

THE ECONOMIC IMPACT
OF CONFLICT-RELATED AND
POLICY UNCERTAINTY SHOCKS:
THE CASE OF RUSSIA

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Abstract

We show how policy uncertainty and conflict-related shocks impact the dynamics of economic activity (GDP) in Russia. We use alternative indicators of “conflict”, relating 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 lead to economic slowdown, with a persistent drop in GDP growth and a short-lived but large increase in country risk.

Keywords: GDP forecasting, natural language processing, social unrest, social conflict, policy uncertainty, geopolitical risk.

JEL classification: E37, D74, N14.

Resumen

En el presente artículo se muestra como la incertidumbre política y las variables que miden el conflicto impactan sobre la actividad económica en Rusia (y en concreto sobre el PIB). Para ello se utilizan diversos indicadores que miden el conflicto, referidos a aspectos específicos de este concepto general: riesgo geopolítico, malestar social, brotes de violencia y conflicto armado interno. Para la incertidumbre sobre el curso de la política económica se emplea el habitual EPU (indicador de incertidumbre de política económica). En el artículo se utilizan dos enfoques empíricos distintos pero complementarios. El primero se basa en un modelo de predicción de frecuencia mixta de series de tiempo (MIDAS), en el que se muestra que los indicadores de conflicto aportan información útil para pronosticar el PIB a corto plazo, incluso controlando por un conjunto amplio de variables macrofinancieras. El segundo enfoque es un modelo de vectores autorregresivos estructural (SVAR), en el que se muestra que los *shocks* de los indicadores de conflicto generan una desaceleración de la actividad, con una caída persistente del crecimiento del PIB y un incremento efímero pero sustancial de las primas de riesgo.

Palabras clave: predicción del PIB, procesamiento natural del lenguaje, malestar social, conflicto social, incertidumbre política, riesgo geopolítico.

Códigos JEL: E37, D74, N14.

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, they can lead to consequences similar to the mere risk of conflict escalation, by influencing market expectations and changing 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), and can in some cases even lead to firms modifying their behaviour in an attempt to influence said policy Hassan et al. (2019). Most studies use cross-country data and draw general results, 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. Two recent works are relevant in this context. In the first, 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. The second work is Zhemkov (2021), which focuses on Russia and in which the author uses a host of traditional macro-financial indicators and models to improve on the 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. The particular indicators that we consider as representing the varied aspects of institutional instability have been demonstrated to be useful when 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).

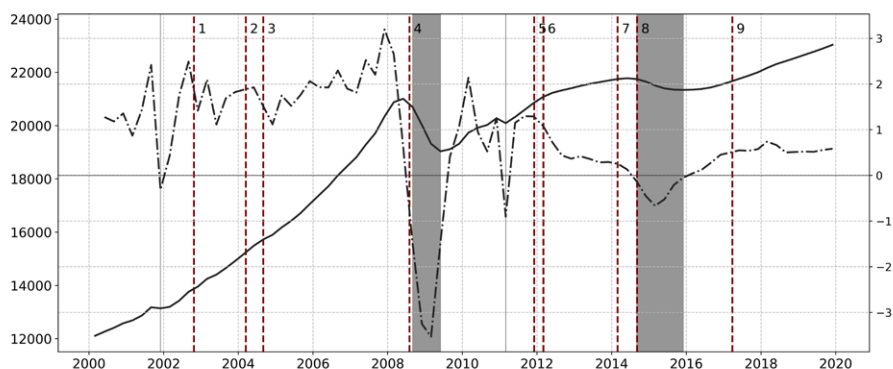
We use two distinct but complementary empirical approaches. The first exercise is based on a time series mixed-frequency forecasting model. More specifically, we show that augmenting the classical mixed-data sampling (MIDAS) combination forecast with indicators such as the risk of conflict, tension, uncertainty and social unrest can achieve a statistically significant 12% reduction in forecast errors. This result highlights the crucial reliance of the Russian economy on institutional stability 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.

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. Figure 1 displays the GDP of Russia for our sample period of January 2000 to December 2019. Note that we do not include 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 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 aftereffects 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.

Figure 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 pro-

duction, 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 points⁵ and the sovereign rating (an average of the ratings of the three major agencies: Standard and Poor’s, Fitch, and Moody’s), linearized 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). We use a novel adaption of this method developed by Charemza et al. (2022) for the case of Russia. 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.

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 follow Diakonova et al. (2022) and employ the mixed-frequency

⁵The 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.

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 Table A.1 for details on the release lags). 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 Akaike 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 2000 Q1 to 2009 Q4, with the forecast then being evaluated using a rolling-window approach. 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.

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)⁶ and comparing it to the RMSFE of some benchmark. Corresponding to the aim of the exercise, this benchmark model is

⁶ $RMSFE = \sqrt{\frac{1}{N} \sum_i^N (y_i - f_i)^2}$, where y_i and f_i are, respectively, the true value of the growth and the forecast at quarter i .

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 addition is a set of text-based variables, which includes the GPR and EPU indexes and variables taken from Mueller and Rauh (2022a). The second set of additional variables comprises the conflict models produced by the latter authors. These are considered as a distinct set because the variables are a result of an additional set of assumptions that go into constructing the models. Finally, we also consider the entire set of indicators together. Table 1 summarises the three sets and their constituent variables.

We first optimise the text variables and the 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 resulting optimised forecast thus shows the gains at least potentially achievable out-of-sample. Such ex-post selection is necessary in order not to exclude the regressors that might display poor individual performance but that, when combined with others, move the combination trend in the correct direction. The optimised combination of all additional variables then removes the regressors excluded from the first two sets. 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. 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.

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.

3.2. The results

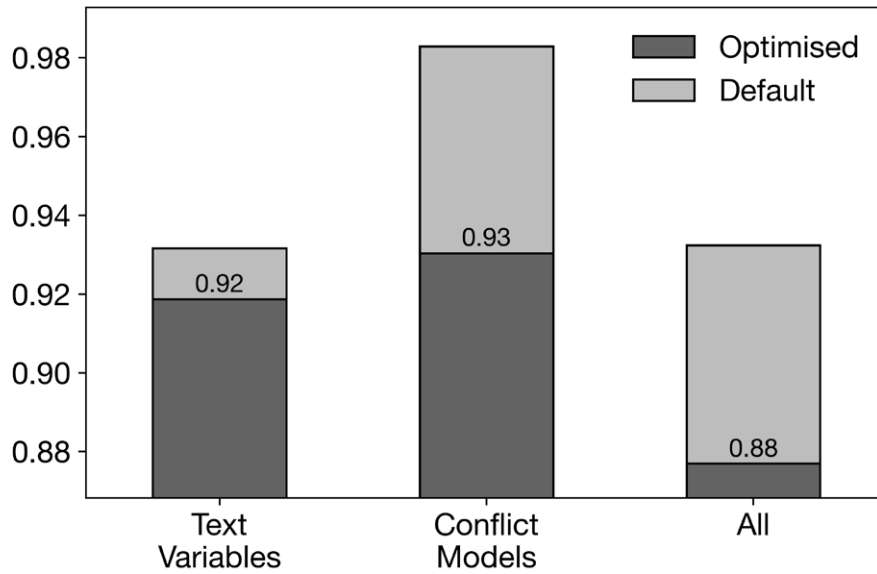
To start with, we find that adding conflict-type and EPU variables improves the forecast for *all* (month, horizon) pairs. To compute this, we average over the models and combination methods. This result holds for both the optimised and non-optimised combinations. Figure 2 summarises the results of our combination forecasts in terms of quantitative improvements⁷. 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. This result is statistically significant at an effective confidence level of 100%.

Figure 3 shows the performance of the optimal combination with month and horizon. There does not seem to be a definitive pattern when changing the forecast month, such that the improvements to forecasts made at the start of the quarter are, when averaged across the considered horizons, of the same relative magnitude as the improvements achievable at the end of the quarter. The trend for horizons tells a different story. For Russia, adding conflict-like and EPU variables brings more value when forecasting long-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, Figure 4 shows how the forecasting improvements change under the four different exercise parameters mentioned previously. First, the results appear robust to both the forecast combination and 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,

⁷The 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.

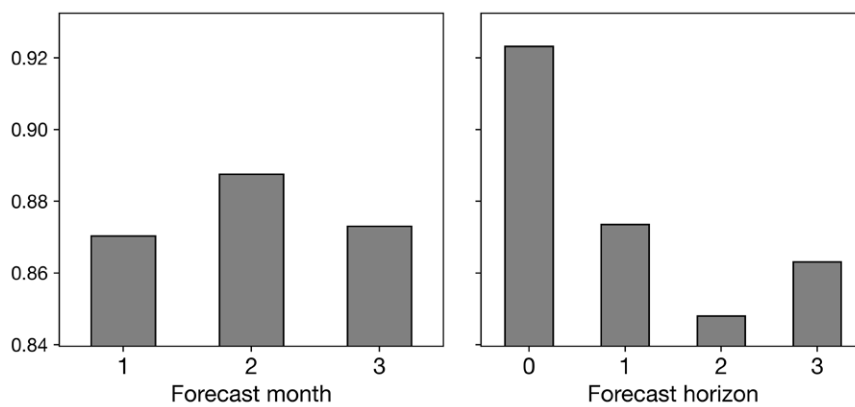
Figure 2: RMSFE relative to benchmark model



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 averages over the three initial months, the four forecast horizons, the four models and the three combination methods.

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.

Figure 3: RMSFE of the optimal combination forecast of quarterly growth relative to the benchmark combination



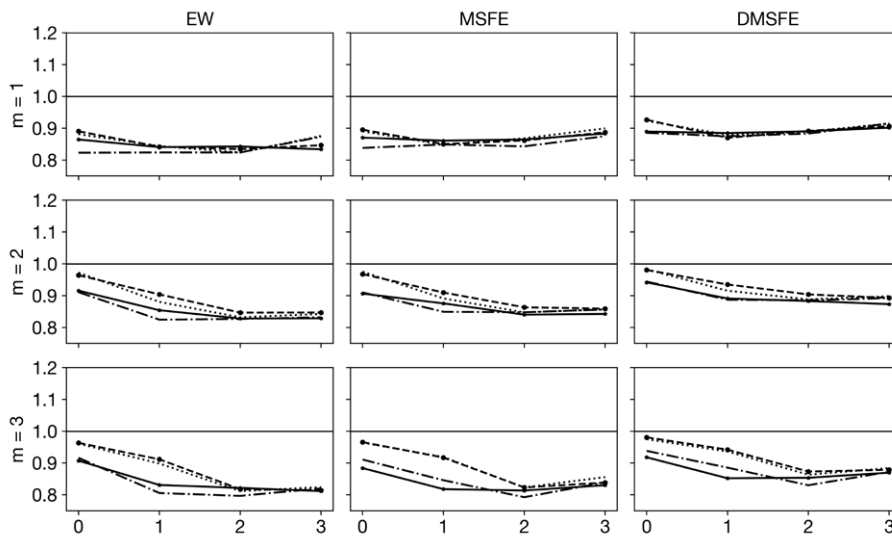
RMSFE of the optimised ‘All’ combination relative to the benchmark combination, averaged first over the four models and three combination methods and then over either months (left plot) or horizons (right plot). See Table 1 for the combination descriptions.

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 from 2000Q3 to 2019Q4.⁸ The models contain the following variables for the Russian economy, in this order: (i) an institutional instability variable in levels (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 the model with the EPU index and the social unrest index, these are considered as endogenous variables, in line with the literature (e.g. Baker et al., 2016), and we include the Chicago Board Options Exchange (CBOE) volatility index (VIX)

Figure 4: 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 points refer to results that are statistically significant at 90% confidence level, apart from ($h = 0, m = 2$, TA-ADL and NEALMON-ADL, all combination methods), and ($h = 0, m = 3$, NEALMON-ADL with EW method, and TA-ADL and NEALMON-ADL with DMSFE method).

⁸We exclude 2000Q1 and 2000Q2 to get rid of outliers. Summary statistics for the variables used in the estimations are reported in Table C.1. Figure C.2 shows the evolution of each variable used in the VAR estimation at the quarterly frequency. Figure C.1 shows the evolution of the four measures of institutional instability at the monthly frequency.

as an exogenous variable in the system to control for global uncertainty shocks.⁹ In contrast, the GPR index and the conflict variable are included as exogenous variables in the system under the assumption of block exogeneity, which means that the equation of the GPR index and of the conflict variable only depend on the constant term and on the autoregressive terms, while the coefficients in front of the endogenous variables (GDP growth, EMBI and inflation) are constrained to be zero. We believe that this is a more realistic assumption due to the specific nature of these two indicators, which tend to be exogenous with respect to a country's economy.

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. However, results are stable when including the optimal number of lags chosen by minimizing the Aikake criterion (see Figure D.1 in the Appendix). 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 to shocks to other variables. In particular, in the models with the EPU index and the social unrest index, we assume that these variables are affected by shocks to the economy with a lag, i.e. these variables are properly endogenous. In contrast, when we consider the geopolitical risk index and the conflict index, we additionally assume that these do not react to shocks to the economy, even with a lag, i.e. they are block exogenous, as mentioned above. Second, the EMBI affects the real economy but does not affect the institutional instability indicators. 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. Results are robust to ordering the institutional instability variable last in the system, i.e. implying that it responds contemporaneously to all shocks in the system (see Figure D.2 in the Appendix).

⁹The 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.

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 Figure 5).

Figure 5 shows the median 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.

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 Putin's dec-

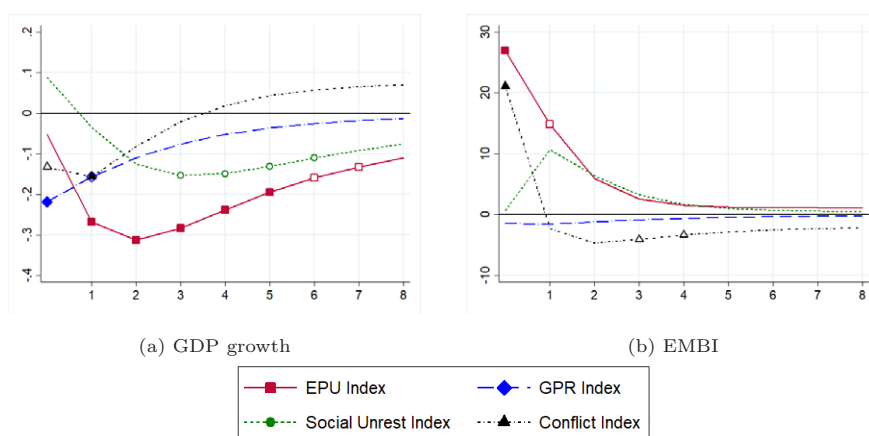


Figure 5: Impulse responses of GDP growth and the EMBI to shocks to alternative measures of institutional instability

Note: Each panel depicts the median 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.

laration of foreign affairs and security policy top priorities, e.g. the Dubrovka Theatre hostage crisis (October 2002),¹⁰, the Chechen Referendum in March 2003,¹¹ 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.¹²

The following points are worth noting. First, the effects are quite persistent: GDP 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 (Figure 5a), whereas the EMBI increases (5b). 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. As for the conflict variable, it exhibits mixed results. GDP growth responses are coherent with the dynamics induced by shocks to the other institutional instability measures, as opposed to the EMBI, which shows a muted response after a conflict shock.

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.

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

¹⁰The 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.

¹¹The referendum approved a new constitution that subordinated Chechnya to Moscow.

¹²'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

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.

Conflict of interest statement

The authors have no conflict of interest to declare.

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Appendix

A. Data

Figure A.1: Information set available in (pseudo)real-time

	m1									m2									m3								
	Previous Quarter			Current Quarter			Previous Quarter			Current Quarter			Previous Quarter			Current Quarter											
	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd									
Real GDP (CNT)																											
HOUSEHOLD																											
Industrial production																											
Retail sales																											
Credit																											
Exports of natural gas																											
Unemployment																											
Production of construction																											
Production of oil																											
SOFT																											
Consumer confidence																											
Business confidence index																											
FINANCIAL MARKETS																											
EMBI spread																											
POLITICAL RISKS																											
Sovereign rating																											
GPA																											
EPU																											
EPU																											
OTHER																											
Social Unrest Index																											
Conflict-related indices																											

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).

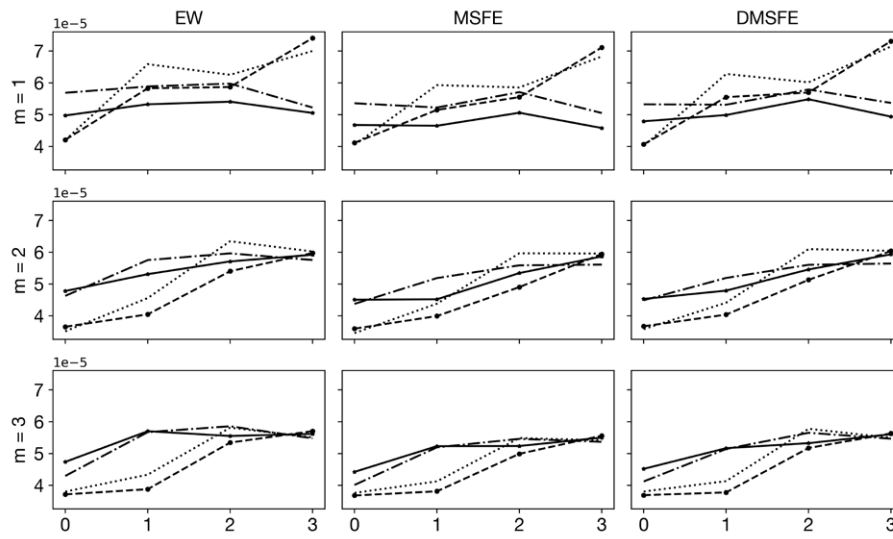
Table A.1: Variables and related transformations

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)	INEMO 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.

B. MSFE of the Benchmark Model

Figure B.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.

C. VAR Descriptive Statistics

Table C.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.

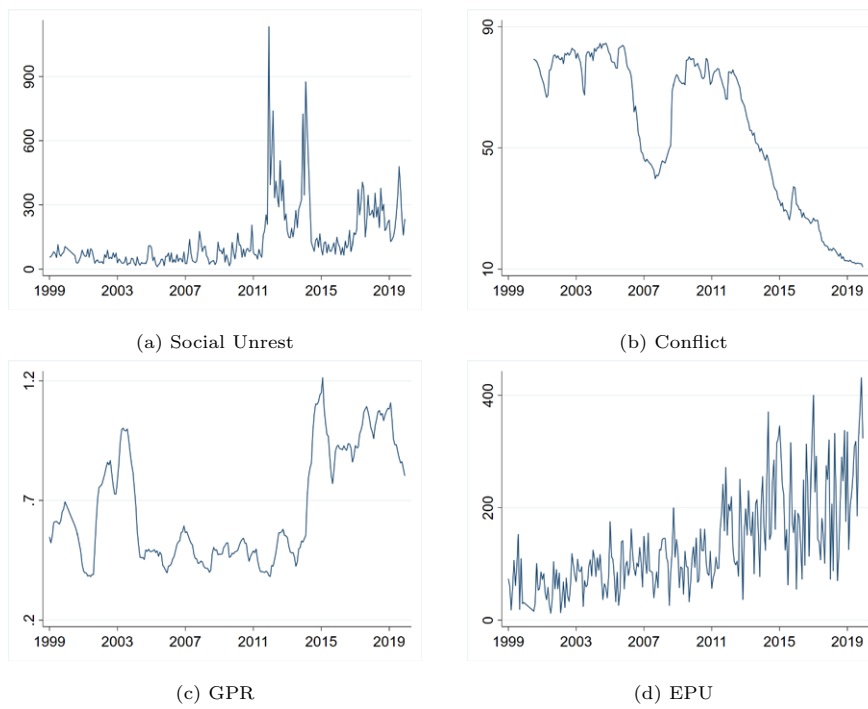


Figure C.1: Variables used in the VAR exercise: monthly frequency

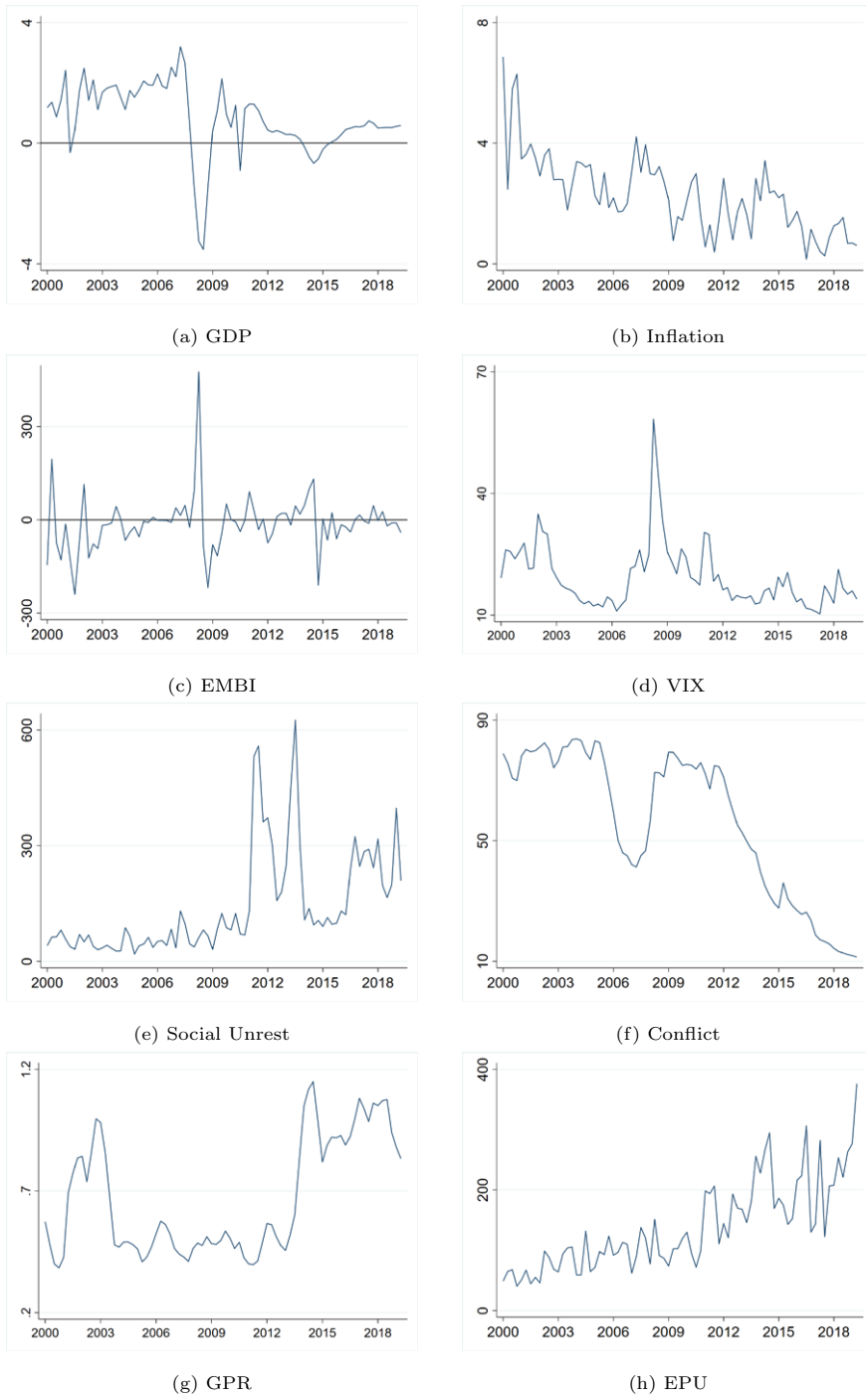


Figure C.2: Variables used in the VAR exercise: quarterly frequency

D. VAR Robustness exercises

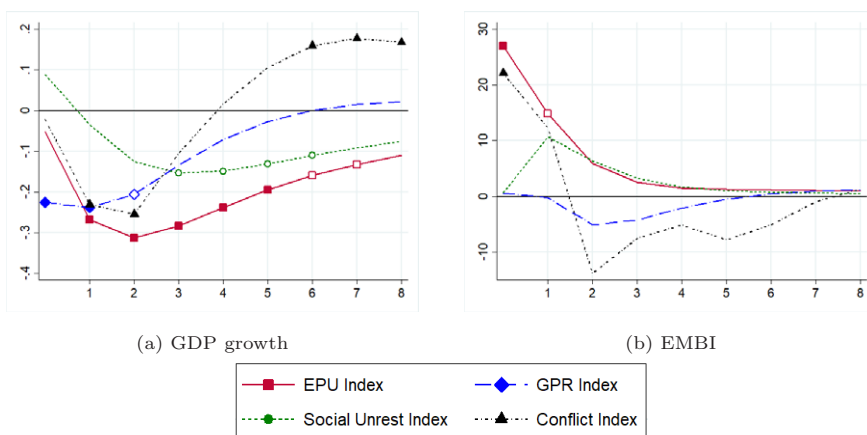


Figure D.1: Robustness: IRF of GDP and the EMBI to shocks to alternative measures of institutional instability. Optimal lags

Note: Each panel depicts the median 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 minimizing the Aikake 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.

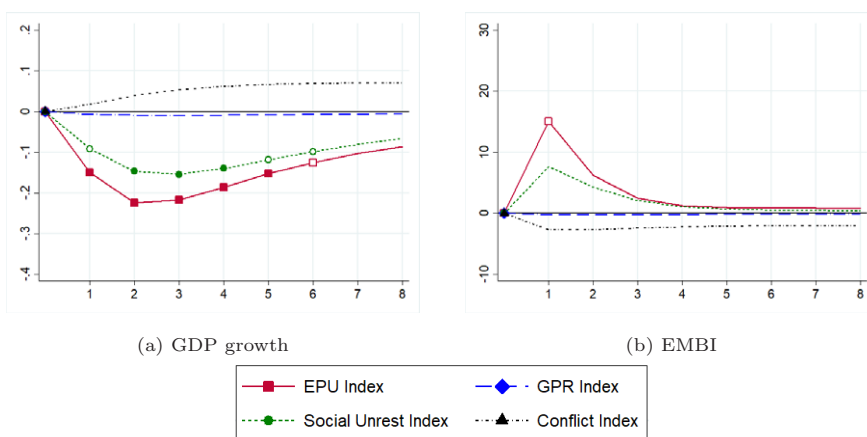


Figure D.2: Robustness: IRFs of GDP and the EMBI to shocks to alternative measures of institutional instability. Institutional instability is ordered last in the VAR model.

Note: Each panel depicts the median 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.

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