The Impact of the Russian-Ukrainian War on Global Financial Markets

Marwan Izzeldin
Lancaster University, Lancaster, LA1 4YW, UK
Email: m.izzeldin@lancaster.ac.uk

Gulnur Muradoglu
Queen Mary University of London, E1 4NS, UK
Email: y.g.muradoglu@qmul.ac.uk

Vasileios Pappas[1]
University of Kent, Kent, ME4 4TE, UK
Email: v.pappas@kent.ac.uk

Athina Petropoulou
SOAS University of London, WC1H 0XG, UK
Email: ap102@soas.ac.uk

Sheeja Sivaprasad
University of Westminster, London, NW1 5LS, UK
Email: s.sivaprasad@westminster.ac.uk

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Abstract

On February 24, 2022, Russia invaded the Ukraine. In this paper, we analyze the response of European and global stock markets alongside a representative sample of commodities. We compare the war response against the recent Covid-19 pandemic and the not-too-distant 2008 global financial crisis. Applying a Markov-switching HAR model on volatility proxies, estimates are made of synchronization, duration and intensity measures for each event. In broad terms, stock markets and commodities respond most rapidly to the Russian invasion; and post-invasion crisis intensity is noticeably smaller compared to both the Covid-19 and the GFC. Wheat and nickel are the most affected commodities due to the prominent exporter status of the two countries.

Keywords: Ukraine war, financial markets, HAR, Markov switching, commodities

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[1] *Corresponding author*: email: v.pappas@kent.ac.uk
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1. Introduction

On February 24, 2022 Russia invaded the Ukraine. Moscow's MOEX index dropped almost 9 per cent in the week following the invasion (Financial Times, 2022d). Stock market indices also registered significant losses, as Figure 1 shows. Far-reaching effects in Europe, and possibly the world, are only beginning to unfold. Supply chain disruptions amplify the upsurge in commodity prices, while a massive refugee influx unfolds with almost 7 million Ukrainians escaping their country.[2]

[Figure 1 around here]

The economic sanctions imposed in the US, Europe and elsewhere suggest that Russia's economy will contract significantly (Pestova, Mamonov, & Ongena, 2022). Rising energy revenues are unlikely to counteract the economic repercussions of the global pull out from Russia. This may prove the greatest hit to the global economy since the Global Financial Crisis (GFC) of 2008; and it may exceed the impact of Covid-19 given the prominent exporter status of the two countries. Countries in Europe, Central Asia, the Middle East and Africa import 75% of their wheat from Russia and Ukraine (World Bank, 2022b). Ukraine's exports of seed oil account for 40% of global exports. Over 13% of corn exports and 5% of wheat exports come from Ukraine. Russia accounts for 25% of global natural gas exports, 18% of coal exports, 11% of crude oil exports, 18% of wheat exports and 14% of fertilizers (World Bank, 2022b). With countries still in a recovery phase from Covid-19, the after-effects of the Russian invasion are likely to have a compounding effect financially. In the aftermath of Covid, forecasts indicated GDP growth of 3.9%; this has been revised to -3.6% (Financial Times, 2022b). Inflation was expected to rise by 7.5% in 2022 (European Commission, 2021). However, the impact on inflation will depend on monetary policy response and is yet to be realized.

[2] Source: https://data.unhcr.org/en/situations/ukraine

Following the invasion, several studies examined the impact of sanctions (Berner, Cecchetti, & Schoenholtz, 2022) on global financial markets (Deng, Leippold, Wagner, & Wang, 2022; L. Huang & Lu, 2022); on macroeconomic risks within the Euro area (Ferrara, Mogliani, & Sahuc, 2022); and on the international monetary system (Brunnermeier, James, & J-P, 2022). However, sanctions are variable across countries, business sectors and corporations.[3] Thus in this paper, we strategically steer away from the sanctions-based literature and examine the impact of the Russian-Ukrainian war on financial market volatility. We obtain and analyse estimates of synchronization, duration and intensity of stock markets and representative commodities for various segments (i.e., energy, precious metals, agricultural and base materials). We also draw comparisons with the impact of the 2008 GFC and the Covid-19 pandemic. These three events constitute the main shocks to the global economy over the past fifteen years. For our research design we employ a Markov-switching HAR model on daily volatility proxies around each crisis. This allows for endogenously identified regime shifts upon which basis we compute metrics for the synchronization, duration, and intensity of each crisis.

The paper contributes to the fast-emerging literature on the impact of the Russian-Ukrainian war upon economic and financial outcomes. Our results show an instantaneous reaction of world stock markets to the Russian-Ukrainian war. This suggests that the invasion was interpreted as “real news” by investors. The timeliness of the response is unlike that of either the GFC or the Covid-19 crises, where a lag of up to seven days is evidenced. The crisis duration metrics, however, suggest that the severity of the Russian-Ukrainian war has been muted compared to either the GFC or the Covid-19. We attribute this to an expectation that the war would not be prolonged. Moreover, it is possible that investors mis-interpret this event.

[3] An extensive list of the sanctions imposed is available by Reuters here: https://graphics.reuters.com/UKRAINE-CRISIS/SANCTIONS/byvrjenzmve/

Past war-like experiences have been markedly different; they have primarily involved one-off terrorist attacks, have been beyond the European continent, and were not met by widespread sanctions. Thereby investors may have been falsely drawing insights from such prior experiences. Commodity insights concur with the stock markets in all but one aspect: intensity. Despite average intensity values being comparable to both the GFC and the Covid-19, specific commodities (e.g., wheat, nickel, lead) reveal strong ongoing pressure in this asset class following the Russian-Ukrainian war crisis. Given the strategic importance to the economy of the affected commodities implications on inflation and supply chain are yet to unfold.

The rest of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 presents a synopsis of the data and the methodology. Section 4 presents and discusses the empirical findings. Robustness analysis is presented in section 5. A final section concludes.

2. Background information

2.1 Volatility and global financial markets

Volatility is important for analysing risk in financial markets; however, it is not directly observable. The increased availability of intraday data has shifted attention to realised measures for volatility modelling. Realised volatility (RV) has been shown to dominate several parametric approximations, including GARCH-type and stochastic volatility (SV) models (Andersen, Bollerslev, Diebold, & Labys, 2003). Volatility is highly persistent, and the flexible and easy-to-estimate heterogeneous autoregressive (HAR) (Corsi, 2009) has emerged as a modelling workhorse (Bollerslev, 2022; Bollerslev, Li, Patton, & Quaedvlieg, 2020; Bollerslev, Patton, & Quaedvlieg, 2016, 2018). That volatility is affected by economic shocks is well-known. To capture structural breaks a variety of transition models may be embedded within the HAR framework.[4] For example, Izzeldin et al. (2021) utilize a smooth-transition HAR (ST-HAR) to identify intensity, timeliness, and homogeneity of the Covid-19 crisis upon G7 stock markets. Parametric models of volatility estimation can also allow for similar dynamics, see for example Pappas et al. (2016) who use a Markov-switching multivariate DCC-GARCH model to examine the synchronicity of the GFC crisis upon European stock markets. Yip et al. (2020) examine the volatility spill-over effects between oil and agricultural products using a Markov-switching setup.

2.2 Global financial markets and geopolitical events

In figure 2 we compare the volatility reaction of financial markets to major geopolitical and key historical events over the last century. Using the S&P 500 index due to its long data availability, we calculate two volatility proxies, namely the realised volatility as the sum of squared returns over the past 22 trading days, and the conditional volatility estimated from a GARCH(1,1) model. In addition, we plot Economic Policy Uncertainty (EPU), which is a news-based indicator, and the historical Geopolitical Risk Index (GPRH), which gauges adverse geopolitical events and related risks obtained from a variety of news-based outlets.[5]

[Figure 2 around here]

Financial markets respond to a wide array of geopolitical events. The sample under consideration contains wars, invasions, terrorist attacks and periods of tension. A cursory inspection finds the response of global financial markets to the Russian-Ukrainian war to be relatively muted compared to other financial crises (e.g., the 2008 Lehman collapse, the 1987

[4] A variety of transition models have been used that typically can be classified according to the nature dynamics they introduce (i.e., discrete, or smooth), the break identification (i.e., exogenous or endogenous) and the number of breaks and regimes allowed. We direct you to Hamilton (1989) and Tsay (2005) for an in-depth discussion.
[5] Due to data limitations EPU data are available from 1985 onwards, see Baker et al. (2016) for details. Caldara and Iacoviello (2022) construct the geopolitical risk index, which is available here. We use the "historical version" for its extended coverage. The index is available here: https://www.matteoiacoviello.com/gpr.htm

Black Monday, and the Covid-19). However, it is more pronounced than that of several terrorist attacks (but not the 9/11) and other instances of war or invasions.

Though wars generally have a strong impact on financial markets, the relevant literature is limited. Not surprisingly, Wisniewski (2016) finds that wars result in widespread destruction of human and physical capital and stock markets fall. Berkman et al. (2011) investigate 447 international political crises – but not all are wars. They find that the global stock market returns would have been higher by 3.6% per annum but for these events. Hudson and Urquhart (2015) study the effect of the second world war (WWII, thereafter) on the British stock market and find that only one of the wartime events classified as important resulted in a structural break. Frey and Kucher (2000) examine the prices of the government bonds of five European countries during WWII. They find that the loss and gain of national sovereignty affected the bond prices of the countries. Frey and Kucher (2001) analyse government bond prices of Germany and Austria traded on the Swiss bourse during WWII. They show that war episodes are clearly reflected in government bond prices. Brown Jr and Burdekin (2002) study German bonds traded on the London stock exchange during WWII and document a negative impact on only two events during the entire conflict course. Waldenström and Frey (2008) observe sudden shifts in sovereign debt yields and spreads in the Nordic bond markets during WWII. Frey and Waldenström (2004) compare sovereign debt prices on the Zurich and Stockholm stock exchanges and conclude that market efficiency has not been affected by WWII.

Some studies examine the impact of US military engagements upon financial markets. Leigh et al. (2003) analyse financial market data to assess the economic consequences of the war with Iraq. They find that net oil importers are most likely to experience adverse effects from the war. Also in respect of Iraq, Rigobon and Sack (2005) find that war risk is associated with declines in Treasury bond yields and equity prices. Amihud and Wohl (2004) find that the Iraqi war is associated with rising stock prices. Perhaps an increasing probability that Saddam

Hussein would be deposed was interpreted as good news by stock market investors. Choudhry (2010) apply a structural break test to investigate the structural shifts in returns and volatility and determine whether such shifts are associated with the events of WWII. Omar et al. (2017) analyse the impact of 64 instances of severe international crisis and classify 43 events as the "war sample". Their event window starts 50 trading days before the outbreak of war and ends 50 trading days thereafter. They find that returns were -3.47% for the World stock market index and -4.67% for S&P 500. Wisniewski (2009) examine the impact of WWII, the Korean war and other US military engagements and provide evidence of how these events are negatively related to the market value of stocks. Based on the discussion above, we conclude that the impact of wars on stock markets and other asset classes is detrimental.

2.3 Covid-19 and global financial markets

The novel corona virus (COVID-19) was first detected in China in December 2019, and the World Health Organization (WHO) declared a pandemic in the following mid-March. The response across financial markets was dire. In a month, the Dow Jones and the S&P 500 fell by 35% and the volatility of the financial markets was comparable to the 2008 GFC (Baker et al., 2020). To curtail the spread rate, governments introduced widespread lockdown measures that impeded global economic activity. Business sectors and countries were affected; relatedly Izzeldin et al. (2021) find adverse effects on all sectors but for the Technology firms, which weathered the pandemic better. Sergi et al. (2021) show that economic outcomes, as tracked by the Barro Misery Index (BMI), are driven by the Covid-19 related cases and deaths, and are reflected on stock market return volatility. Benkraiem et al. (2022) conclude that financial contagion is more intense in America than in Asia.

3. Data and Methodology

3.1 Data

We examine global financial market reactions in three crises events, namely the 2008 Global Financial Crisis, the Covid-19 pandemic, and the 2022 Russian invasion of Ukraine. For each event, we use the [-3,3] months estimation window using daily data.[6] Our choice of the benchmark date ($t = 0$) on each occasion is: i) the Lehman Brothers collapse on 15/9/2008; ii) the announcement of Italy's lockdown on 9/3/2020; iii) the invasion day on 24/2/2022, respectively.[7]

Volatility data for the stock markets comprise the realised variance for a selection of global stock markets obtained from the OxfordMan institute realized library.[8] *Realised variance* (RV) is calculated as the sum of squared intraday returns (Andersen, Bollerslev, Diebold, & Ebens, 2001; Andersen et al., 2003; Barndorff-Nielsen & Shephard, 2002) as:

$$RV_t = \sum_{j=1}^{K} r_{t,j}^2 \tag{1}$$

where j subscripts each of the K equally spaced 5-minute subintervals in each day. We compute the realised volatility and express it in percentage annualized format for the rest of the analysis.

Volatility data for the commodities are not available via the realized library. Hence, we resort to conditional parametric volatility estimators of the GARCH family. Specifically, consider a $T \times 1$ vector of demeaned asset returns r_t, the conditional variance is estimated as a GARCH(1,1) process:

$$r_t | \mathcal{F}_{t-1} \sim N(0, h_t^2) \tag{2}$$

[6] Our window length choice is consistent with Omar et al. (2017). As robustness we also use a larger window [-6,6] months for the 2008 GFC and the Covid-19 crisis and the results remain qualitatively similar. Thus, we retain our [-3,3] specification for consistency purposes across the three events.
[7] For the Covid-19 event benchmark date we concur with the Nozawa and Qiu (2021) study.
[8] The realised measures are obtained from the Oxford Man Institute of Quantitative Finance database here: https://www.oxford-man.ox.ac.uk/our-research/realized-library/

$$h_t^2 = \omega + au_{t-1}^2 + br_{t-1}^2 \quad (3)$$

Subsequently we compute the conditional volatility and express it in percentage annualized format for the rest of the analysis.

Table 1 presents key descriptive statistics for the realised volatility across the sampled countries for the three crisis periods under examination. Brazil, Norway and Denmark emerge as the countries with the highest average realised volatility for the GFC, Covid-19 and Russian-Ukrainian war crises respectively. By contrast, Singapore exhibits the lowest average realized volatility during the GFC and war periods, and the second lowest during the Covid-19.

[Table 1 around here]

Table 2 presents key descriptive statistics for the conditional volatility of commodities over the three periods of crisis under examination. Lead, oil and natural gas are the commodities with the highest average conditional volatility for the GFC, Covid-19 and Russian-Ukrainian war periods respectively. By contrast, gold exhibits the lowest average conditional volatility during the GFC and Russian-Ukrainian war periods. Soyabean shows the lowest conditional volatility during the Covid-19.

[Table 2 around here]

3.2 Methodology

Modelling realised measures has relied extensively on the heterogeneous autoregressive model (HAR) (Corsi, 2009). The superior performance of the HAR in modelling and forecasting realised volatility is well-established (Bollerslev, 2022; Bollerslev et al., 2020, 2016). Compared to ARFIMA, estimation and forecasting are more easily obtained from HAR models. Following Corsi (2009) the HAR model is defined as:

$$h_t = c + \beta^{(d)} h_{t-1} + \beta^{(w)} h_t^{(w)} + \beta^{(m)} h_t^{(m)} + e_t \tag{4}$$

where $e_t \sim iid(0, \sigma^2)$ with $h_t^{(w)}$ and $h_t^{(m)}$ defined as follows:

$$h_t^{(w)} = \frac{1}{5}(h_{t-1} + h_{t-2} + h_{t-3} + h_{t-4} + h_{t-5}) \tag{5}$$

$$h_t^{(m)} = \frac{1}{22}(h_{t-1} + h_{t-2} + \cdots + h_{t-21} + h_{t-22}) \tag{6}$$

To allow for non-linear dynamics in the volatility process we allow for a Markov-switching structure. Markov-switching models have been used in conjunction with the GARCH family of models for similar purposes in Pappas et al. (2016). By contrast, Izzeldin et al. (2021) use a smooth transition variant of the HAR to accommodate crisis periods. Contrary to smooth-transition models, Markov-switching allows for a discrete shift in the regime, which is more appropriate for our setup where we compare financial market volatility during the three crises.[9] Markov-switching models utilise a latent state variable $(s_t = m)$ to denote the state m of the economy in period t, with $m = 1, \dots, M$. By construction, a Markov-switching model estimates the transition probability from the data. To allow for more realistic dynamics during each of the turmoil periods, we assume that the HAR parameters related to the weekly and monthly volatility are regime invariant. The following Markov-switching HAR model is estimated using maximum likelihood and robust standard error:

$$h_t = c_{s_t} + \beta_{s_t}^{(d)} h_{t-1} + \beta^{(w)} h_t^{(w)} + \beta^{(m)} h_t^{(m)} + e_t \tag{7}$$

where the regime probabilities are given as:

$$\Pr\left(s_t = m_i | s_{t-1} = m_j\right) \; \forall \; i, j = 0,1 \tag{8}$$

For each of the three financial crises under consideration, we compute synchronization, duration and intensity measures following Pappas et al. (2016). To assess the synchronization

[9] For robustness we estimate a smooth-transition HAR model. The results of this analysis are in the robustness section.

of each financial crisis, we compare the estimated crisis transition date for each index (T_i) with the respective benchmark date (T^*). In particular,

$$Sync\ (days)_i = T_i - T^* \tag{9}$$

where i indexes the index. Positive (negative) values indicate a lag (lead) in the transition, relative to the benchmark date for the particular index.

The duration of each crisis is measured as the time spent within the crisis regime, as identified by the MS-HAR model. It is expressed in days and as percentage, formally as:

$$Duration\ (days)_i = \sum_{t_i=T_i}^{T} t_i | s_{t_i} = 1 \tag{10}$$

and

$$Duration\ (\%)_i = \frac{\sum_{t_i=T_i}^{T} t_i | s_{t_i} = 1}{\sum_{t_i=T_i}^{T} t_i | s_{t_i} = 1 + \sum_{t_i=T_i}^{T} t_i | s_{t_i} = 0} \tag{11}$$

where $s_{t_i} = (0)1$ denotes the crisis (calm) regime for each i index.

The intensity of the crisis is defined as the percentage logarithmic change in the volatility level between the two regimes, following the transition to the crisis event. Higher values of the intensity denote a stronger crisis experience. Crisis intensity is defined as:

$$Intensity\ (\%)_i = \ln\left(\frac{\sum_{t_i=T_i}^{T} h_{t_i,i} | s_{t_i} = 1 / \left(\sum_{t_i=T_i}^{T} t_i | s_{t_i} = 1\right)}{\sum_{t_i=T_i}^{T} h_{t_i,i} | s_{t_i} = 0 / \left(\sum_{t_i=T_i}^{T} t_i | s_{t_i} = 0\right)}\right) \tag{12}$$

To be classified within a regime, we require a minimum probability threshold equal to 0.80.[10]

4. Results

[10] We conduct robustness analysis to this value, in the range of [0.70-0.90] and our results are qualitatively similar.

4.1 Global stock markets

Figures 3 and 4 present the realised volatility (rebased at 1) for each crisis event and for a representative sample of countries. The threshold line is centred at each crisis date, with the graph showing the pre- and post-three-month evolution window. A cursory inspection finds the response during the Covid-19 to be more pronounced than the GFC and the Russian-Ukrainian war events.

[Figures 3 and 4 here]

Table 3 presents the synchronization, duration and intensity measures for each of the GFC, Covid-19 and Russian-Ukrainian war crises. In each table, we report the median for each country and the median values for key country groupings namely the G7 economies, the European countries, and the rest of the world (RoW). Next, we discuss these results by measure focusing on Europe. Crisis synchronization median values suggest an instantaneous reaction of stock markets to the invasion news. This is observed for the Europe group, but also for the G7 and the RoW groups. The timeliness of the response is unlike those pertaining to the GFC or Covid-19 events. In the GFC crisis, synchronization show Europe to respond with a 4-day lag, and the G7 taking the longest at seven days. During the Covid-19, Europe responds at a 1-day lag; yet G7 and RoW take longer.

Coming now to discuss percentage duration, we find Europe values at 7.25%, suggesting that stock markets spent a significantly shorter period in the crisis regime compared to the GFC, and the Covid-19. A similar result is observed for the RoW countries. We discuss intensity values next. Our results show that crisis intensity for Europe following the Russian-Ukrainian war stands at 89.89%, significantly higher than either the GFC (at 73.76%) or the Covid-19 (at 82.16%). The G7 and RoW values during the Russian-Ukrainian war are 69.08% and 71.31% respectively. Interestingly, these values are lower for the G7 group compared to both the GFC and the Covid-19 (77.67% and 86.70% respectively), however they are comparable across all crises for the RoW group.

In summary our analysis of the stock markets here suggests that their volatility response to the Russian-Ukrainian war crisis has been instantaneous. This is unlike the GFC or Covid-19 where a certain lag was observed. We believe that the instantaneous reaction of stock markets shows that the invasion was interpreted as "real news" by investors. Despite the prolonged summoning of Russian forces at the Ukrainian borders, an actual invasion had not been discounted by the markets and was considered unlikely, until it materialized. The crisis intensity, however, suggests that the severity of the Russian-Ukrainian war has been, on a global scale, muted compared to either the GFC or the Covid-19. We find this puzzling given the severity of such an incident. It is plausible that investors mis-interpret this event. Past warlike experiences have been markedly different in the sense that they involve mainly one-off terrorist attacks and/or have been away from the European continent. Thereby investors may be falsely drawing insights from such prior experiences and underestimating the real implications of the Russian-Ukrainian war (Financial Times, 2022e; The Guardian, 2022b). However, as Russia's aggression in Ukraine remains unabated, the world seems to embrace that the transition into a long-term conflict appears a likely scenario (BBC, 2022; Financial Times, 2022a). Besides, the prolonged conflict has even led banks to downgrade their growth forecasts (JP Morgan, 2022).

[Table 3 around here]

4.2 Commodities

Figures 5 and 6 present the conditional volatility of commodities (rebased at 1) for each crisis event and for a representative sample of commodities. The threshold line is centered at each crisis date, with the graph showing the pre- and post-three-month evolution window. A cursory inspection of the graphs shows that commodities are affected in a comparable way across the three crisis events. Furthermore, the nature of each crisis appears to be particularly relevant for specific commodities. Base materials such as copper and nickel are more affected following the GFC, whereas oil is more affected following the Covid-19 crisis. The Russian-Ukrainian war crisis appears to have had a more profound impact on the agricultural commodities and nickel.

[Figures 5 and 6 here]

Table 4 presents the synchronization, duration and intensity measures for all commodities in our sample. In addition, we report median values for all commodities and for each commodity segment (i.e., energy, precious metals, agricultural and base materials). We discuss synchronization, duration and intensity measures in turn, starting by the overall commodity measures and then focusing on the specific commodity segments. Crisis synchronization median values suggest that commodities respond with a 2-day lag after the invasion materialized; this is earlier than either the GFC or the Covid-19 crises. The early response of commodities is largely driven by the precious metals and base materials that have reacted faster. Agricultural commodities responded with a 2-day lag, which is comparable to the GFC crisis results. By contrast, the agricultural commodities reacted latest in the Covid-19 crisis, with a 17-day lag.

We now proceed to discuss percentage duration values. During the Russian-Ukrainian war, the median duration has been at 6.42%, significantly lower than either the GFC (at 6.81%) or Covid-19 (at 7.38%) crises. High duration values are evidenced for precious and base metals. Agricultural commodities show approximately two times higher median duration value during the Russian-Ukrainian war compared to the Covid-19.

Commodity intensity during the Russian-Ukrainian war has been at 23.65%, which is similar to the other two crises. However, this aggregate result masks the heterogeneity across commodity segments. Specifically, crisis intensity during the Russian-Ukrainian war has been the highest for the base materials (at 38.26%) and lowest for the precious metals (at 18.36%). Within the agricultural commodities, with an intensity value of 48.87%, wheat is the most severely affected. The high crisis intensity value for wheat may be partially explained by the uncertainty over Ukraine and Russia, both within the largest exporters worldwide, being able to meet world demand (FAO, 2022). Nickel has been the most severely affected commodity with an intensity value at 116.65%. This is largely explained by the sanctions over Russia, a top-3 nickel exporter, in conjunction with rising demand that is associated with its use in electric vehicles (Daniel, 2022).

In sum our analysis for the commodities reveals that they have responded faster in the Russian-Ukrainian war compared to either of the GFC or Covid-19 crises. By contrast, the crisis duration and intensity values suggest that commodities have been affected during the Russian-Ukrainian war in a comparable way to the other two crises. Still, the particularly high duration and intensity values for specific commodities reflect the strong ongoing pressure on commodities and have been highlighted as a cause for concern. In particular, a stressed commodity market could have several ramifications, such as triggering food crises to putting pressure on the derivative trading platforms (Financial Times, 2022e).

[Table 4 around here]

5. Robustness

In the main analysis the transition between volatility regimes has been discrete and modelled via a Markov-switching HAR model. We perform a robustness check using a smooth transition specification, which allows for an analogue-like transition between regimes.[11] Common in both specifications is the endogenous identification of the transition between the regimes. In the smooth transition HAR (ST-HAR) model the transition between two regimes is governed by the exponential function, see Izzeldin et al. (2021) for more details. Of the HAR parameters, we assume the constant and the daily component to be regime dependent, while weekly and monthly volatility components are regime invariant. The following equation is estimated via nonlinear least square techniques and Newey-West robust standard errors:

$$
\begin{aligned}
h_t = \beta_0 + \beta^{(d)} h_{t-1} + \beta^{(w)} h_t^{(w)} + \beta^{(m)} h_t^{(m)} \\
+ \left(\delta_0 + \delta^{(d)} h_{t-1}\right) \times \left(1 - \exp\left(-\gamma/\sigma_{s_t}^2 (s_t - \psi)^2\right)\right) \\
+ e_t
\end{aligned}
\tag{13}
$$

where s_t is a threshold variable with unknown threshold (ψ) and slope (γ) values; β_0, δ_0 and $\beta^{(d)}, \delta^{(d)}$ are the threshold coefficients for the constant and the daily component respectively; ε_t is the stochastic error term. The threshold coefficient (ψ) gauges the synchronicity of the transition, with high (low) values indicating a lag (lead) in the transition. The slope coefficient may be interpreted as the transition speed between regimes, with high (low) values giving evidence towards an abrupt (gradual) shift.

Table 5 presents the median estimated slope and threshold parameters of the ST-HAR model for the stock markets (Panel A) and commodities (Panel B). Based on their estimated values we compare the transition patterns across regimes for each crisis.[12]

[11] See Teräsvirta (1994) for more details. Smooth transition models have been used in financial and economic context (Bradley & Jansen, 2004; Caggiano, Castelnuovo, & Figueres, 2017; Ghoshray, 2010; A. Huang & Hu, 2012; Tse, 2001; Zhang, 2013).

[12] For brevity we only report slope and threshold coefficients from the ST-HAR model; full results are available upon request from the authors.

[Table 5 around here]

As compared to either the GFC or the Covid-19 crisis, the lower threshold coefficient value during the Russian-Ukrainian war indicates the earlier response of the global stock markets (see Panel A) and commodities (see Panel B) to the event. Thus, it corroborates the main findings of the paper.

The slope coefficient is the highest for the G7 stock markets during the Russian-Ukrainian war (7.78) suggesting an abrupt regime change, more pronounced than either the Covid-19 (6.14) or the GFC (2.23). The fact that European stock markets respond in a smoother fashion to the Russian-Ukrainian war compared to the Covid-19 (1.55 vs 9.26) substantiates further our main finding that investors may be falsely assessing the severity and the duration of the event.

Similar to global stock markets, commodities record the largest slope coefficient during the Russian-Ukrainian war compared to either of the GFC or Covid-19 crisis. The abrupt transition is mainly driven by agricultural commodities (e.g., wheat) and base materials (e.g., nickel), a result that is consistent with the main analysis. Interestingly, precious materials show a more muted response compared to past crises.

5. Discussion and conclusions

The Russian-Ukrainian war has led to great volatility across global markets. We analyze the volatility response of European and global stock markets and a representative sample of commodities to the war crisis and compare it against the recent Covid-19 pandemic and the 2008 global financial crisis.

This study employs a Markov-switching HAR model on volatility proxies and obtains estimates of synchronization, duration and intensity for each crisis event. The Markov-switching HAR model allows for an endogenously identified regime shift.

Our results show an instantaneous reaction of global stock markets to the Russian-Ukrainian war, which suggests that the invasion was interpreted by investors as real news. This is markedly different to the GFC or the Covid-19 crises, where there was a lagged response. The crisis duration metrics suggest that the severity of the Russian-Ukrainian war has been muted compared to either the GFC or the Covid-19. We attribute this to the market expectations that the war would not be prolonged. The findings for commodity markets concur with that of stock markets except for one aspect: *intensity*. Commodities generally appear to have weathered the Russian-Ukrainian war crisis in a similar way to the Covid-19 and GFC crises. However, crisis intensity values for specific commodities reveal strong ongoing pressure in this asset class, and to the economy given the strategic importance of some of these commodities.

In the short-term the Russian-Ukrainian war is expected lead to lower economic growth and rising inflation. Annual GDP growth in 2023 is projected to slow to 2.25% worldwide, to 0.5% in the US and to 0.25% in the Euro area; well below pre-war forecasts (OECD, 2022). Following the gradual global economic recovery from the Covid-19 pandemic, inflationary pressure had already been building up. However, the Russian-Ukrainian war, with its impact on energy and food prices, has accelerated the inflationary pressure worldwide.[13] On the energy front, the heavy reliance of the EU on Russia leaves the former vulnerable to gas supply reductions through the Nord Stream 1 pipeline (Eurostat, 2022; Financial Times, 2022c; World Bank, 2022c). Besides, the within-EU heterogeneity on gas reliance leaves the union vulnerable to political tension, for example over the proposed 15% voluntary reduction in gas usage (The Guardian, 2022a).

[13] Global inflation had risen to over 6% in February 2022, its highest level since 2008 and it is running well above targets in almost all advanced economies (World Bank, 2022c).

The long-term consequences of the war in Ukraine will depend on current policy responses and priorities. Most recently, policy makers have been promoting energy efficiency and low-carbon sources of energy production, which is in line with the "green" goals of a transition away from fossil fuels to arrest climate change. However, such goals may become more elusive if policy makers rank energy security and affordability higher in their agenda. On the food market front, production shortfalls, trade disruptions and increased input costs raise commodity prices, most notably wheat. Ukrainian wheat exports, that account for nearly 10 percent of global exports, ceased after the closure of Ukrainian Black Sea ports. Exporting wheat overland is more expensive than by sea (World Bank, 2022a). Rising food prices and disruptions to trade pose risks to the coherence of the society. Besides, food security ranks high on the policy makers' agendas; thus necessitating international cooperation on these issues. With regard to metal markets, our results show that nickel has been heavily affected. Russia accounts for 20 percent of high-grade nickel used in batteries. Sanctions have disrupted supply from Russia's mining giant "Nornickel". The production of stainless steel, which accounts for 70 percent of nickel consumption is slowing, mainly in China (World Bank, 2022a). Developments in these commodities may affect the affordability of clean forms of transportation, and ultimately jeopardise the transition to a low-carbon economy.

The macroeconomic impact via commodity markets and rising inflationary pressure may plunge global economies into recession. Stakeholders are concerned about commodity-driven contagion effects that could have significant implications on financial markets and the real economy (Financial Times, 2022e). It remains to be seen what remedial steps will be taken to tackle a global recession. Future studies can further examine the impact of the Russian-Ukrainian war and its far-reaching effects on global economies as the war unfolds.

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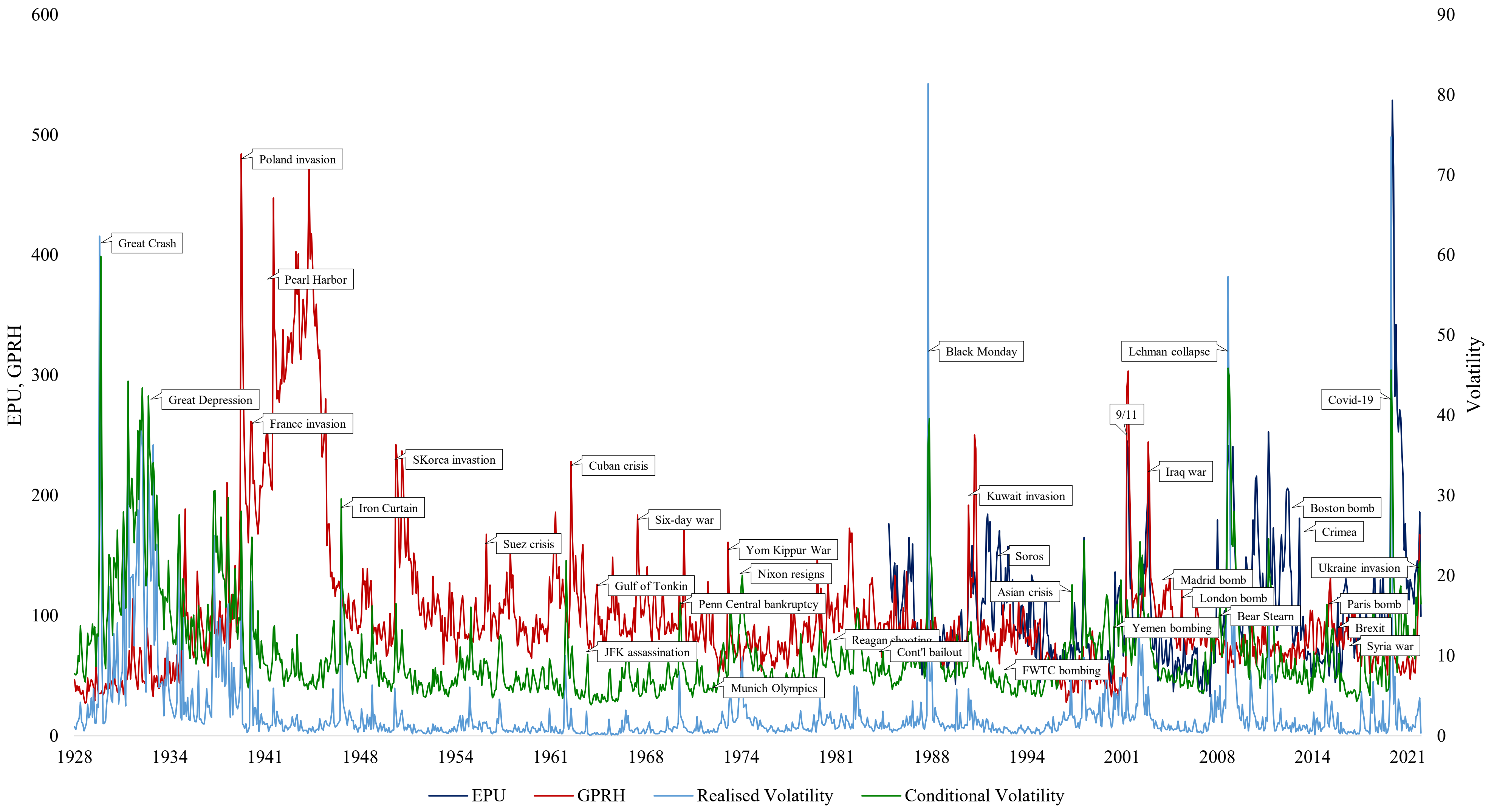
Figure 1. Major stock market indices response following the Russian-Ukrainian invasion.

Notes: The figure shows daily percentage return of major stock market indices following the invasion. Source: Financial Times; Bloomberg

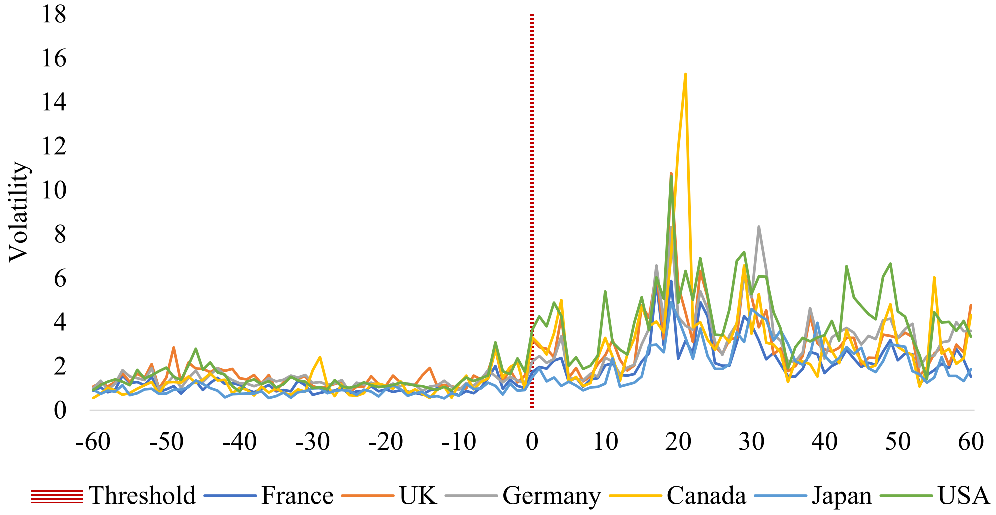
Figure 2. Financial market's reaction in main geopolitical and historic events.



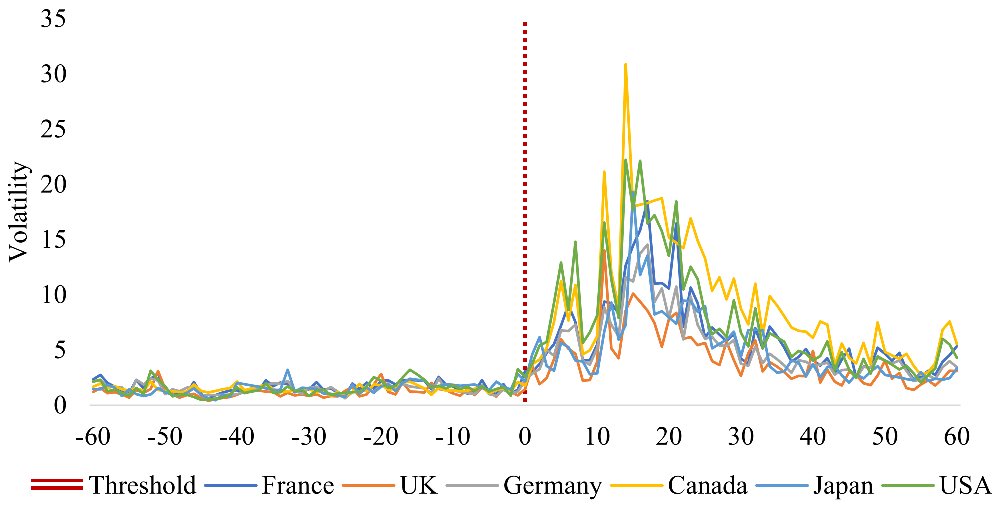
Notes: We use the S&P 500 returns to calculate: i) realized volatility, as the sum of squared returns over the past 22 trading days; ii) conditional volatility, based on a GARCH(1,1) model. The Economic Policy Uncertainty (EPU) is a news-based indicator of economic uncertainty and is available from 1985 onwards. GPRH is the historical geopolitical risk index.

Figure 3. Stock market volatility response of G7 economies in GFC, Covid-19 and Russian-Ukrainian war.

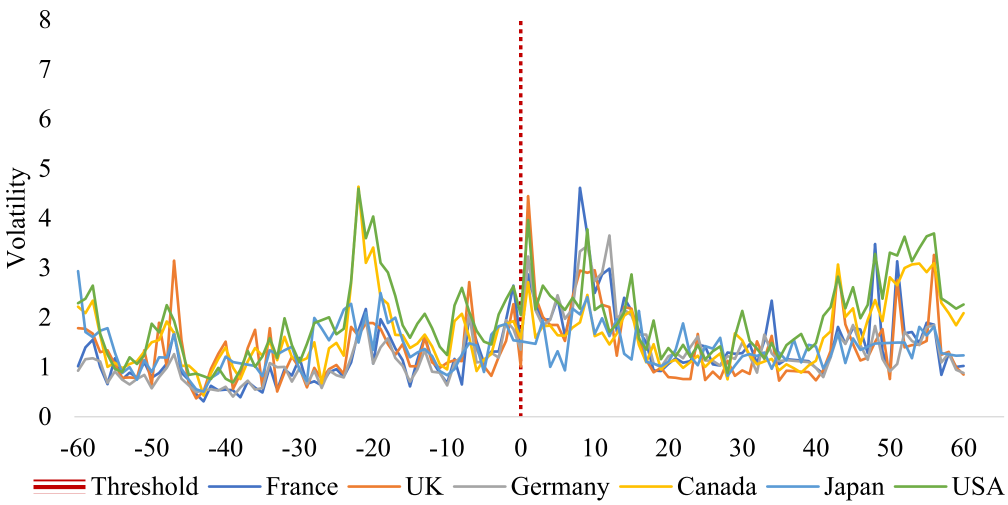
Panel A. GFC



Panel B. Covid-19

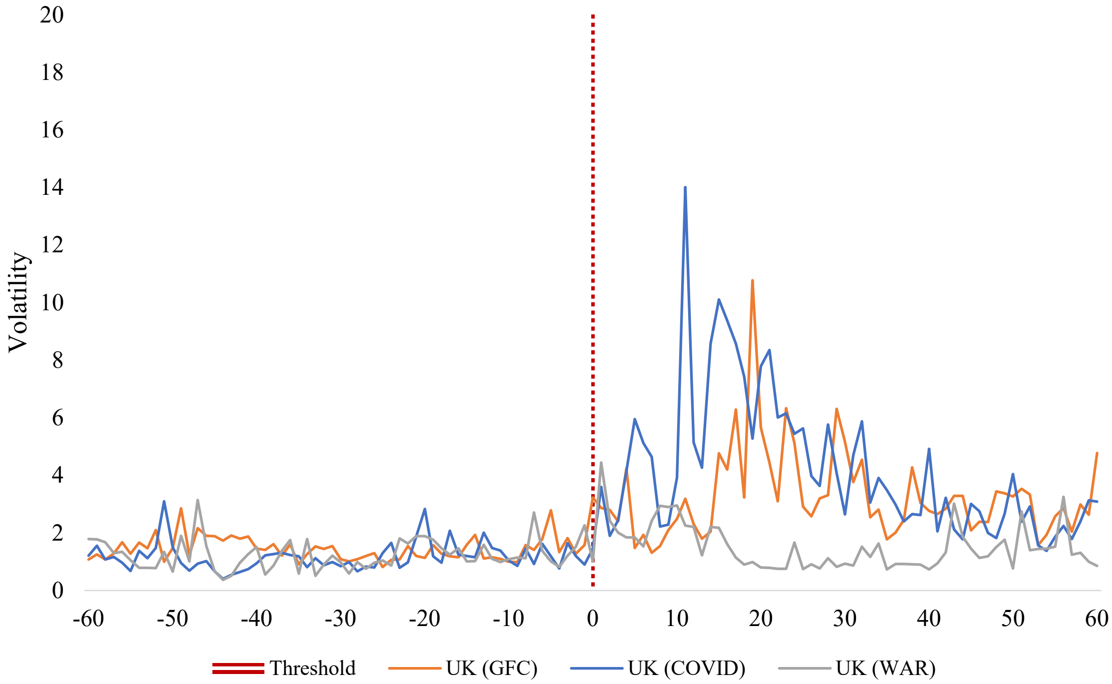


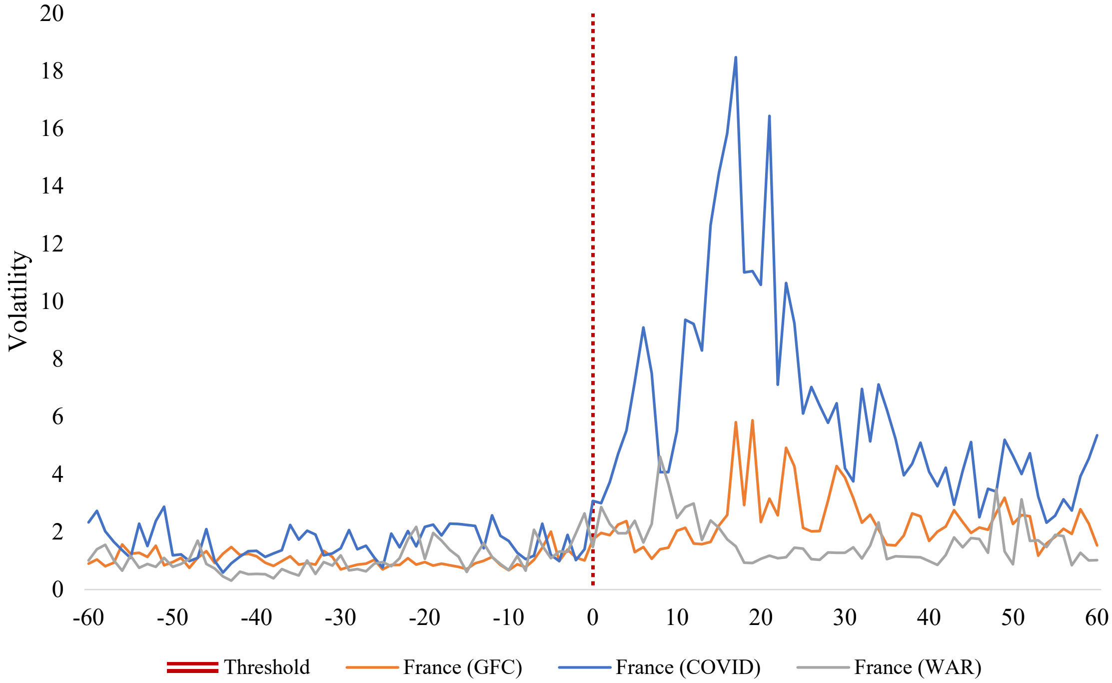
Panel C. Russian-Ukrainian war



Notes: The graphs present realized volatility (rebased at 1) for the G7 countries (with the exception of Italy). The zero on the horizontal axis corresponds to the day of the respective crisis, namely top graph: 15/08/2008 (the Lehman collapse for the GFC crisis); middle graph: 24/02/2020 (Italy lockdown for the COVID-19 crisis); bottom graph: 24/02/2022 (Invasion in Ukraine).

Figure 4. Realized volatility response specific countries.

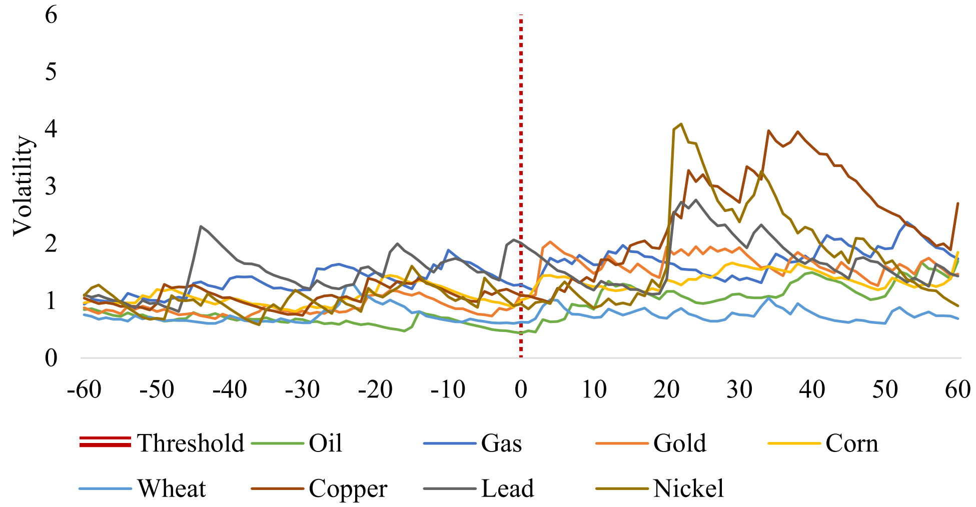




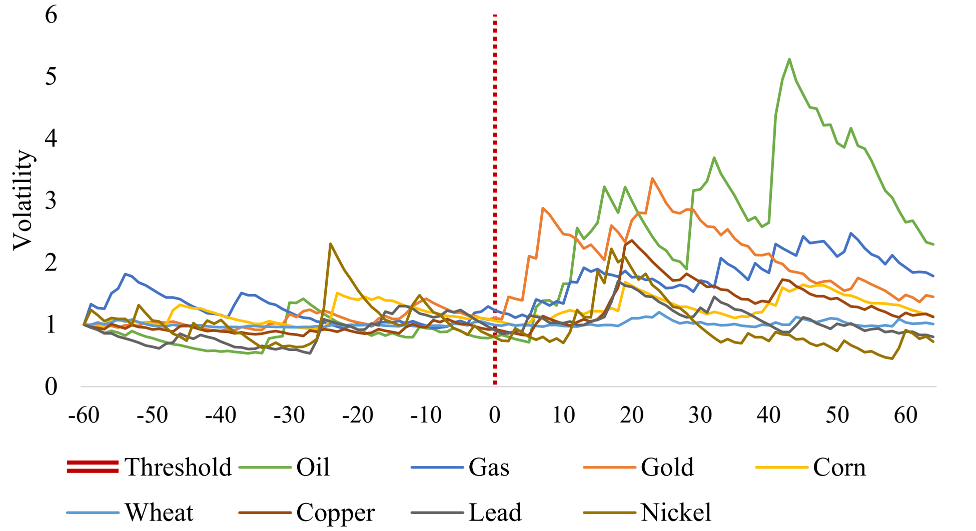
Notes: The graphs present realized volatility (rebased at 1) for representative G7 countries. The zero on the horizontal axis corresponds to the day of the respective crisis.

Figure 5. Conditional volatility response of commodities.

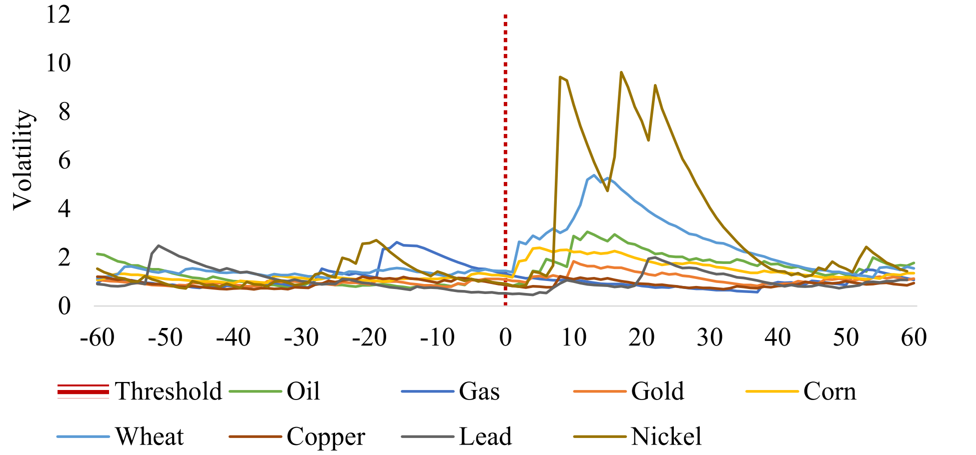
Panel A. GFC



Panel B. Covid-19

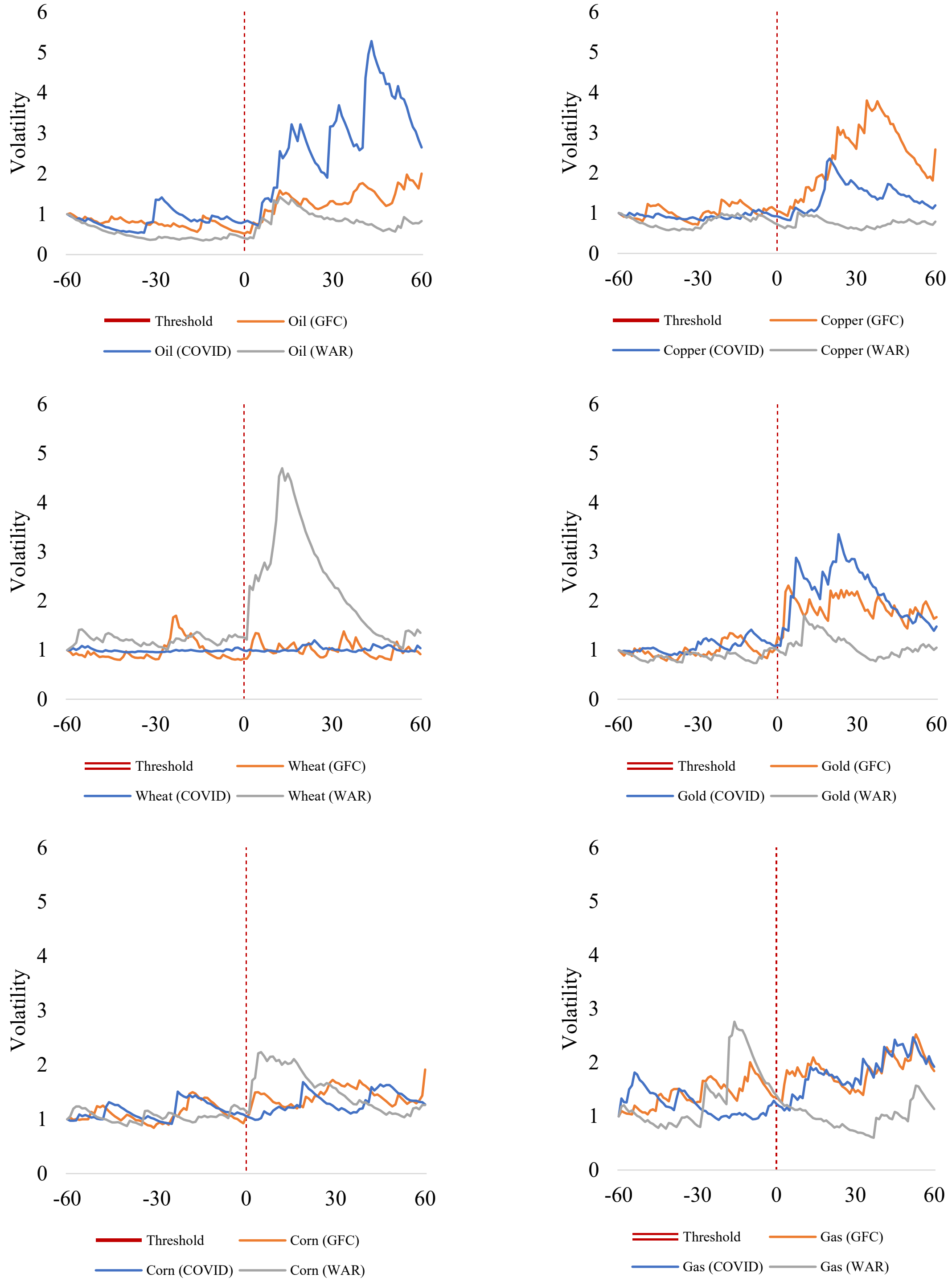


Panel C. Russian-Ukrainian war



Notes: The graphs present conditional volatility (rebased at 1) for selected commodities. The zero on the horizontal axis corresponds to the day of the respective crisis, namely top graph: 15/08/2008 (the Lehman collapse for the GFC crisis); middle graph: 24/02/2020 (Italy lockdown for the COVID-19 crisis); bottom graph: 24/02/2022 (Invasion in Ukraine).

Figure 6. Conditional volatility response of commodities.



Notes: The graphs present conditional volatility (rebased at 1) for selected commodities. The zero on the horizontal axis corresponds to the day of the respective crisis, namely top graph: 15/08/2008 (the Lehman collapse for the GFC crisis); middle graph: 24/02/2020 (Italy lockdown for the COVID-19 crisis); bottom graph: 24/02/2022 (Invasion in Ukraine).

Table 1. Descriptive statistics – stock markets.

	GFC			COVID-19			WAR		
	Mean	Range	SD	Mean	Range	SD	Mean	Range	SD
Australia	1.435	3.122	0.651	1.295	6.673	1.247	0.741	0.309	1.652
Belgium	1.739	5.131	0.825	1.349	5.873	1.093	0.999	0.591	4.635
Brazil	2.512	7.106	1.564	1.515	6.066	1.330	0.865	0.268	1.405
Canada	2.478	16.517	2.192	0.998	5.948	1.048	0.706	0.295	1.830
China	2.178	4.109	0.680	0.795	2.156	0.421	0.861	0.428	2.213
Denmark	2.330	8.127	1.476	1.124	4.635	0.762	1.357	0.737	5.728
Finland	2.317	7.821	1.433	1.055	3.591	0.753	0.993	0.742	7.345
France	2.062	6.339	1.187	1.388	6.393	1.217	1.170	0.610	3.686
Germany	2.135	6.877	1.344	1.270	5.342	1.056	1.060	0.512	2.680
Great Britain	2.223	9.516	1.367	1.534	7.930	1.325	0.921	0.472	2.665
Hong Kong	1.951	5.976	1.121	0.840	4.573	0.526	1.102	0.502	2.878
India	2.245	6.600	1.019	1.306	8.974	1.286	0.848	0.309	1.745
Italy	–	–	–	1.215	4.951	0.982	0.922	0.457	2.725
Japan	1.833	5.054	1.164	1.029	6.060	0.916	0.849	0.263	1.481
Korea	1.971	7.124	1.274	1.092	4.647	0.785	0.716	0.233	1.297
Mexico	1.670	6.230	1.102	0.967	3.128	0.518	0.885	0.293	1.964
Netherlands	1.998	5.352	1.048	1.306	6.275	1.224	1.112	0.492	2.810
Norway	2.443	7.735	1.489	1.562	13.760	1.668	1.152	0.526	3.497
Pakistan	1.255	3.481	0.774	1.261	5.640	0.866	0.673	0.357	2.396
Portugal	–	–	–	0.971	3.671	0.776	0.926	0.411	2.233
Singapore	0.906	0.017	0.005	0.807	3.219	0.577	0.563	0.175	1.290
Spain	1.855	5.283	0.894	1.342	6.314	1.107	1.030	0.509	2.875
Sweden	2.142	6.985	1.284	1.053	4.207	0.799	1.132	0.790	8.239
Switzerland	1.744	5.043	0.876	1.305	7.153	1.371	0.759	0.292	1.608
USA	2.315	8.099	1.513	1.287	6.304	1.356	1.079	0.444	2.178

Notes: The table reports key descriptive statistics for the realized volatility in each period of investigation. Mean volatility is expressed in annualized percentage terms. Range is defined as the difference between maximum and minimum values. GFC refers to the 2008 global financial crisis; WAR to the 2022 Russian-Ukrainian war. Realized measures are not available for Italy and Portugal during the GFC period.

Table 2. Descriptive statistics - commodities.

	GFC			COVID-19			WAR		
	Mean	Range	SD	Mean	Range	SD	Mean	Range	SD
Oil (WTI)	4.395	5.610	1.550	6.438	21.042	5.668	3.784	5.064	1.393
Oil (Brent)	3.899	5.777	1.430	4.580	11.589	3.140	3.545	5.598	1.430
Natural gas	3.819	3.606	0.816	4.057	4.076	1.113	6.190	11.271	2.491
Gold	2.481	2.670	0.828	1.289	1.969	0.527	1.142	1.130	0.228
Silver	4.535	7.363	1.968	2.220	3.958	1.039	1.766	1.313	0.290
Platinum	3.507	5.102	1.280	2.389	4.210	1.151	2.080	2.780	0.539
Palladium	3.893	6.011	1.655	3.607	7.843	1.872	3.723	5.330	1.169
Corn	3.173	2.683	0.610	1.567	0.983	0.242	1.910	2.012	0.546
Lumber	3.173	2.683	0.610	1.567	0.983	0.242	1.910	2.012	0.546
Soybean	2.882	2.634	0.637	1.074	0.653	0.164	1.695	1.527	0.335
Wheat	4.399	3.975	0.780	3.652	0.878	0.161	3.486	7.607	1.857
Sugar	3.190	2.053	0.488	2.102	1.982	0.448	1.790	0.667	0.142
Coffee	2.227	1.277	0.295	2.497	2.514	0.495	2.346	1.529	0.328
Cotton	2.778	4.412	1.150	1.949	2.077	0.571	2.002	1.352	0.310
Aluminum	2.635	6.437	1.224	1.248	2.246	0.473	2.195	4.563	0.925
Nickel	6.591	16.229	3.496	1.930	3.527	0.741	2.513	3.729	0.866
Copper	3.059	5.551	1.598	1.561	2.058	0.469	4.333	15.580	4.143
Tin	6.717	13.922	3.275	1.976	4.181	0.995	1.852	1.083	0.304
Lead	7.134	8.909	1.916	1.863	2.185	0.456	2.176	6.005	1.319
Zinc	5.898	9.810	2.159	1.361	1.512	0.408	1.656	3.170	0.663

Notes: The table reports key descriptive statistics for the conditional volatility in each period of study. Mean volatility is expressed in annualized percentage terms. Range is defined as the difference between maximum and minimum values. GFC refers to the 2008 global financial crisis; WAR to the 2022 Russian-Ukrainian war.

Table 3. Synchronization, duration, and intensity measures – stock markets.

Country	Sync (Days)	Duration (Days)	Duration (%)	Intensity (%)	Sync (Days)	Duration (Days)	Duration (%)	Intensity (%)	Sync (Days)	Duration (Days)	Duration (%)	Intensity (%)
	Panel A. GFC				Panel B. Covid-19				Panel C. War			
Australia	11	10	13.89	64.58	1	8	11.43	97.30	0	6	8.70	78.95
Belgium	2	8	12.70	77.18	1	15	21.43	68.78	0	5	7.35	94.08
Brazil	1	23	42.59	43.64	0	12	16.00	87.56	-9	13	20.31	53.02
Canada	3	13	22.03	98.31	10	2	2.67	126.53	0	2	2.90	54.59
China	3	7	9.46	68.55	1	6	8.00	90.58	0	12	17.39	76.36
Denmark	4	13	19.40	64.42	0	9	17.31	74.21	47	1	1.45	150.19
Finland	-6	9	12.16	81.67	2	12	16.44	77.20	47	1	1.45	189.92
France	17	3	4.11	98.56	0	20	39.22	51.42	-8	5	7.25	73.57
Germany	4	8	11.11	73.76	0	14	18.92	67.06	-8	5	8.33	82.96
Great Britain	4	8	11.11	81.57	10	2	2.67	97.96	-8	8	11.94	89.89
Hong Kong	3	7	9.33	63.67	14	2	2.67	123.42	11	5	7.35	84.69
India	0	15	21.43	42.01	14	1	1.33	165.51	-9	42	50.00	66.26
Japan	11	9	13.04	57.72	2	11	17.19	66.47	0	7	43.75	78.21
Korea	18	11	18.97	67.11	10	2	2.70	110.39	6	4	6.45	45.14
Mexico	-5	8	10.96	86.40	13	5	6.76	99.45	-5	1	1.45	83.65
Netherlands	1	19	32.76	43.48	4	2	2.70	89.69	-1	2	3.03	56.10
Norway	1	10	14.71	58.77	1	13	17.81	91.93	7	4	5.80	82.44
Pakistan	-5	1	1.33	34.96	10	1	1.33	188.87	14	2	2.90	78.30
Spain	4	6	8.00	80.93	10	6	8.11	109.40	27	2	2.90	137.45
Sweden	-5	13	19.70	63.96	4	7	11.67	72.05	0	45	65.22	60.47
Switzerland	4	6	8.70	69.46	10	4	5.33	97.02	0	5	7.25	90.13
USA	10	4	5.56	65.26	0	13	17.81	82.16	47	2	2.90	133.76
G7	**7.00**	**8.00**	**11.11**	**77.67**	**6.50**	**5.00**	**9.20**	**86.70**	**-4.00**	**4.50**	**6.85**	**69.08**
Europe	**4.00**	**8.00**	**12.16**	**73.76**	**1.00**	**12.00**	**17.31**	**82.16**	**0.00**	**5.00**	**7.25**	**89.89**
RoW	**3.00**	**9.00**	**12.43**	**64.92**	**7.00**	**5.50**	**7.38**	**98.38**	**0.00**	**3.50**	**5.19**	**71.31**

Notes: The table presents estimates of Sync (days), Duration (days), Duration (%) and Intensity (%) measures for the 2008 global financial crisis (panel A), the Covid-19 crisis (panel B) and the Russian-Ukrainian war (panel C). For a definition of the measures, we refer you to section 3.2

Table 4. Synchronization, duration, and intensity measures – commodities.

Commodity		Sync (Days)	Duration (Days)	Duration (%)	Intensity (%)	Sync (Days)	Duration (Days)	Duration (%)	Intensity (%)	Sync (Days)	Duration (Days)	Duration (%)	Intensity (%)
		Panel A. GFC				Panel B. Covid-19				Panel C. War			
Energy	Oil (WTI)	3	10	13.7	22.86	6	11	14.67	49.65	10	4	5.63	43.71
	Oil (Brent)	3	11	14.67	23.62	6	4	5.33	11.08	4	4	5.63	19.52
	Natural gas	-10	13	17.57	14.32	-3	11	14.67	14.02	38	2	2.82	1.01
	Median	**3.00**	**11.00**	**14.67**	**22.86**	**6.00**	**11.00**	**14.67**	**14.02**	**10.00**	**4.00**	**5.63**	**19.52**
Precious Metals	Gold	3	16	23.88	29.31	2	6	8.00	25.69	-5	4	5.80	13.08
	Silver	2	4	5.33	10.29	5	5	6.76	23.36	-5	11	15.49	17.07
	Platinum	-3	10	13.33	17.74	-1	3	4.00	10.79	-4	5	7.04	25.25
	Palladium	3	4	5.41	32.36	5	8	10.67	53.32	-5	13	18.57	19.64
	Median	**2.50**	**7.00**	**9.37**	**23.53**	**3.50**	**5.50**	**7.38**	**24.53**	**-5.00**	**8.00**	**11.27**	**18.36**
Agriculture	Corn	2	5	6.76	8.79	19	2	2.67	25.75	2	2	2.82	29.20
	Lumber	2	5	6.76	8.79	19	2	2.67	25.75	2	2	2.82	29.20
	Soybean	6	10	13.7	16.41	17	2	2.67	18.59	-4	5	7.04	18.96
	Wheat	3	9	12.33	23.78	19	10	13.70	9.84	2	4	5.63	48.87
	Sugar	4	10	13.51	18.7	-5	2	2.67	24.30	4	3	4.23	12.16
	Coffee	-5	5	6.76	19.28	-3	6	8.11	41.86	-8	12	17.14	22.05
	Cotton	21	5	6.85	29.75	4	6	8.22	19.78	4	15	22.39	16.73
	Median	**3.00**	**5.00**	**6.85**	**18.70**	**17.00**	**2.00**	**2.67**	**24.30**	**2.00**	**4.00**	**5.63**	**22.05**
Base Metals	Aluminum	32	2	2.67	56.95	11	4	5.33	37.15	-6	9	12.86	35.45
	Nickel	21	1	1.33	85.92	12	4	5.56	49.50	8	5	7.14	116.65
	Copper	5	10	13.51	6.72	17	2	2.70	32.93	-7	2	2.94	28.22
	Tin	27	3	4	40.24	-9	8	10.96	43.71	-8	18	25.71	21.49
	Lead	-2	3	4.11	20.46	5	6	8.11	21.85	21	2	2.82	72.14
	Zinc	21	2	2.7	44.29	-9	6	14.67	49.65	21	5	7.25	41.07
	Median	**21.00**	**2.50**	**3.35**	**42.27**	**8.00**	**5.00**	**6.84**	**40.43**	**1.00**	**5.00**	**7.20**	**38.26**
All	**Median**	**3.00**	**5.00**	**6.81**	**21.66**	**5.00**	**5.50**	**7.38**	**25.72**	**2.00**	**4.50**	**6.42**	**23.65**

Notes: The table presents estimates of Sync (days), Duration (days), Duration (%) and Intensity measures for the 2008 global financial crisis (panel A), the Covid-19 crisis (panel B) and the Russian-Ukrainian war (panel C). For a definition of the measures, we refer you to section 3.2

Table 5. Robustness analysis.

	Slope coefficient (γ)			Threshold coefficient (ψ)		
	GFC	Covid-19	War	GFC	Covid-19	War
Panel A. Stock markets						
G7	2.23	6.14	7.78	2.68	2.01	1.95
Europe	0.61	9.26	1.55	2.12	2.51	1.67
RoW	0.99	5.28	1.62	3.16	2.54	1.95
Panel B. Commodities						
Energy	3.29	22.90	13.81	3.33	2.84	0.24
Precious Metals	8.18	7.29	2.59	2.33	2.60	1.69
Agriculture	0.52	2.08	3.22	2.45	1.57	2.35
Base Metals	2.16	0.42	74.25	1.83	2.67	3.22
All	1.17	2.10	3.37	2.53	2.63	1.95

Notes: The table presents estimated coefficients for the ST-HAR model parameters, see section 5 for more details. We refer you to section 3.1 of the paper for classifications of stock markets and commodities.

Highlights

- We analyse stock market and commodity reaction to the Russian-Ukrainian war
- We compare synchronization, duration and intensity of the war to other crises
- Financial markets responded earlier to the war event than either the GFC or Covid-19
- Intensity metrics, show the war to be muted compared to the GFC or Covid-19
- High crisis intensity reveals ongoing pressure to commodities