International Economics 174 (2023) 69–90

Contents lists available at ScienceDirect

International Economics

journal homepage: www.elsevier.com/locate/inteco

The economic impact of conflict-related and policy uncertainty shocks: The case of Russia ☆

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ARTICLE INFO

JEL classification:
E37
D74
N16

Keywords:
Russia
Forecasting
Social unrest
Social conflict
Policy uncertainty
Geopolitical risk

ABSTRACT

We show that policy uncertainty and conflict-related shocks impact the dynamics of economic activity (GDP) in Russia. We use alternative indicators of "conflict", referring to specific aspects of this general concept: geopolitical risk, social unrest, outbreaks of political violence, and escalations into internal armed conflict. For policy uncertainty we employ the workhorse economic policy uncertainty (EPU) indicator. We use two distinct but complementary empirical approaches. The first is based on a time series mixed-frequency forecasting model: we show that the indicators provide useful information for forecasting GDP in the short run, even when controlling for a comprehensive set of standard high-frequency macro-financial variables. The second approach is a SVAR model. We show that negative shocks to the selected indicators yield economic slowdown, with a persistent drop in GDP growth and a short-lived but large increase in country risk.

1. Introduction

The literature has suggested multiple channels through which conflict and institutional instability can affect economic growth. The most direct economic effects of armed conflict and protests occur when these result in the physical destruction of private property (Johnson et al., 2002; Besley and Mueller, 2018). Indirectly, however, conflict and social unrest can influence market expectations and change asset prices, investment and hiring strategies, and other otherwise standard strategies of households and firms (Zussman and Zussman, 2006; Besley and Mueller, 2012). Expectations are also precisely what is affected by uncertainty regarding the future course of economic and general government policy (Bloom, 2009; Baker et al., 2016). In fact, expectations can even lead to firms modifying their behaviour in an attempt to influence economic policies (Hassan et al., 2019). Literature studying these effects mostly focuses on using cross-country data to draw general conclusions, for example, for developing versus developed countries or other particular groupings (see, for example, Diakonova et al., 2022).

In this paper, we focus on the case of one country, Russia, and analyse the impact of policy uncertainty and conflict-related shocks on economic activity. Three recent works are relevant in this context. The first, Guriev and Melnikov (2016), is one of the earliest works to highlight the potential of big data to create meaningful indicators of institutional instability in economic contexts. The authors explore how conflict and the economic environment impact on social capital, utilising two high-frequency text-based measures: relevant news searches to proxy the intensity of conflict, and search engine searches to arrive at the components of social

☆ The opinions expressed in this paper are the responsibility of the authors and do not necessarily coincide with those of the Banco de España or the Eurosystem. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. We thank Mario Alloza, Matias Pacce, Erik Andres Escayola, and participants at the RCEA-Europe International Conference on Global Threats to the World Economy for comments.

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https://doi.org/10.1016/j.inteco.2023.03.002

Available online 16 March 2023

capital. In the second work, Charemza et al. (2022) develop an economic policy uncertainty index (EPU, Baker et al., 2016) for Russia. Using the latest natural language processing (NLP) techniques, they reduce the dependency of the resulting indicator on the arbitrary choices of the researcher and show that, compared to alternatives, their index has a stronger link to macroeconomic aspects such as industrial production. This work is thus representative of the increased awareness of the effect of institutional instability on economic processes, as well as of the need to have access to accurate and objective indicators. Finally, Zhemkov (2021) focuses on Russia and using a host of traditional macro-financial indicators and models improves the results of traditional benchmark models when forecasting economic growth.

In our study, we use the EPU indicator to proxy policy uncertainty, and a wealth of indicators that refer to specific aspects of the concept of 'conflict': geopolitical risk, social unrest, outbreaks of political violence, and escalations into internal armed conflict. All the indicators that we are considering in this paper have been demonstrated to be useful for understanding the economy. Increases in the geopolitical risk (GPR) index (Caldara and Iacoviello, 2022) can predate unemployment and falling stock prices, and shocks to global GPR imply a declining global outlook. The IMF's recently developed index of reported social unrest (RSUI, Barrett et al., 2020) has been shown to foresee the fall in manufacturing and services, as well as the subsequent decrease in output (Hadzi-Vaskov et al., 2021). The conflict models of Mueller and Rauh (2022a) have been shown to shed light on the economic growth of three major Latin American economies (see Diakonova et al., 2022). The EPU has been widely used in multiple contexts, and its effects were shown to affect a wide range of macroeconomic aspects (see Ghirelli et al. (2019, 2021) for applications to developing economies, as well as the references quoted therein).

We use two distinct but complementary empirical approaches. The first exercise is based on a time series mixed-frequency forecasting model. More specifically, we show that augmenting the classical mixed-data sampling (MIDAS) combination forecast with indicators such as the risk of conflict, tension, uncertainty and social unrest can achieve a statistically significant 12% reduction in forecast errors. This result highlights the significant impact of a deterioration of institutional stability on the Russian economy, and provides further evidence of the utility of big data-based real-time indicators. A second exercise studies the macroeconomic impact of conflict-related and EPU shocks on the Russian economy by means of vector autoregression (VAR) models. Our results confirm that alternative indicators deliver the same narrative: institutional instability shocks in Russia yield economic slowdown, with a persistent drop in GDP growth and a short-lived but large increase in country risk. In particular, GDP growth takes more than two years to revert to trend after a shock, while the emerging market bond index (EMBI) reverses more quickly, within one year. To put these findings into context, we observe the evolution of our institutional instability indexes against recent Russian foreign affairs, and identify some episodes that are associated with sudden increases in the institutional instability indexes of a magnitude that resembles the size of the shocks we considered when computing the impulse responses in the VAR exercise. The shock to the conflict variable is equivalent to the Russo-Georgian war that took place in August 2008. The shock to the social unrest index corresponds to specific events of the 2014 Russo-Ukrainian war. The shock in the Russian GPR index corresponds to events related to the second Chechen war and Putin's declaration of foreign affairs and security policy top priorities (2002Q4–2003Q3). Finally, a shock of one standard deviation in the EPU index is equivalent in magnitude to the Global Financial Crisis.

Our results can certainly be extrapolated to the recent events associated to the Russian invasion of Ukraine. The institutional instability indicators dramatically increased in the recent Russo-Ukrainian war. To make an example, the EPU rose by about 500 points in February 2022, at the time of the Russian invasion of Ukraine—an increase comparable in size, although even larger, to the peak that the indicator experienced during the Covid-19 crisis, and certainly larger than the structural shocks estimated by the model until 2019. Nonetheless, to avoid misspecification problems, we do not include the last part of the data sample in our analysis.[1] However, in Section 4.4 we carry out a conditional forecast exercise for GDP and EMBI, to obtain the dynamics of GDP and EMBI for the most recent period based on the structural shocks estimated by the model for the sample period until 2019q4. Our results suggest that the current crisis is heavily dragging down Russian economy.

The paper is structured as follows. In Section 2 we describe the dataset, which consists of both the standard macroeconomic indicators and the institutional instability indicators. Section 3 then details the forecasting exercise with the MIDAS approach, while Section 4 centres on estimating impulse responses using VAR analysis. Finally, in Section 5 we present our conclusions and potential directions for future work.

2. Data

The macroeconomic variable of interest is quarterly GDP in 2016 prices and seasonally adjusted. The data source is the Federal State Statistics Service of Russia. Fig. 1 displays the GDP of Russia for our sample period of January 2000 to December 2019. Note that we will not include in the empirical analysis the COVID-19 crisis period, as fluctuations in the economic indicators during that time can safely be assumed to be traceable to the health-related exogenous shock. Note also that, as mentioned above, we do not include the most recent period that includes the Russian invasion of Ukraine in February 2022, as not enough data is yet available to properly assess macroeconomic developments surrounding this episode. The displayed GDP traces two major crises: the 2008 recession, when the Global Financial Crisis was compounded by dropping oil prices and the effects of the Georgian conflict, and the crisis of 2014 that followed yet another drop in oil prices as well as international sanctions in the wake of Ukraine-related events. The 2008 recession halved the average growth rate of 2% and the 2014 crisis almost halved it again, with growth in the last three years before the Coronavirus pandemic standing at 0.5% every quarter. About 15% of our data corresponds to negative growth, with both instances of recession following geopolitical conflicts.

[1] We estimate the model until 2019q4 to avoid the misspecification of empirical models that could arise from the Covid-19 pandemic, as commonly done in the literature (e.g. Alvarez and Odendahl, 2022).

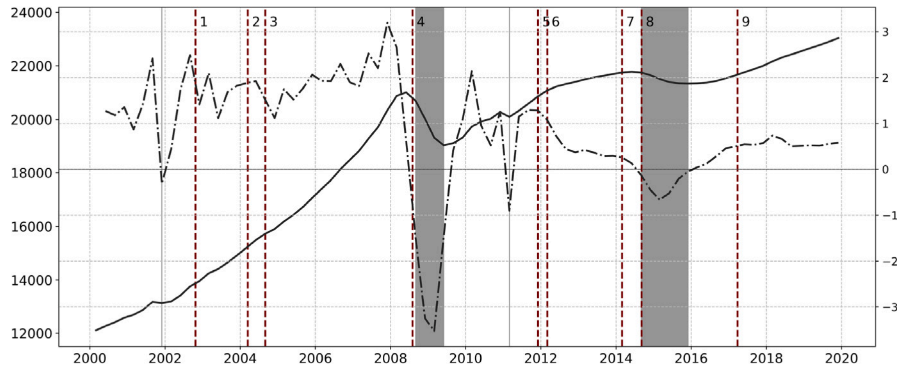


Fig. 1. Russian GDP and select institutional instability and political events. Russian GDP (left axis, solid line) and the quarter-on-quarter (QoQ) growth in percentages (right axis, dash-dotted line). Grey vertical lines and shaded areas correspond to quarters of negative growth. Red dashed vertical lines represent events associated with institutional instability: (1) the Dubrovka terrorist attack in Moscow, (2) Putin elections, (3) Beslan school siege, (4) Georgian conflict, (5) legislative elections, (6) Putin elections, (7) Crimea referendum, (8) Minsk Agreements, (9) anti-corruption protests.

The explanatory variables used are given in Table A.1 and depend on the particular exercise. For the forecasting work, we consider 25 indicators. For macro-financial data we use a set of widely used indicators, namely (i) "hard indicators": an industrial production index, a retail sales index, the unemployment rate, credit to the private sector in real terms, construction sector production, the volume of natural gas exports, the production of oil; and (ii) "soft indicators": a consumer confidence index and some sort of business confidence index—in concrete terms, the percentage of respondents that report expecting an increase in industrial production in the survey conducted by the IMEMO (Primakov Institute of World Economy and International Relations of Russia); (iii) financial markets and political risk indicators: the Emerging Market Bond Index (EMBI+) spread in basis points[2] (which we refer to as Country Risk), and the sovereign rating (an average of the ratings of the three major agencies: Standard and Poor's, Fitch, and Moody's), linearised using a scale from 21 (AAA) to 12 (BBB–) and 0 (RD or D).

As regards social unrest, conflict and policy uncertainty, we rely on measures elaborated using textual analysis applied to newspaper sources. These are increasingly used to measure conflict events or other political risks and uncertainties. These news-based measures have the advantage of being available and updated at monthly frequencies or greater. One of the hallmarks of text-based indexes is the economic policy uncertainty (EPU) measure by Baker et al. (2016). The second measure we use is the geopolitical risk index elaborated by Caldara and Iacoviello (2022). The third aspect of institutional instability we focus on comprises a set of risk measures from the webpage conflictforecast.org, which follows the methodology of Mueller and Rauh (2022a,b). The page provides a monthly out-of-sample forecast for the outbreak of "armed conflict" and "any violence" three and twelve months into the future, which we interpret here as a measure of broader political fragility. The forecast relies on variables that capture the conflict history of a country (monthly conflict event data updates from Uppsala Conflict Data Program, UCDP) and the news landscape through automated news summaries from a corpus of over five million articles. The fourth measure we use is the new social unrest index developed by Barrett et al. (2020) at the IMF, which is also based on counts of relevant media reports.

Overall, the variables we consider in our exercise are stationary. Hard variables that follow a trend over time are log-differenced so that their mean is constant over time (e.g. GDP, industrial production, and so on. See Table A.1 for details on how variables are treated). Other variables are included in levels, because changes in levels is what matters from an economic point of view: e.g. confidence indicators and institutional instability indicators. Note that these indexes are by construction mean stationary, since they fluctuate around their mean (e.g. the EPU index, the GPR index, the consumer confidence index).

For completeness, Table A.2 in Appendix A reports the *p*-value of the augmented Dickey–Fuller test that a variable follows a unit root process. A rejection of the null-hypothesis implies that the variable is stationary. The test is performed on each variable used in the analysis at a quarterly frequency considering alternative specifications (including up to 5 lags). Overall, these results confirm that the variables we consider in our analysis are stationary.[3]

3. First approach: forecasting exercise

3.1. The model

In this section, we quantify the gains made in forecasting Russian quarterly GDP by adding the EPU index and conflict-type indicators to the broad standard set of monthly macroeconomic time series described in the previous section. In doing so, we

[2] The yield of a Russian synthetic external debt bond minus the equivalent yield of a US bond of the same maturity (in this case, five years). These series are published daily by JP Morgan and have been sourced from Refinitiv.

[3] For three institutional instability indicators (the EPU index, Any.Viol.3.text and Arm.Conf.3.best) we fail to reject the test at the quarterly frequency. Since it is known that the augmented Dickey–Fuller test performs poorly in presence of small samples, we repeat the test on monthly data, which allows to reject the null hypothesis of unit root process. Hence for these cases, we report in the table the *p*-value of the test based on monthly frequency. For GPR index, Arm.Conf.12.text, and Any.Viol.3.best, we report results of the test including the drift option, which allows to reject the presence of unit root.

follow Diakonova et al. (2022) and employ the mixed-frequency MIDAS framework to produce combination forecasts. These are then evaluated for their accuracy when compared to the forecasts made without considering the new set of variables. The MIDAS framework is one of several methods in the literature to solve the temporal (dis)aggregation issue (Ghysels et al., 2004), and one that has repeatedly demonstrated its usefulness when targeting growth predictions (see references within Diakonova et al., 2022).

We perform the exercise in pseudo-real time, so that different regressors become available with different time lags depending on when in the quarter the forecast is being made (see Fig. A.1 for details on the release lags). Our data covers twenty years, from January 2000 until December 2019. We divide this equally into a 10 years (40 quarters) in-sample, and a further 10 years of forecasting period. The MIDAS specification requires selecting the relative weighting of lagged regressor values, and we consider two functions: simple time-averaging (TA) and the normalised exponential Almon polynomials (NEALMON) with 21 potential parameter choices. We also include the same two specifications but with an added autoregressive element. The number of temporal lags in the latter is determined by the Aikaike information criterion (AIC) using a simple autoregressive model (AR), and the number of such lags in the regressor is set to be a maximum of 12 so as not to prejudice those variables with larger release lags. Both the NEALMON parameters and the optimal regressor lags are first optimised in-sample from 2000Q1 to 2009Q4, with the forecast then being evaluated one quarter ahead using a recursive-window approach. For each set of parameter values, a total of 40 forecasts are thus made for each regressor. We compute individual forecasts and combine them using one of the three standard combination methods. Four forecast horizons are considered, with nowcasting during the first month of every quarter additionally requiring a backcast of one quarter due to the lagged release of the GDP estimate. To carry out our forecasts, we use the *midasr* package.[4]

The final results are therefore distinguished by the following parameters:

- Month in the quarter when the forecast is made: 1, 2, 3
- Forecast horizon: 0, 1, 2, 3
- Models: Time-averaging (TA), time-averaging with autoregressive element (TA-ADL), NEALMON and NEALMON-ADL
- Combination methods: Equal weighting (EW), mean squared forecast error (MSFE) and discounted MFSFE (DMSFE) with a discount rate of 0.9

Forecasts are evaluated according to their accuracy by computing the root mean square forecast error (RMSFE)[5] and comparing it to the RMSFE of some benchmark. Corresponding to the aim of the exercise, this benchmark model is taken to be the combination forecast produced using a standard set of macroeconomic variables. This is then compared to the forecast produced by the same set of variables with the addition of three different categories of indicators, which we create to ease the interpretation of the results. The first set of extra indicators is what we call "Text Variables". It is the set of text-based variables that consists of GPR, EPU, RSUI, and the some relevant shares of topic attention that are taken from Mueller and Rauh (2022a). The second set of additional variables is what we label as "Conflict Models". It consists of eight distinct indicators measuring the likelihood the onset of conflict, as produced by Mueller and Rauh (2022a). These are grouped into a distinct set because these indicators are the outcomes of supervised learning, trained on actual fatalities data. Finally, we also consider the entire set of indicators together. Table 1 summarises the three sets and their constituent variables.

Table 1
Regressor combinations.

Combination name	Variable groups	Variables excluded on optimisation
Benchmark	Traditional + Standard	–
Text variables	Traditional + Standard + Text-based variables	GPR
Conflict models	Traditional + Standard + Conflict models	AnyViol.3.best, AnyViol.12.text, Arm.Conf.3.text, Arm.Conf.12.text, AnyViol.3.text
All	Traditional + Standard + Text-based variables + Conflict models	GPR AnyViol.3.best, AnyViol.12.text, Arm.Conf.3.text, Arm.Conf.12.text, AnyViol.3.text

Note: See Table A.1 for individual regressor constituents of the variable groups. The criteria for excluding a regressor from an optimised model is that its exclusion improves the RMSFE relative to the benchmark forecast in at least 90% of the (month, forecast, horizon) pairs, where the RMSFE for each pair is averaged over the four models and the three forecast combination methods.

We first optimise the combinations of text variables and conflict model sets by getting rid of regressors whose exclusion improves, on the whole, the accuracy of the combination forecast compared to the benchmark (the details of the exercise can be found in the Appendix B). Table 1 shows the result of this optimisation. To improve on the benchmark, we exclude the GPR index from the text-based variable group, as well as five models from the conflict models group.

[4] We use the R project software. See https://CRAN.R-project.org/package=midasr.

[5] $RMSFE = \sqrt{\frac{1}{N}\sum_i^N (y_i - f_i)^2}$, where y_i and f_i are, respectively, the true value of the growth and the forecast at quarter i.

3.2. The results

To start with, we find that adding conflict-type and EPU variables improves the forecast for *all* (month, horizon) pairs. This holds for both the optimised and non-optimised combinations. Fig. 2 summarises the results of our combination forecasts in terms of quantitative improvements.[6] First, we see that adding institutional instability indicators to the standard set of variables improves the growth forecasts even before any optimisation. In general, text-based indicators generate greater predictive value than the derived conflict models. This could either be because the text variables include indicators that trace several aspects of institutional instability rather than just conflict or because of the additional set of assumptions that went into creating the conflict models. This result holds with optimisation. Optimisation itself can reduce the relative error by up to 0.05. However, the optimal model for predicting Russian GDP is one that includes both indicators of conflict risk *and* text-based variables (the optimised "All" combination). Adding these variables to the traditional macroeconomic set lowers the RMSFE by 12%, on average.[7]

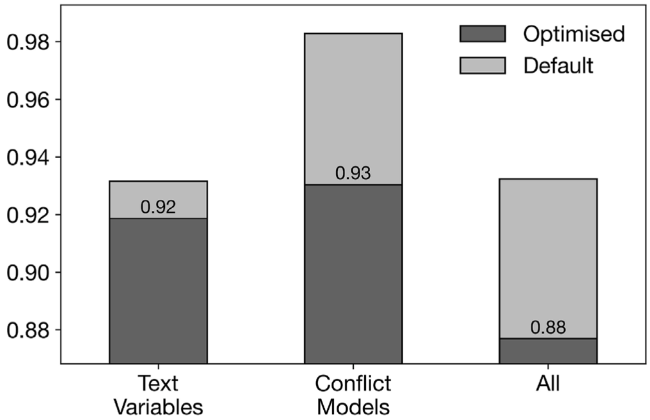


Fig. 2. RMSFE relative to benchmark model. The RMSFE of three combination forecasts relative to the benchmark combination. The three "Default" combinations add, respectively, text-based variables, conflict models and both sets to the benchmark combination (see Table 1). The three "Optimised" combinations subsequently remove the worst-performing indicators. The relative RMSFE values are frequentist averages over the three initial months, the four forecast horizons, the four models, and the three combination methods (the parameters listed in the bullet points in the main body of the text).

We now evaluate how the forecasting improvements change under the four different exercise parameters mentioned previously: forecast month, forecast horizon, forecast combination method, and the specific MIDAS aggregation model used. Fig. 3 shows disaggregated results for the optimised "All" variable combination. The first aspect to note is that the results appear robust to both the forecast combination method and the MIDAS model, with no single choice of the two definitively outperforming the rest. There is a slight tendency for models without an autoregressive term to bring more value, but apart from a few months and horizons these differences are too slight to be significant. Secondly, we see that institutional instability variables add more value when nowcasting (horizon of 0) at month 1 than at subsequent months, which is supported by the fact that after the first month more traditional macroeconomic information about the current quarter becomes available. In addition to that, comparing forecasts made at differing horizons, we see that adding institutional instability variables brings more value when forecasting medium-term than when estimating the current quarter's growth. It is an open question whether this is a consequence of the particular structure of the economy, with institutional instability being more indicative of long-term changes, or whether this is a feature associated with our particular combination of in- and out-of-sample temporal frames. Finally, we note that the overwhelming majority of these improvements are statistically significant at a 95% confidence level (Diebold and Mariano, 1995). Moreover, statistically significant improvements can be achieved for any (month, horizon) pair using the two non-auto-regressive models. Table 2 shows one such example, done with a particular MIDAS model and forecasts combination method. It compares the improvements given by the different groups of institutional instability variables. Adding each group can be more or less beneficial, depending on the forecast month and horizon—but including both types of variables in the forecast set is always optimal, and brings improvements independent of the temporal parameters. The table summarises the main result of this section, that adding institutional instability indicators significantly improves GDP forecasting done with traditional macroeconomic variables.

[6] The majority of the results shown in the body of the paper are averaged values of the relative error, that is, the RMSFE of the model relative to the RMSFE of the benchmark. For the sake of completeness, in the Appendix we also report the disaggregated MSFE of the benchmark model.

[7] The 12% improvement is an average over the relative RMSFE at each of the (month, horizon, model, combination method) parameter sets. For each set, we compare two values: the RMSFE of the forecast of the optimised combination, and the RMSFE of the forecast with just the traditional and standard variables. We then perform a paired t-test with non-equal variance to test the hypothesis that the two sets of errors come from the same distribution. The null hypothesis is rejected at the significance level corresponding to $p = 3 * 10^{-36}$.

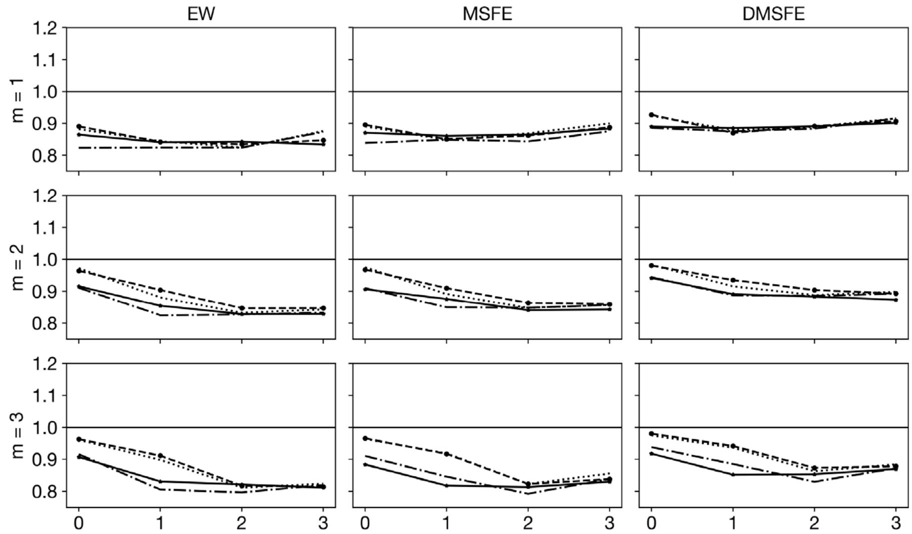


Fig. 3. RMSFE of the quarterly combination forecast. Relative RMSFE of the optimal combination forecast compared to the benchmark combination of only the traditional and standard indicators (the optimised 'All combination, see Table 1). Columns correspond to the different combination methods. Starting months *m* are separated by rows, and the abscissa shows the forecast horizons *h*. Lines represent individual regressor models—solid with marker: TA; dashed with marker: TA-ADL; dot-dashed: NEALMON; dotted: NEALMON-ADL. Values below the marked horizontal line at 1 indicate that the model is outperforming the benchmark. All the values refer to results that are statistically significant at 95% confidence level using the Diebold–Mariano test, apart from ($h = 0$, $m = 2, 3$, TA-ADL and NEALMON-ADL, all combination methods).

Table 2
Relative RMSFE for the optimised models, with months (rows) and horizons (columns). "TV", "CM", and "All" are shorthand names for the following combinations, specified in Table 1: Text Variables, Conflict Models, and All. Shown are the results for TA model and Equal Weights combination scheme. All the values have been tested (Diebold and Mariano, 1995), and are statistically significant with p = 0.01.

		0	1	2	3
1	TV	0.91	0.90	0.91	0.89
	CM	0.93	0.90	0.90	0.91
	All	0.86	0.84	0.84	0.83
2	TV	0.96[a]	0.92	0.89	0.89
	CM	0.94[a]	0.89	0.89	0.89
	All	0.92	0.85	0.83	0.83
3	TV	0.95[a]	0.89	0.88	0.87
	CM	0.94	0.91	0.90	0.89
	All	0.91	0.83	0.82	0.81

[a]The three values statistically significant with p = 0.05.

4. Second approach: the macroeconomic effects of conflict-like and EPU shocks

4.1. The model

In this section, we focus on four alternative measures of institutional instability for Russia: the EPU index, the GPR index, a social unrest index and a conflict variable ('Arm.Conf.12.best', following the notation defined above). We estimate the VAR models using quarterly data[8] from 2000Q3 to 2019Q4.[9] The models contain the following variables for the Russian economy, in this order: (i) an institutional instability variable (in turn, the EPU index, the geopolitical risk index, the social unrest index, the conflict index); (ii) the EMBI in changes, as a proxy for financial markets; (iii) GDP in quarter-on-quarter growth rates (seasonally adjusted); and (iv) the headline consumer price index (CPI) in quarter-on-quarter growth rates (seasonally adjusted). In addition, we include the Chicago

8 We run quarterly SVAR models since our monthly institutional instability indicators are very volatile. For this reason, we did not estimate mixed frequency SVAR or monthly SVAR models.

9 We exclude 2000Q1 and 2000Q2 to get rid of outliers. Summary statistics for the variables used in the estimations are reported in Table D.1. Fig. D.2 shows the evolution of each variable used in the VAR estimation at the quarterly frequency. Fig. D.1 shows the evolution of the four measures of institutional instability at the monthly frequency.

Board Options Exchange (CBOE) volatility index (VIX) as an exogenous variable in the system to control for global uncertainty shocks.[10]

All VAR models are estimated using OLS. The baseline specification is estimated including one lag of the endogenous variables to keep the model as parsimonious as possible, since the estimations rely on a rather short time span.[11]

We rely on a recursive identification à la Cholesky to identify the structural shocks in the model, by ordering the variables as explained above. The order of variables can be justified as follows. First, institutional instability affects all variables in the system contemporaneously but does not react instantaneously to shocks to other variables (however, institutional instability is affected by shocks to the economy with a lag, i.e. it is properly endogenous to the system). Second, the EMBI affects the real economy but does not affect the institutional instability indicators contemporaneously. Third, GDP growth responds to shocks to institutional instability and financial variables in the same quarter but does not react to inflation. Finally, inflation is contemporaneously responsive to economic events (financial variables and GDP shocks), as well as to institutional instability shocks. Ordering conflict-like and EPU indicators before economic variables implies that the former react contemporaneously only to their own shocks and that fluctuation in institutional instability is unrelated to the business cycle.[12]

4.2. Results

We now track the macroeconomic effects of the selected indicators by looking at the impulse response functions (IRFs) of GDP growth rates and the EMBI, based on the aforementioned models (see Fig. 4).

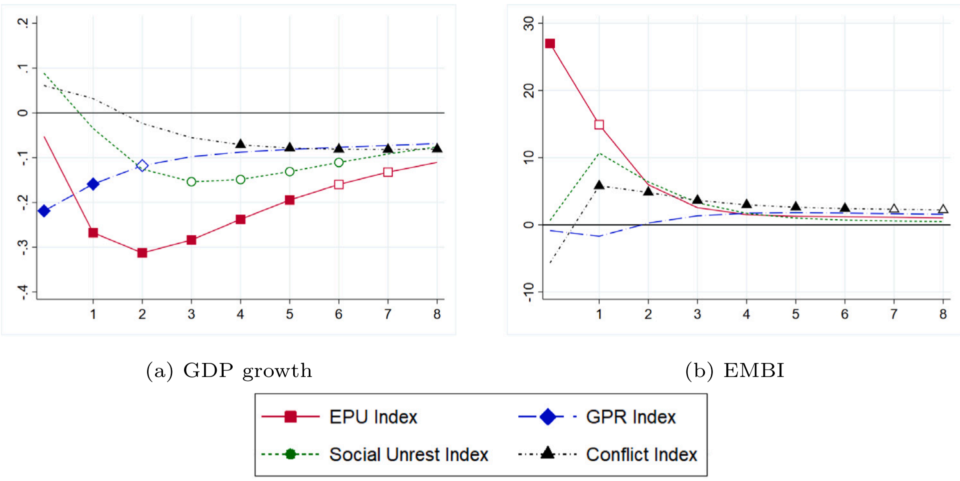


Fig. 4. Impulse responses of GDP growth and the EMBI to shocks to alternative measures of institutional instability. *Note:* Each panel depicts the impulse response of the specified variable to a rise of one standard deviation in one of the alternative measures of institutional instability, namely the EPU index (red line), geopolitical risk index (blue line), social unrest index (green line), and armed conflict 12 best (black line). Filled (empty) symbols indicate statistical significance at the 5% (10%) level, while lines without symbols represent not-significant estimates. The horizontal axis measures quarters since the shock.

Fig. 4 shows the impulse responses to an unexpected increase in institutional instability of one standard deviation. In each figure, red lines indicate the IRFs associated with the EPU index, while blue, green and black lines depict the IRFs referring to the geopolitical risk index, the social unrest index and the conflict index, respectively. Filled (empty) symbols indicate statistical significance at the 5% (10%) level, while lines without symbols represent not-significant estimates. These IRFs are also shown one by one along with their 95% confidence intervals in Appendix E (see Figs. E.1 and E.2 for GDP and EMBI responses, respectively).

A shock of one standard deviation in the EPU index is equivalent in magnitude to the Global Financial Crisis. A one standard deviation shock to the conflict variable is equivalent to the Russo-Georgian war that took place in August 2008. A one standard deviation shock to the social unrest index corresponds to specific events of the 2014 Russo-Ukrainian war, e.g. the armed conflicts that occurred in April between the Armed Forces of Ukraine and Russian-backed separatists from the self-declared Donetsk and Luhansk Republics. Finally, a shock of one standard deviation in the Russian GPR index corresponds to the sharp increase in the index that took place in the period between 2002Q4 and 2003Q3, which saw events related to the second Chechen war and

[10] The VIX represents a measure of global financial risk. It reflects market expectations regarding the relative strength of near-term price changes in the S&P 500 index. Because it is derived from the prices of S&P 500 index options with near-term expiration dates, it generates a 30-day forward projection of volatility.

[11] Results are stable when including the optimal number of lags chosen by minimising the Aikaike criterion (see Fig. F.1 in the Appendix).

[12] Results are robust to different ordering of the variables in the system (see Figs. F.2 and F.3 of the Appendix).

Putin's declaration of foreign affairs and security policy top priorities, e.g. the Dubrovka Theatre hostage crisis (October 2002),[13] the Chechen Referendum in March 2003,[14] and Putin's speech on April 18, 2002, in which he explicitly declared creating a Commonwealth of (former Soviet) Independent States as the top priority of Russian leadership, attributing to Russia the role of centre of gravitation in the region.[15] Following Boeckelmann and Stalla-Bourdillon (2021), Fig. E.6 in Appendix E compares the evolution of the estimated structural shocks of the institutional instability indicators with the aforementioned episodes. As expected, the institutional instability shocks do jump significantly during these events. This is comforting, and reassures us that the shocks we use to compute the IRFs indeed capture institutional instability.

The following points are worth noting. First, the effects are quite persistent: GDP growth rate takes more than 2 years to revert to trend after the shock in institutional instability, whereas the EMBI reverts more quickly, within a year. Second, the responses show the expected signs. A rise in institutional instability induces a decline in GDP growth (Fig. 4(a)), whereas the EMBI increases 4(b). When uncertainty increases, GDP drops by 0.3 pp, while the EMBI increases by 25 pp. Responses to shocks to the geopolitical risk and social unrest indexes are in line with responses to EPU shocks in terms of sign and magnitude, albeit somewhat less statistically significant. For instance, the GDP growth response to geopolitical risk shocks is significant only for the first two quarters, while the response to social unrest seems to be more long-lasting. Responses to shocks in the conflict variable are coherent with the dynamics and the persistence induced by shocks to the other institutional instability measures, although slightly smaller in magnitude.

Overall, our models based on alternative measures of institutional instability confirm the same story: high institutional instability in Russia yields economic slowdown, with a persistent drop in GDP growth and a short-lived but high magnitude increase in country risk.

As a complementary exercise, we follow Bloom (2009) and estimate the VAR model by using binary versions of our social stability indicators which take value one when the level of our original indicators rise significantly above their mean, and zero otherwise. This ensures us that identification comes only from these large shocks rather than from the smaller ongoing fluctuation (Bloom, 2009). The threshold to define large shocks is one standard deviation above the mean, which approximately corresponds to considering values in level that lie in the last quartile of the distribution of the original indicators.[16] Results are shown in Fig. 5, and overall confirm our baseline findings. In particular, the IRF based on the binary versions of our institutional instability indexes are similar to those based on the original ones, although slightly less significant (for a detailed comparison, see Figs. E.4 and E.5 in Appendix E). Given the limited time frame we are considering, this is expected, since binary indicators throw away much of the variation in the original indicators.

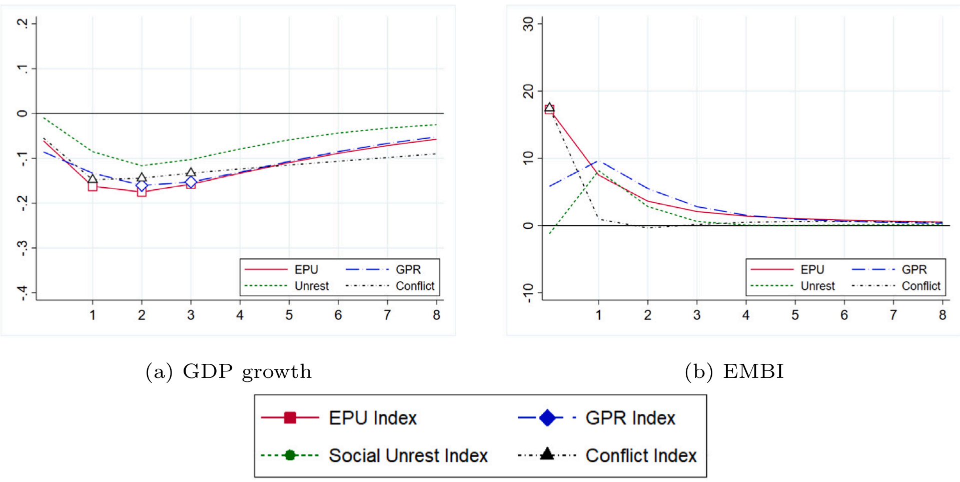


Fig. 5. Impulse responses of GDP growth and the EMBI to shocks to binary versions of the institutional instability indicators. *Note:* Each panel depicts the impulse response of the specified variable to a rise of one standard deviation in binary versions of the following institutional instability indicators: EPU index (red line), geopolitical risk index (blue line), social unrest index (green line), and armed conflict 12 best (black line). Each binary indicator takes value one if the level of the original indicator is one standard deviation above the mean. Filled (empty) symbols indicate statistical significance at the 5% (10%) level, while lines without symbols represent not-significant estimates. The horizontal axis measures quarters since the shock.

[13] The Dubrovka hostage crisis was the takeover of a Moscow theatre by armed Chechen terrorists, which involved 850 hostages and the deaths of at least 170 people. The attackers demanded the withdrawal of Russian forces from Chechnya and an end to the Second Chechen War.

[14] The referendum approved a new constitution that subordinated Chechnya to Moscow.

[15] 'Poslanie Prezidenta Rossii Federalinom Sobrani' [Russian Presidential Address to the Federal Assembly], 18 April 2002, http://www.kremlin.ru/appears/2002/04/18/0000_type63372_28876.shtml.

[16] Fig. E.3 in Appendix E shows the evolution of each institutional instability indicators along with this threshold, which define large shocks and allows to identify the events explaining the results of the binary versions of our institutional instability indicators.

4.3. Robustness

We run the following robustness exercises, whose results are all reported in Appendix F.

First, we estimate the VAR model by including the optimal number of lags chosen by minimising the Aikaike criterion. The impulse responses are stable and confirm the main results (see Fig. F.1 in the Appendix).

Second, we check that results are robust to ordering institutional instability variables in different positions. In particular, results are robust when these indicators are ordered second in the system, and placed after the EMBI indicator (see Fig. F.3 in the Appendix). This implies that country risk is considered as the most exogenous variable, i.e. it affects contemporaneously all variables in the system but does not react instantaneously to shocks to other variables. This is a strong assumption, since financial variables are very reactive and hence typically considered as among the most endogenous ones in VARs (Foroni et al., 2017).[17] In addition, results remain stable when institutional instability indicators are ordered last in the system, i.e. implying that they respond contemporaneously to all shocks in the system (see Fig. F.2 in the Appendix).

Third, we estimate the impulse responses by means of local projections following Jordá (2005). In sum, we apply the same specification of the baseline VAR model (one lag) and we estimate sequential regressions in which the dependent variable (in turn, GDP growth and EMBI) is shifted several steps ahead (up to 8 quarters) and regressed on the institutional instability indicator controlling for lagged values of the dependent variable and the other regressors.[18] Results are reported in Figs. F.4 and F.5 in Appendix. For GDP, the responses to shocks to the EPU and the GPR index are quite in line with our benchmark results both in terms of significance and magnitude, which reassure us that our VAR is not misspecified. By contrast, responses to social unrest and conflict become significantly negative with some lag (i.e. one or almost two years after the shock, respectively), while VAR results suggested a more immediate negative response. As for EMBI, the response to EPU shock is consistent with our baseline results and shows a short-lived positive response of about 30 pp. However, the EMBI response is very bumpy and imprecise, suggesting that VAR structure helps identify the impact of institutional instability shocks, while the local projection specification seems too flexible. This holds as a general comment to all EMBI responses.

4.4. Conditional forecast for the most recent period

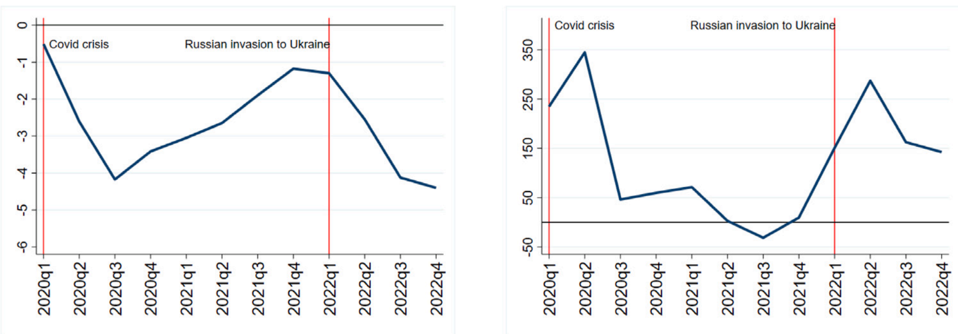
As already mentioned, our analysis relies on data until 2019q4 because of the effects of the pandemic on empirical models. However, in this section we carry out a conditional forecast exercise for GDP and EMBI in order to extrapolate our results to the current Ukraine crisis. In a nutshell, we use the structural shocks estimated by the model considering the sample period until 2019q4 and combine them with observed values of the EPU index for the out-of-sample period 2022q1-2022q4 to obtain the dynamics of GDP and EMBI for the most recent period.

For the first quarter of the first forecasting period, we proceed as follows. (i) Compute the unconditional forecast for the variables in the system based on the estimated reduced form VAR. (ii) Compute the EPU shock as the difference between the observed EPU and the unconditional forecast of the EPU index. (iii) Compute the initial values of the impulse responses of the endogenous variables to the aforementioned EPU shock, and add them back to the unconditional forecast in order to obtain the forecast conditional to the observed value of the EPU index. Then, we repeat this procedure for each subsequent quarter, to build up the forecast dynamics of GDP and EMBI for 2020q1-2022q4, conditional on the observed values of the EPU index and based on the structural shocks of the VAR model.

Results of this exercise are reported in Fig. 6. According to the conditional GDP forecast, Russian GDP fell by 4pp during the Covid crisis, and dropped again by the same amount since 2022q1, at the time of the Russian invasion of Ukraine. Hence, according

[17] For instance, Foroni et al. (2017) estimate a small VAR to explain the impact of oil market shocks on US stock returns, and place their financial variable last in the system.

[18] In the estimation, we use the Newey–West (1987) correction to adjust standard errors for serial correlation.



(a) GDP growth (b) EMBI

Fig. 6. Conditional forecast of GDP growth and the EMBI to EPU shocks. *Note:* Each panel depicts the forecast of the specified variable conditional to the observed values of the EPU index for the period 2020q1-2022q4, and based on the estimated structural EPU shocks estimated by the model based on the period 2000q3-2019q4. The two vertical red lines depict the Covid-19 crisis and the current crisis between Russia and Ukraine.

to our model and based on the structural shocks estimated considering the period until 2019, the drop in GDP induced by this last crisis is large and comparable in size to the Covid crisis (−4pp). Similarly, the EMBI rises importantly in both crisis. In line with our results, the increase in the country risk is sizeable but short-lived.

5. Conclusions

We show that policy uncertainty and conflict-related shocks impact the dynamics of economic activity (GDP) in Russia. We use alternative indicators of ‘conflict’ referring to specific aspects of this general concept, namely geopolitical risk, social unrest, outbreaks of political violence and escalations into internal armed conflict. For policy uncertainty, we employ the workhorse EPU indicator. We use two distinct but complementary empirical approaches. The first is based on a time series, mixed-frequency forecasting model: we show that the indicators provide useful information for forecasting GDP in the short run, even when controlling for a comprehensive set of standard high-frequency macro-financial variables. The second approach is a structural vector autoregressive (SVAR) model. We show that negative shocks to the selected indicators yield economic slowdown, with a persistent drop in GDP growth and a short-lived but large increase in country risk. Our work suggests several open questions for future research. One is the issue of whether the added value of institutional instability indicators increases during times of stress. While our preliminary calculations indicate that that indeed might be the case, it might be worthwhile to investigate it in a more systematic way, and for a range of economies. Secondly, we note that our results rely on a linear setup. As a avenue for further research, it would be interesting to see if more complex (non-linear) setups help improving the estimation of the reaction of economies to conflict shocks.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data and the codes are available upon request.

Appendix A. Data

See Fig. A.1 and Tables A.1, A.2.

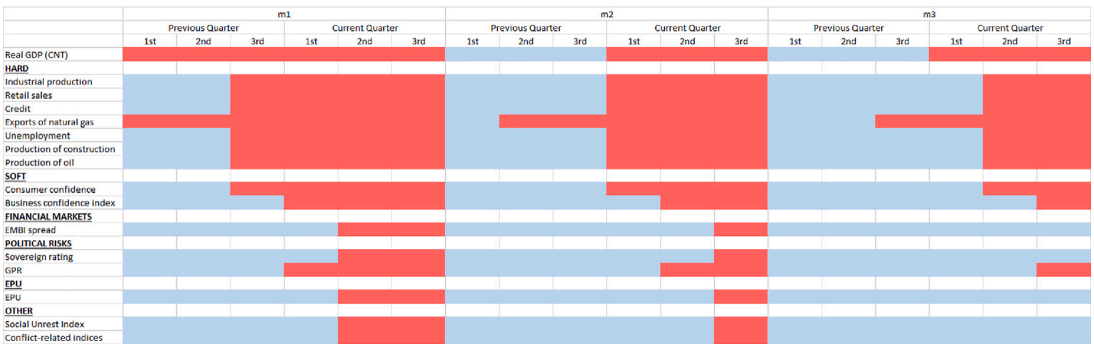


Fig. A.1. Information set available in (pseudo)real-time. The dark blocks correspond to no information being available. The first row of the table corresponds to the month in which the forecast is computed; the second and third rows correspond to the time for which the information is available. Thus, for example, in month 1 industrial production is known only up to and including month 2 of the previous quarter. Note that the only quarterly variable in the table is GDP. The last row of ‘conflict-related indices’ corresponds to all the conflict models and text-based variables produced by Mueller and Rauh (2018) (see Table A.1 for the list of the variables used).

Table A.1
Variables and related transformations.

Variable	Shorthand	Regressor category	Notes	Sources
GDP*	GDP	Dependent variable	Quarter-on-quarter growth rate seasonally adjusted (SA)	National Statistics Offices
Industrial production	Ind.Prod.	Traditional: hard	Industrial prod. index (SA)	National Statistics Offices
Retail sales	Ret.Sales	Traditional: hard	Retail sales index (SA)	National Statistics Offices
Credit	Credit	Traditional: hard	Nominal credit to private sector deflated by CPI	IMF/National Statistics Institute
Exports of natural gas	Exports	Traditional: hard	Volume, SA	National Statistics Offices
Unemployment rate	Unempl.Rate	Traditional: hard	Rate, SA	National Statistics Offices
Production of construction	Prod.Constr.	Traditional: hard	Volume (SA)	National Statistics Offices
Production of oil	Oil Output	Traditional: hard	Volume (SA)	National Statistics Offices
Consumer confidence	Cons.Conf.	Traditional: soft	Level (SA)	OECD
Business confidence index	Bus.Conf.Ind.	Traditional: soft	Level (SA)	IMEMO Primakov Institute of World Economy and International Relations
Sovereign rating	Sov.Rat.	Standard: Political	Average SP, Moody's, Fitch	SP, Moody's and Fitch
Emerging markets bond index*	EMBI	Standard: Financial	Spread over US Treasury, bps	JP Morgan
Geopolitical risk index*	GPR	Text-based variables	Level	Caldara-Iacovello
Economic policy uncertainty*	EPU	Text-based variables	Level	Baker et al. https://www.policyuncertainty.com/
Reported social unrest index*	Soc.Unr.	Text-based variables	Level	RSUI IMF
Topic: politics	Top.Pol.	Text-based variables	topic1	Mueller and Rauh
Topic: economics	Top.Econ.	Text-based variables	topic6	Mueller and Rauh
Topic: conflict	Top.Conf.	Text-based variables	topic10	Mueller and Rauh
Armed conflict 12 months text	Arm.Conf.12.text	Conflict models	Text model	Mueller and Rauh
Armed conflict 12 months best*	Arm.Conf.12.best	Conflict models	Best model	Mueller and Rauh
Armed conflict 3 months text	Arm.Conf.3.text	Conflict models	Text model	Mueller and Rauh
Armed conflict 3 months best	Arm.Conf.3.best	Conflict models	Best model	Mueller and Rauh
Any violence 12 months text	AnyViol.12.text	Conflict models	Text model	Mueller and Rauh
Any violence 12 months best	AnyViol.12.best	Conflict models	Best model	Mueller and Rauh
Any violence 3 months text	AnyViol.3.text	Conflict models	Text model	Mueller and Rauh
Any violence 3 months best	AnyViol.3.best	Conflict models	Best model	Mueller and Rauh
CBOE volatility index**	VIX	Exogenous Variable	Volatility of options on S&P 500 with near-term expiration dates	Chicago Board of Exchange (CBOE)
Headline consumer price index**	Infl.	Traditional: hard	quarter-on-quarter growth rates (SA)	National Statistics Offices

Note: Before analysis, both GDP and the hard indicators in the 'traditional' set of variables are transformed using the quarter-on-quarter and month-on-month difference of the logarithm of the baseline values. Month-on-month differencing is also applied to the EMBI. Non-starred and single-starred variables are used in the forecasting exercise; starred and double-starred variables are used in the VAR analysis.

Table A.2
Augmented Dickey–Fuller test (*p*-value).

Lags	0	1	2	3	4	5
GDP	0.02	0.01	0.00	0.00	0.06	0.26
Inflation	0.00	0.13	0.06	0.03	0.16	0.23
VIX	0.01	0.01	0.08	0.12	0.20	0.13
Ind.Prod.	0.00	0.00	0.00	0.00	0.00	0.02
Ret.Sales	0.00	0.02	0.15	0.28	0.33	0.39
Credit	0.00	0.00	0.15	0.54	0.23	0.24
Exports	0.00	0.00	0.00	0.00	0.00	0.00
Unempl.Rate	0.00	0.00	0.00	0.00	0.01	0.00
Prod-Constr.	0.00	0.00	0.00	0.00	0.00	0.00
Oil Output	0.00	0.00	0.13	0.32	0.44	0.45
Cons.Conf.	0.01	0.00	0.00	0.01	0.01	0.04
Bus.Conf.Ind.	0.00	0.02	0.01	0.03	0.01	0.01
Sov.Rat.	0.00	0.00	0.00	0.00	0.00	0.00
GPR[a]	0.06	0.00	0.02	0.04	0.13	0.03
EPU[b]	0.00	0.00	0.01	0.14	0.26	0.46
EMBI	0.00	0.00	0.00	0.00	0.00	0.00
Top.Pol.	0.00	0.00	0.01	0.08	0.04	0.08
Top.Econ.	0.02	0.02	0.05	0.12	0.10	0.22
Top.Conf.	0.00	0.00	0.01	0.29	0.12	0.14
Arm.Conf.12.text[a]	0.08	0.06	0.08	0.03	0.01	0.01
Arm.Conf.12.Best	0.97	0.88	0.90	0.81	0.87	0.85
Arm.Conf.3.text	0.01	0.00	0.02	0.10	0.04	0.01
Arm.Conf.3.best[c]	0.10	0.06	0.07	0.07	0.05	0.09
Any.Viol.12.text	0.02	0.01	0.02	0.05	0.02	0.03
Any.Viol.12.best	0.05	0.02	0.03	0.06	0.06	0.10
Any.Viol.3.text[b]	0.02	0.03	0.03	0.05	0.13	0.15
Any.Viol.3.best[a]	0.04	0.09	0.09	0.09	0.11	0.06
Soc.Unr.	0.02	0.01	0.09	0.12	0.26	0.39

Note: The table shows the P-value of the augmented Dickey–Fuller test at the quarterly frequency for alternative specifications (up to 5 lags) including the constant. A p-value < 0.05 rejects the null-hypothesis that the variable follows a unit root.

[a]The test include the drift option. For Arm.Conf.12.Best, excluding the constant allows to reject the null of unit root process at 10% level.

[b]The test is run on monthly data. For Arm.Conf.12.Best, excluding the constant allows to reject the null of unit root process at 10% level.

[c]The test is run on monthly data with the drift option. For Arm.Conf.12.Best, excluding the constant allows to reject the null of unit root process at 10% level.

Appendix B. Optimisation of the forecasting exercise

The final optimal forecasting model is created as follows: first, an optimal model is found for each of the three combination sets (Text Variables, Conflict Models, and All Variables); second, the three separate optimal models are compared based on the average reduction in the RMSFE with respect to the benchmark. The model that displays the greatest reduction is then chosen to be the final optimal model.

The first step, that of optimising each of the three combination sets, involves excluding the worst-performing variables ex-post. We do not perform ex-ante selection because some regressors might display poor individual performance, and yet, when grouped with others in a combination forecast, nevertheless move the forecast in the correct direction.

Specifically, for each of the Text Variables and Conflict Models combinations, we: 1. Compute the RMSFE of the model that includes all the variables added on top of the standard set of variables, and compare its RMSFE with the RMSFE of the benchmark model that only includes the standard variables. 2. For each of the extra (non-standard) variables, create a model that *excludes* that variable. In other words, a model that includes the standard variables and all but one additional variable. 3. Compare the relative RMSFE of a model with that variable excluded to relative RMSFE of the model with the variable present. 4. Compute the fraction of (months, horizons, MIDAS models, Combination methods) in which excluding that variable *improves* the forecast. 5. The optimal model for that combination is taken to be one without the variables whose exclusion improves the results in at least 80% of the cases.

After computing the optimised Text Variables and Conflict Models combinations, we proceed to define the optimised combination of "All" variables. We take such a combination to contain all the additional institutional instability variables with the exception of the regressors excluded from the two optimised models above. Note that we only ever remove the worst-performing institutional instability regressors and not the standard macroeconomic variables, thereby keeping the benchmark forecast as a valid comparison.

Finally, it is worth underlining that the optimisation is performed out of sample. We first use in-sample data to train the individual models and perform one-step ahead forecasts with the recursive window. The RMSFEs that are then used to compare the models and the benchmarks are the RMSFEs of the resulting out-of-sample forecasts.

Figs. B.1 shows how excluding certain variables improves on the specific combination models. Based on these results, and the cutoff of 80%, the optimal Text Variables combination excludes GPR, the optimal Conflict Models combination excludes five variables

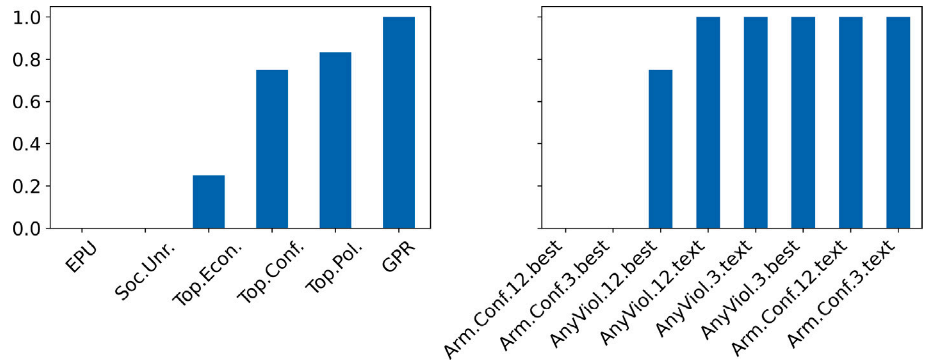


Fig. B.1. Probability to get a lower relative RMSFE using a combination with the variable excluded. The relative RMSFE is with respect to a benchmark model with just the standard variables. The probability is computed as a fraction of all the parameters, which includes all the months, forecast horizons, MIDAS models, and combination methods. The left subfigure corresponds 7to the removal of variables from the Text Variables set, the right subfigure from the Conflict Models set.

(Table 1), and the optimal All Variables combination excludes the six variables above. The resulting optimal model used in the exercise is then the optimised All Variables combination

Appendix C. MSFE of the benchmark model

See Fig. C.1.

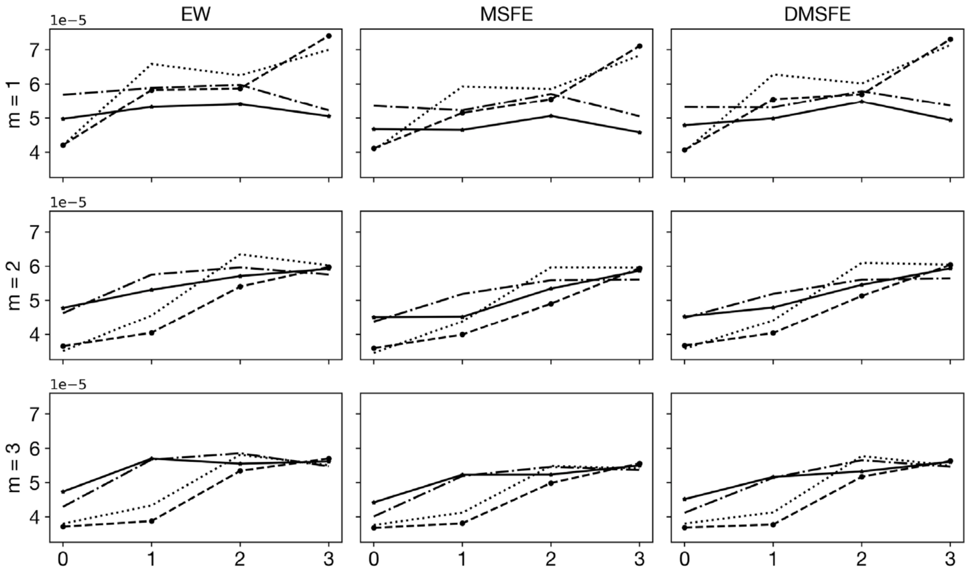


Fig. C.1. MSFE of the benchmark model of the quarterly combination forecast. MSFE of the benchmark combination of only the traditional and standard indicators. Note that the quarterly growth is expressed in fraction rather than percentages (i.e. the values are not scaled by 100). Columns correspond to the different combination methods. Starting months *m* are separated by rows, and the abscissa shows the forecast horizons *h*. Lines represent individual regressor models—solid with marker: TA; dashed with marker: TA-ADL; dot-dashed: NEALMON; dotted: NEALMON-ADL.

Appendix D. VAR descriptive statistics

See Table D.1 and Figs. D.1, D.2.

Table D.1
Descriptive statistics.

Variable	Transformation	Mean	SD	Min	p50	Max	N
VIX	Level	19.35	7.89	10.30	16.89	58.32	78
GPR	Level	0.67	0.24	0.38	0.55	1.15	78
EPU	Level	137.93	73.67	40.29	119.58	376.05	78
Conflict	Level	−56.23	−24.18	−11.42	−67.58	−83.76	78
Social unrest	Level	141.33	133.92	18.59	87.01	625.75	78
EMBI	First diff.	−11.88	90.86	−239.67	−9.44	476.17	78
GDP	Q-o-Q growth rate	0.82	1.16	−3.53	0.69	3.19	78
Inflation	Q-o-Q growth rate	2.29	1.30	0.15	2.17	6.86	78

Note: This table reports descriptive statistics of the variables used in the VAR exercise.

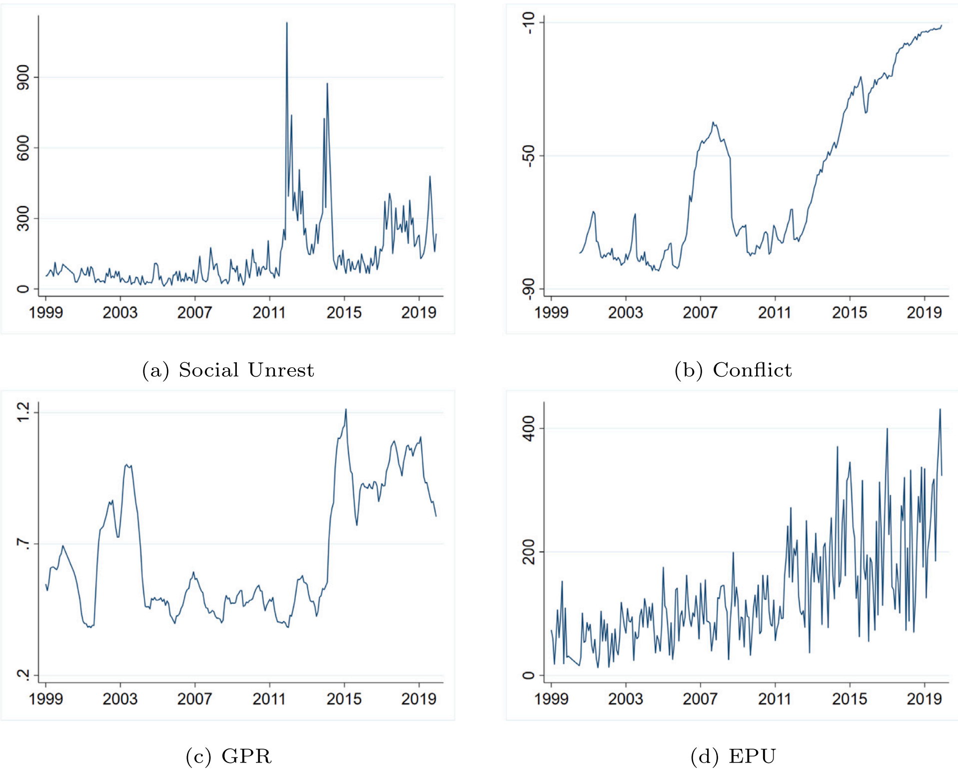
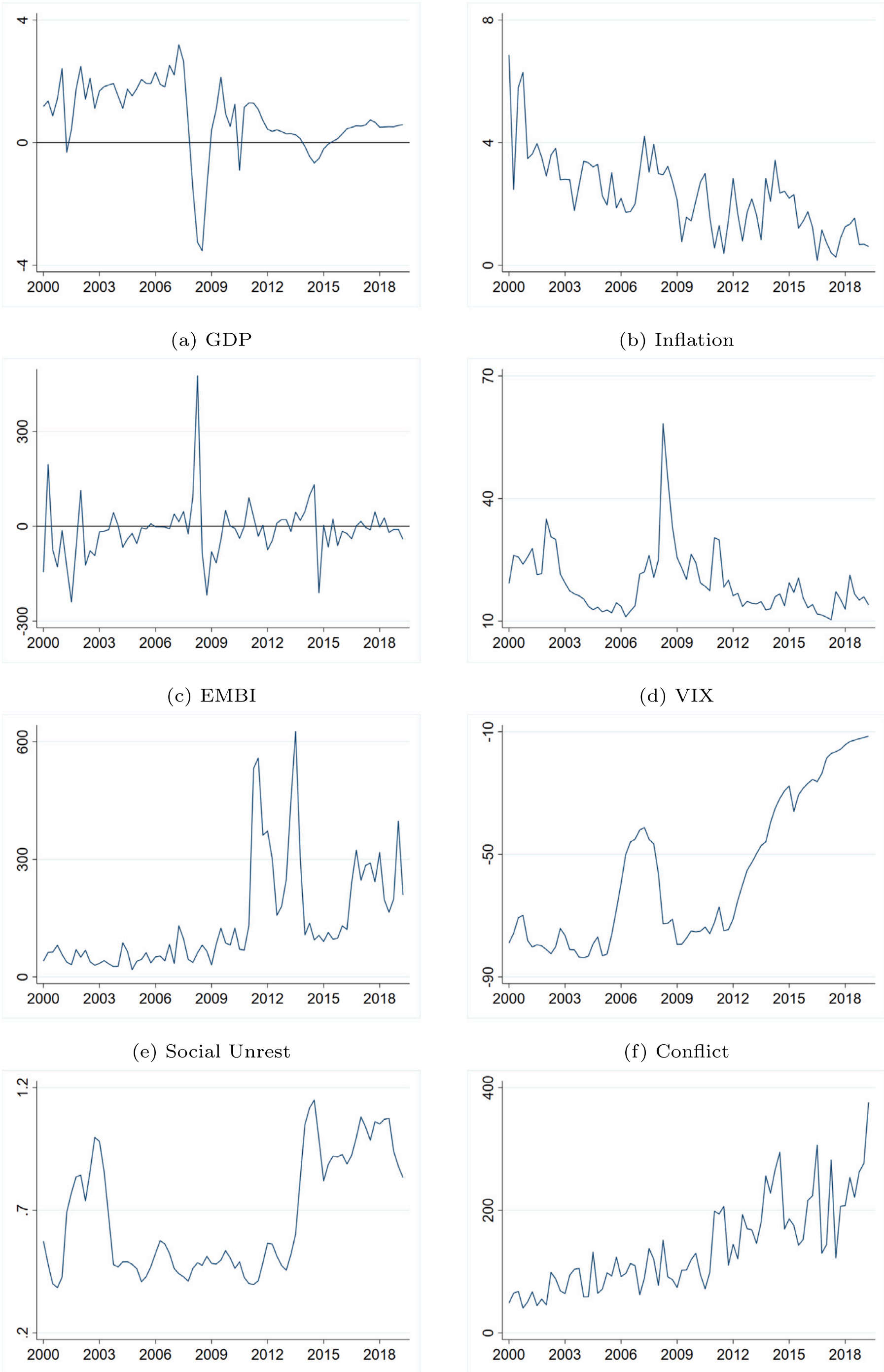


Fig. D.1. Variables used in the VAR exercise: monthly frequency.



(a) GDP (b) Inflation

(c) EMBI (d) VIX

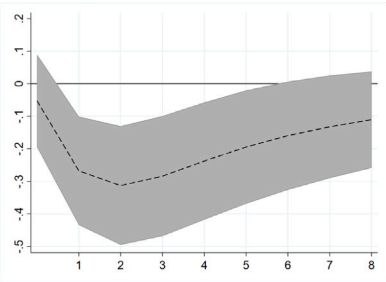
(e) Social Unrest (f) Conflict

(g) GPR (h) EPU

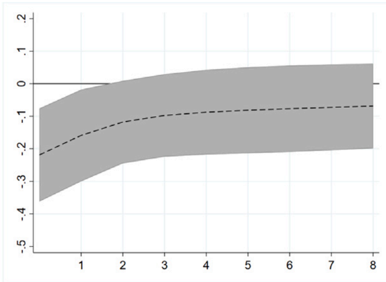
Fig. D.2. Variables used in the VAR exercise: quarterly frequency.

Appendix E. VAR additional results

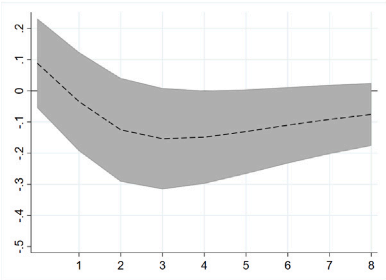
See Figs. E.1–E.6.



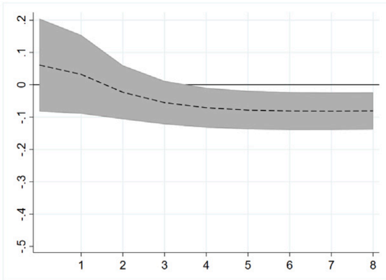
(a) EPU



(b) GPR

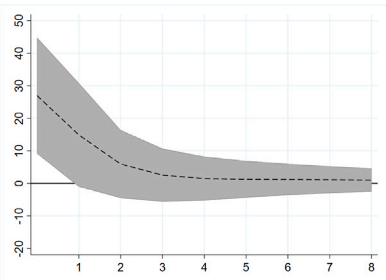


(c) Social Unrest

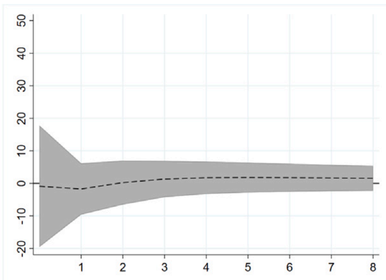


(d) Conflict

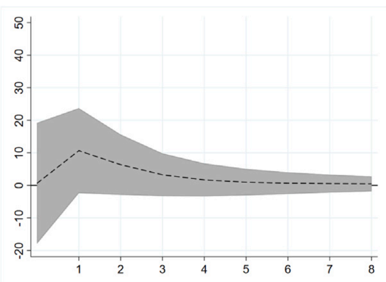
Fig. E.1. Additional results: IRFs of GDP to shocks to alternative measures of institutional instability, along with their 95% confidence bounds. *Note:* Each panel depicts the impulse response of GDP to a rise of one standard deviation in the EPU index E.1(a), the geopolitical risk index E.1(b), the social unrest index E.1(c) and armed conflict 12 best index E.1(d), along with their 95% confidence bounds. The horizontal axis measures quarters since the shock. The institutional instability index is ordered last in each model.



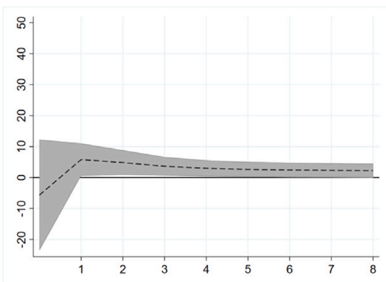
(a) EPU



(b) GPR

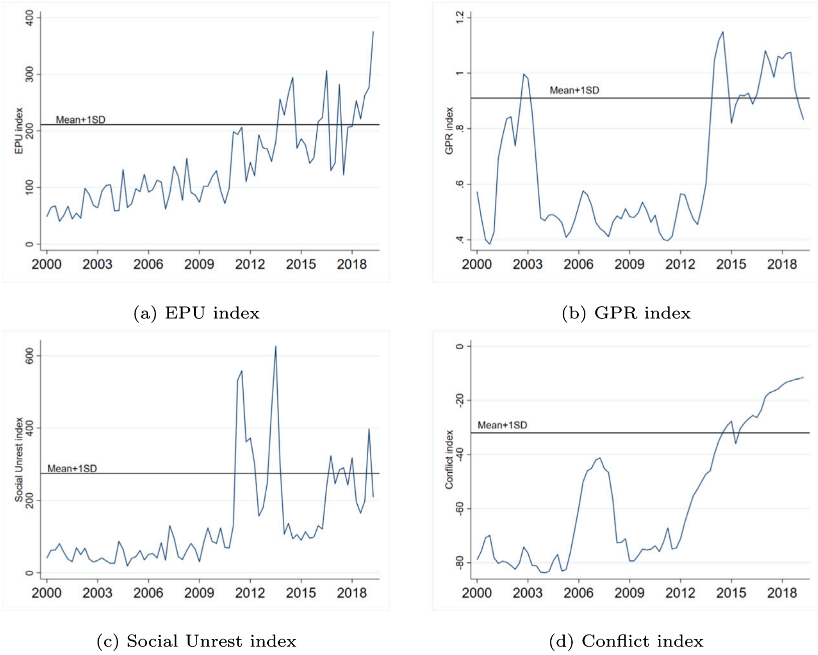


(c) Social Unrest



(d) Conflict

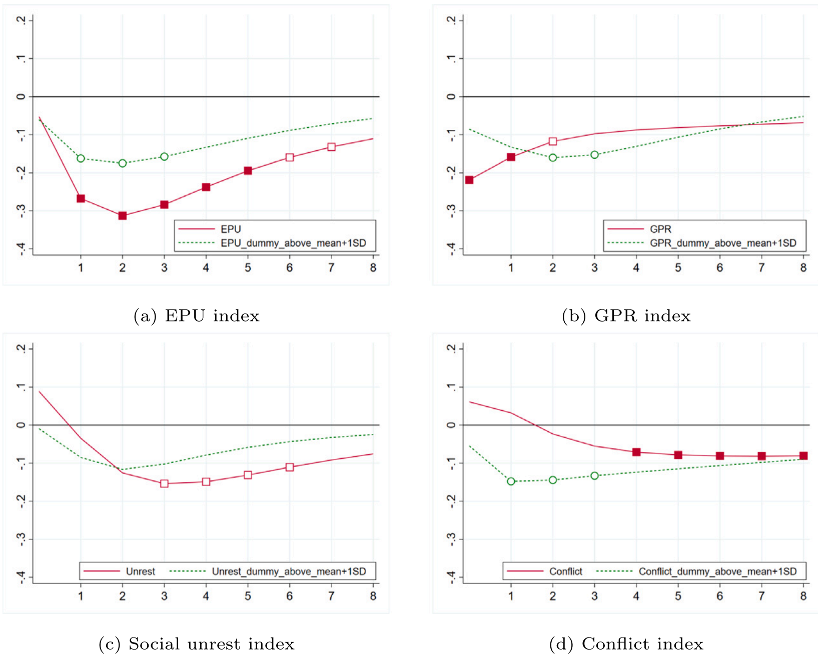
Fig. E.2. Additional results: IRFs of EMBI to shocks to alternative measures of institutional instability, along with their 95% confidence bounds. *Note:* Each panel depicts the impulse response of EMBI to a rise of one standard deviation in the EPU index E.2(a), the geopolitical risk index E.2(b), the social unrest index E.2(c) and armed conflict 12 best index E.2(d), along with their 95% confidence bounds. The horizontal axis measures quarters since the shock. The institutional instability index is ordered last in each model.



(a) EPU index (b) GPR index

(c) Social Unrest index (d) Conflict index

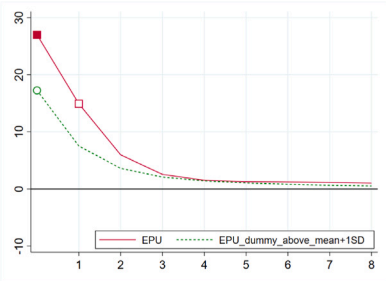
Fig. E.3. Peaks exploited when defining dummy versions of the institutional instability indicators. *Note:* Each panel depicts the evolution of the original (continuous) institutional instability indicators together with the threshold that is used to define the dummy version of these indicators, that take value one when the level of the indicators rise significantly above their mean, and zero otherwise. The threshold is defined as one standard deviation above the mean, which approximately corresponds to considering the values of the original indicators that lie above the 75 percentile of their distribution.



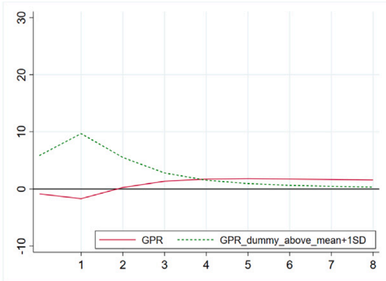
(a) EPU index (b) GPR index

(c) Social unrest index (d) Conflict index

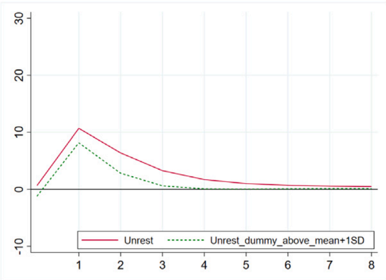
Fig. E.4. IRF of GDP to shocks to original measures of institutional instability as well as to their binary versions. *Note:* Each panel depicts the response o GDP growth to shocks to the original institutional instability indicators (red line) and to the binary versions of these institutional instability indicators (green line). Filled (empty) symbols indicate statistical significance at the 5% (10%) level, while lines without symbols represent not significant estimates. The horizontal axis measures quarters since the shock. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



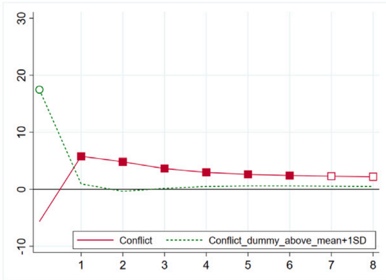
(a) EPU index



(b) GPR index

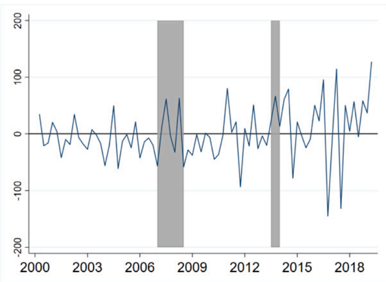


(c) Social unrest index

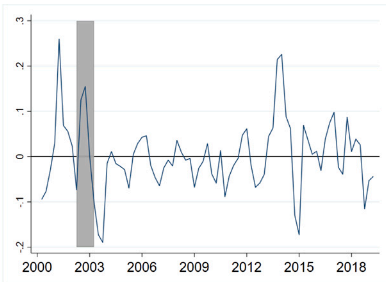


(d) Conflict index

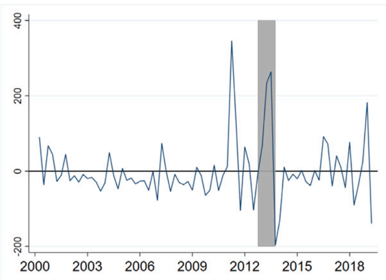
Fig. E.5. IRF of EMBI to shocks to original measures of institutional instability as well as to their binary versions. *Note:* Each panel depicts the response of EMBI to shocks to the original institutional instability indicators (red line) and to the binary versions of these institutional instability indicators (green line). Filled (empty) symbols indicate statistical significance at the 5% (10%) level, while lines without symbols represent not significant estimates. The horizontal axis measures quarters since the shock. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



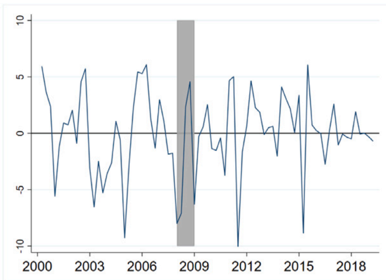
(a) EPU



(b) GPR



(c) Social Unrest

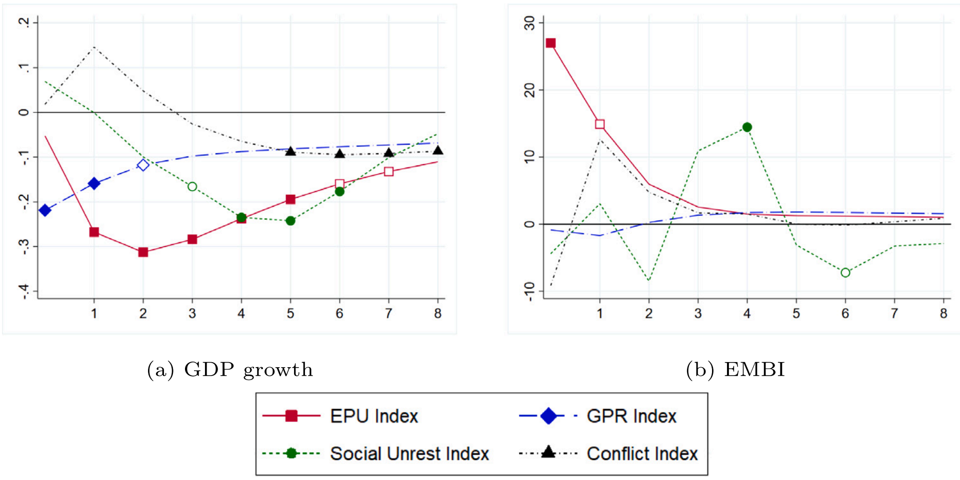


(d) Conflict

Fig. E.6. Additional results: Structural shocks against the timeline of related events. *Note:* Each panel shows the structural shock of the corresponding institutional instability indicator estimated by the VAR model. The grey areas depict events which in the main text we consider as examples of impulses used in the IRF estimation, i.e. episodes in which the institutional instability indicator shows a variation of about one standard deviation: for the EPU (panel E.6(a)), the Great recession; for the GPR index (panel E.6(a)), the second Chechen war and Putin's declaration of foreign affairs and security policy top priorities (2002Q4-2003Q3); for the social unrest index (panel E.6(c)), the 2014 Russo-Ukrainian war; for the conflict index (panel E.6(d)), the 2008 Russo-Georgian war.

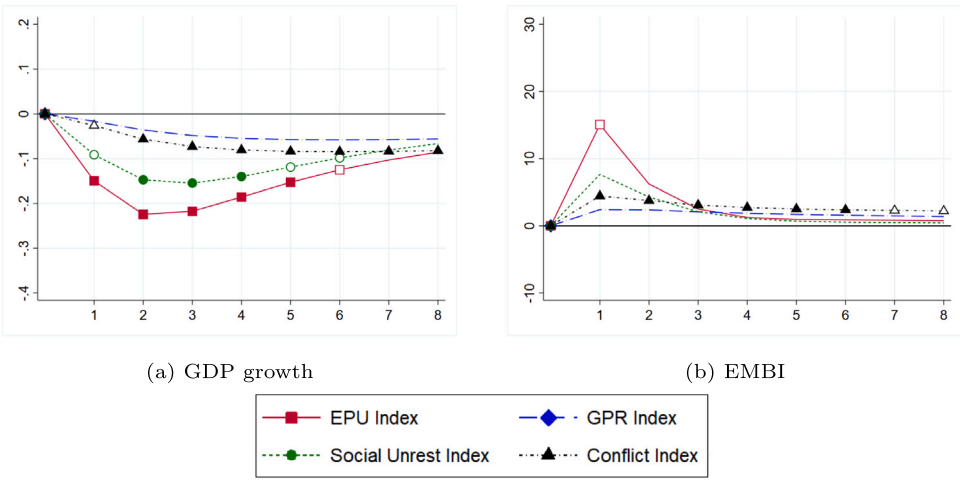
Appendix F. VAR robustness exercises

Figs. F.1–F.5.



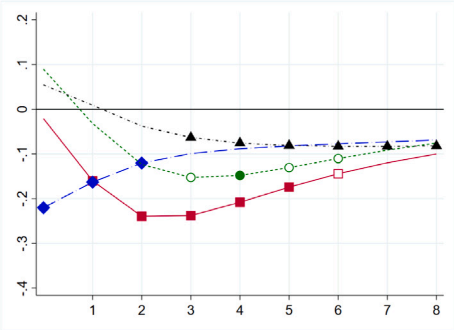
(a) GDP growth (b) EMBI

Fig. F.1. Robustness: IRF of GDP and the EMBI to shocks to alternative measures of institutional instability. Optimal lags. *Note:* Each panel depicts the impulse response of the specified variable to a rise of one standard deviation in one of the alternative measures of institutional instability, namely the EPU index (red line), geopolitical risk index (blue line), social unrest index (green line) and armed conflict 12 best (black line). Filled (empty) symbols indicate statistical significance at the 5% (10%) level, while lines without symbols represent not significant estimates. The horizontal axis measures quarters since the shock. The optimal lags are chosen by minimising the Aikaike criterion, imposing a maximum of 4 lags, namely one lag for the EPU and social unrest indexes, two lags for the geopolitical risk index and three lags for the conflict variables.

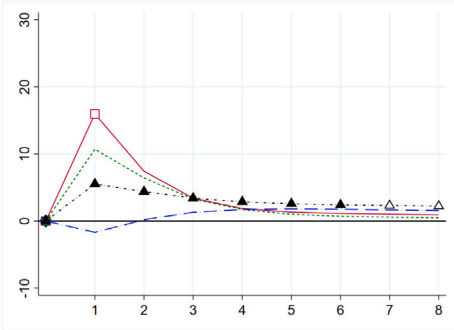


(a) GDP growth (b) EMBI

Fig. F.2. Robustness: IRFs of GDP and the EMBI to shocks to alternative measures of institutional instability. Institutional instability is ordered last in the VAR model. *Note:* Each panel depicts the impulse response of the specified variable to a rise of one standard deviation in one of the alternative measures of institutional instability, namely the EPU index (red line), geopolitical risk index (blue line), social unrest index (green line) and armed conflict 12 best (black line). Filled (empty) symbols indicate statistical significance at the 5% (10%) level, while lines without symbols represent not significant estimates. The horizontal axis measures quarters since the shock. The institutional instability index is ordered last in each model.

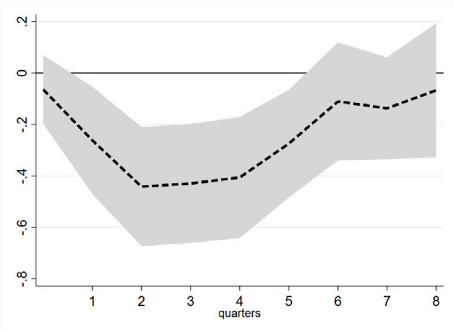


(a) GDP growth

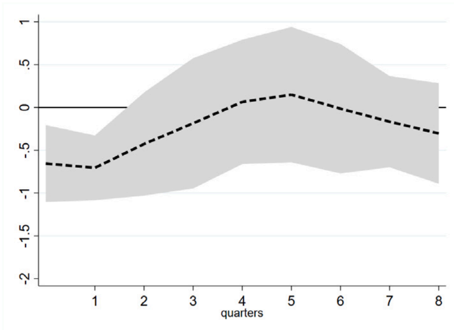


(b) EMBI

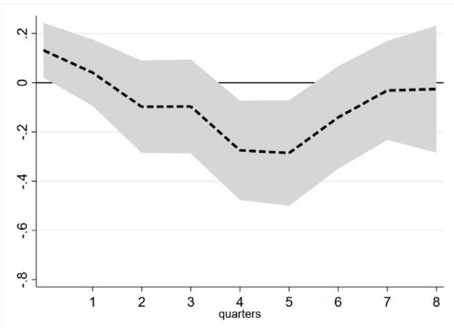
Fig. F.3. Robustness: IRFs of GDP and the EMBI to shocks to alternative measures of institutional instability. Institutional instability is ordered second in the VAR model. *Note:* Each panel depicts the impulse response of the specified variable to a rise of one standard deviation in one of the alternative measures of institutional instability, namely the EPU index (red line), geopolitical risk index (blue line), social unrest index (green line) and armed conflict 12 best (black line). Filled (empty) symbols indicate statistical significance at the 5% (10%) level, while lines without symbols represent not significant estimates. The horizontal axis measures quarters since the shock. The institutional instability index is ordered second in each model.



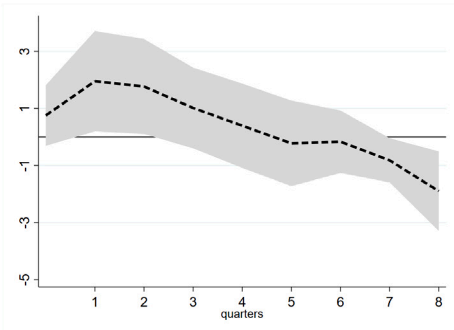
(a) EPU



(b) GPR

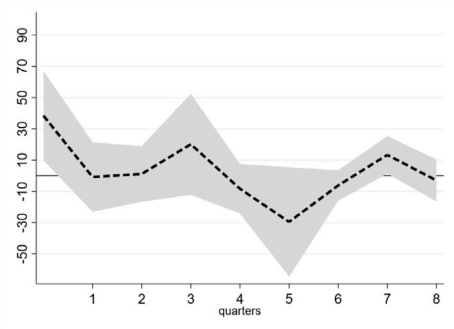


(c) Social Unrest

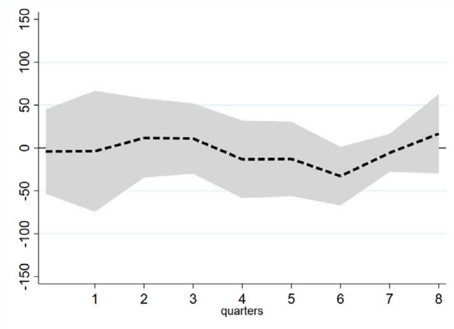


(d) Conflict

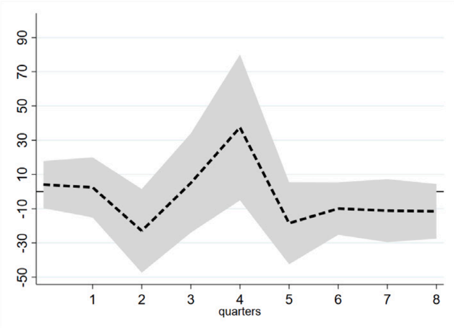
Fig. F.4. Robustness results: GDP growth responses by means of local projections. *Note:* Each panel shows the impulse response of GDP to shocks of one standard deviation to the institutional instability variable of interest, along with the 10% confidence bands, obtained by means of local projections. To ensure comparability, we use the same specification used in the baseline VAR (which include only one lag).



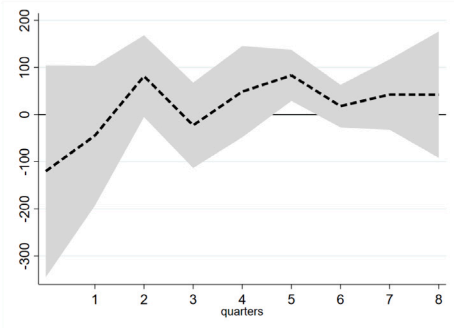
(a) EPU



(b) GPR



(c) Social Unrest



(d) Conflict

Fig. F.5. Robustness results: EMBI responses by means of local projections. *Note:* Each panel shows the impulse response of EMBI to shocks of one standard deviation to the institutional instability variable of interest, along with the 10% confidence bands, obtained by means of local projections. To ensure comparability, we use the same specification used in the baseline VAR (which include only one lag).

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