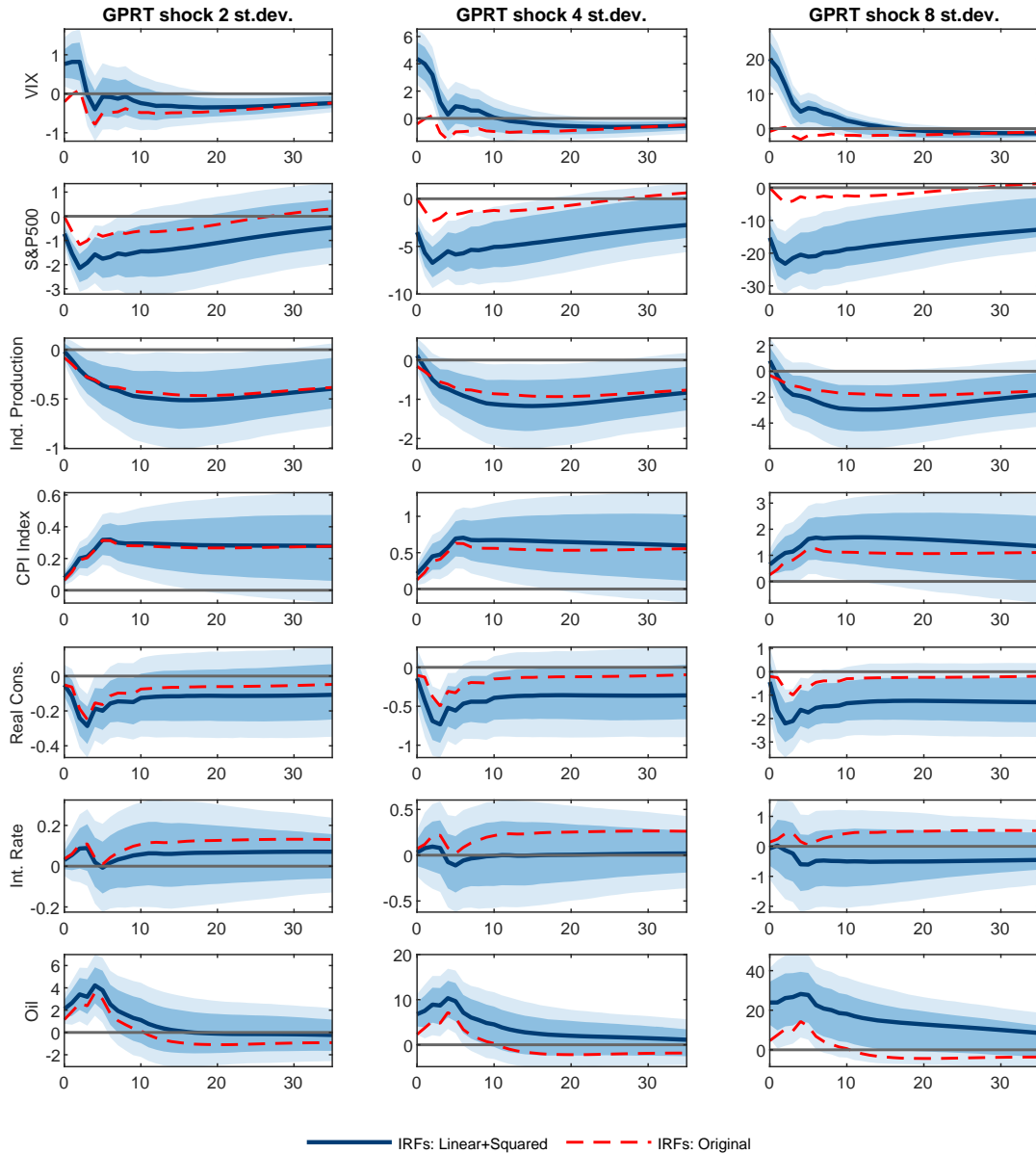

Notes: The solid blue line represents the point estimate, while the shaded bands the 68% and 90% confidence intervals estimated via bootstrap. The left column shows the responses to the linear shock, while the right column the responses to the non-linear shock.

Appendix Figure C3. GPRT shock: Linear vs Non-Linear responses estimated from the VARX
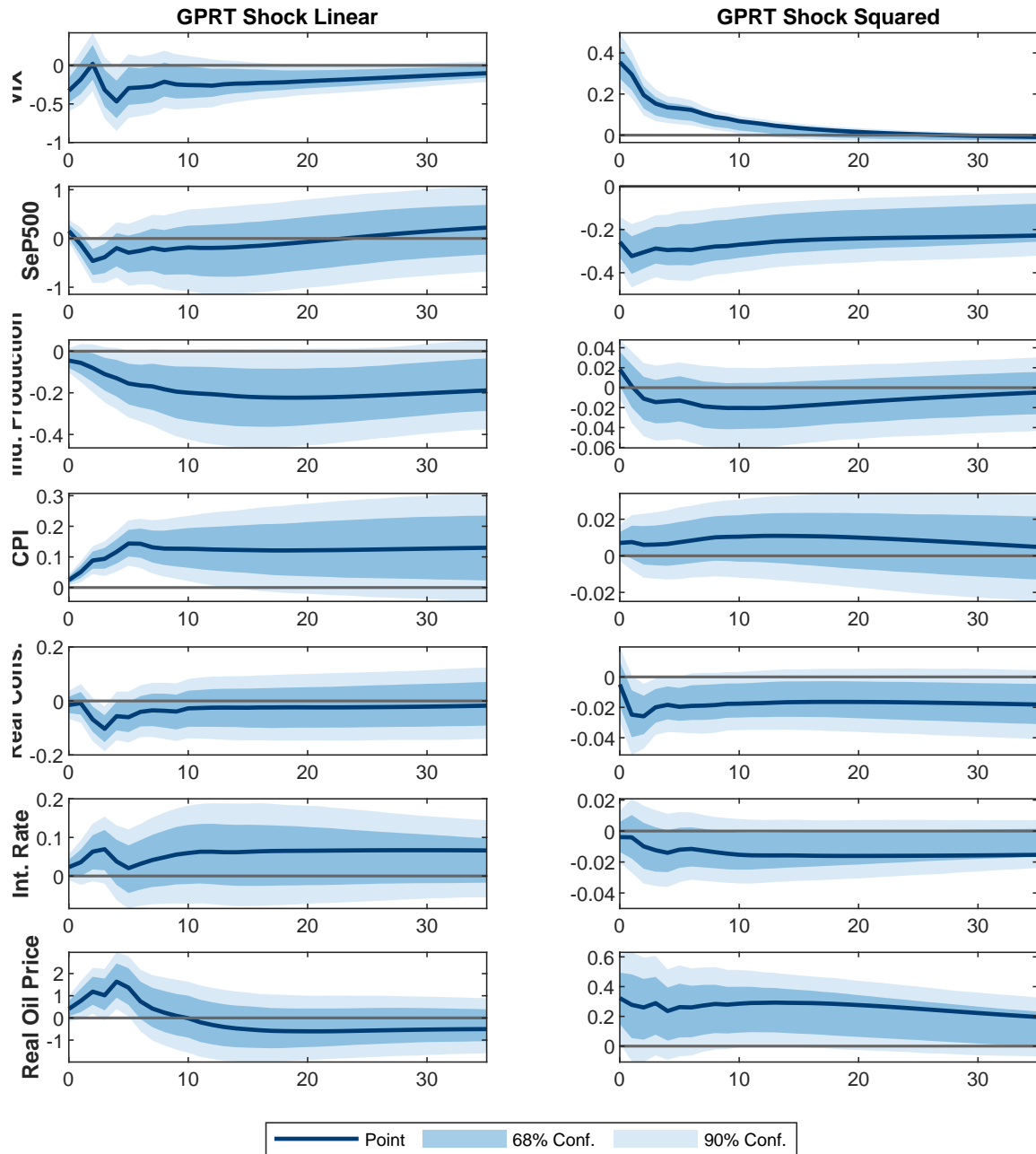
Notes: *The solid blue line represents the point estimate, while the shaded bands the 68% and 90% confidence intervals estimated via bootstrap. The left column shows the responses to the linear shock, while the right column the responses to the non-linear shock.*

Appendix Figure C4. GPRA: IRFs of the VARX summing the linear and the non-linear responses to a GPRA shock
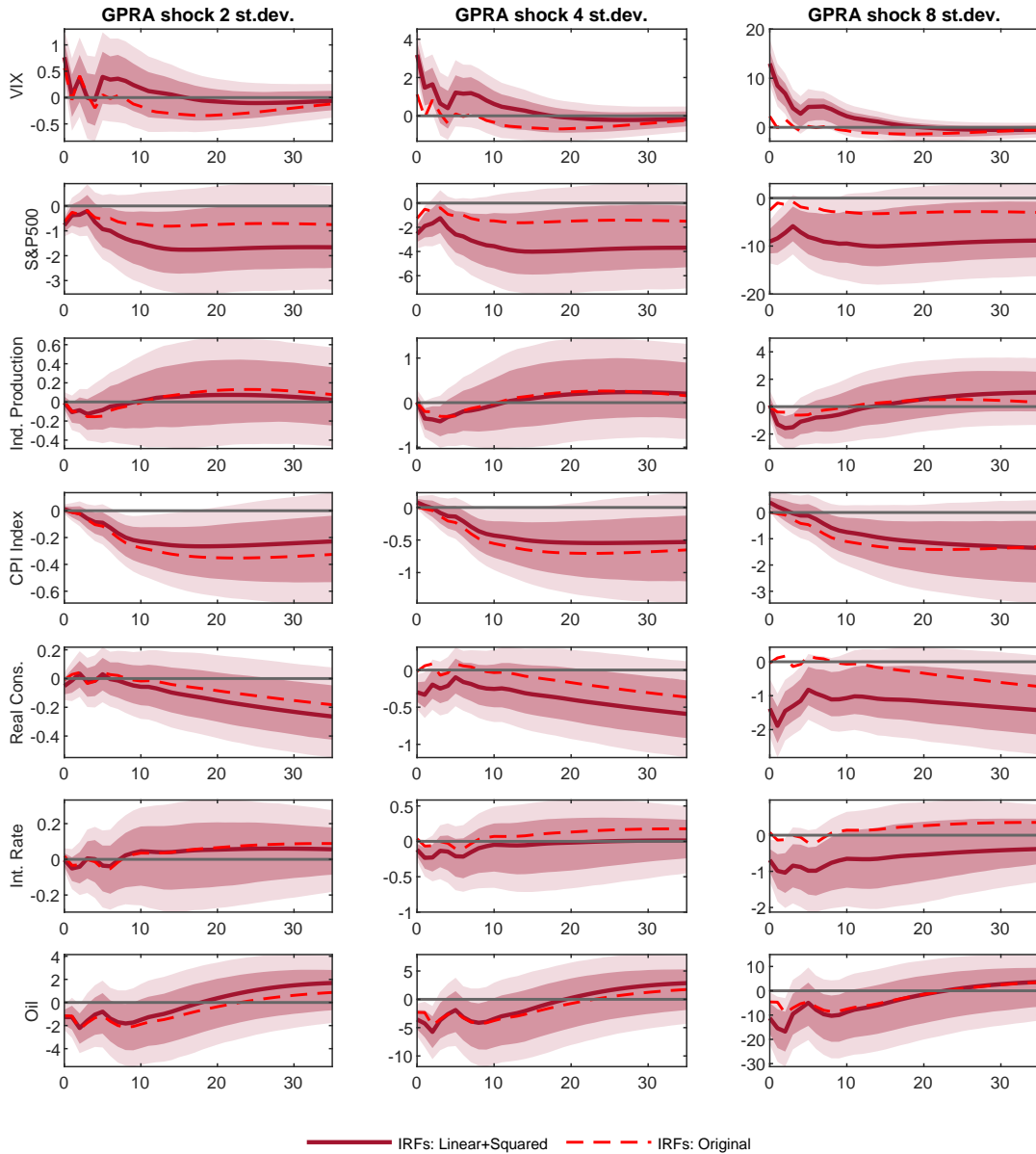
Notes: The solid blue line represents the point estimate of the overall linear and non-linear responses estimated in the second step, while the shaded bands the 68% and 90% confidence intervals estimated via bootstrap. The dashed red line shows the responses of the first step SVAR. Each column depicts a different standard deviation of the shock.

Appendix Figure C5. GPRT: IRFs of the VARX summing the linear and the non-linear responses to a GPRT shock

Notes: The solid blue line represents the point estimate of the overall linear and non-linear responses estimated in the second step, while the shaded bands the 68% and 90% confidence intervals estimated via bootstrap. The dashed red line shows the responses of the first step SVAR. Each column depicts a different standard deviation of the shock.

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