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The Role of Economic Policy Uncertainty in Predicting Output Growth in Emerging Markets: A Mixed-Frequency Granger Causality Approach

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Abstract

We employ time series data to empirically determine the causal relationship between economic policy uncertainty and the GDP growth rates of seven emerging market economies while controlling for the effect of oil price, interest rates and the CPI. Due to differences in sampling frequencies between the GDP series and other variables, a multi-horizon mixed frequency VAR model is employed. This model fully exploits the mixed frequency Granger causality test in order to circumvent the distorting effects of temporal aggregation. The empirical results show a strong statistical evidence for direct causality flowing from economic policy uncertainty (EPU) to GDP in Chile, India and Mexico while a weaker statistical evidence is found for Brazil, Colombia and Russia. For comparative analysis, the low frequency Granger causality test is also employed and strong statistical evidence of direct causality flowing from EPU to GDP in Brazil, Chile, India, Mexico and Russia is uncovered. Analyzing the causal patterns uncovered in both specifications show that the low frequency Granger causality results are less intuitively appealing than those that are obtained from the mixed frequency Granger causality test. The results have empirical as well as policy implications which are discussed.

Keywords: Economic policy uncertainty, mixed frequency, Granger causality, temporal aggregation, emerging market economies.

JEL Codes: E32, E37, C32

1. Introduction

Economic policies instituted or modified by government can have very serious implications for domestic and international firms and can go a long way to positively or negatively alter the operational workings of domestic businesses. This is why speculations as to policy direction can be quite detrimental to fast paced decision making by domestic and international business stakeholders from firms and businesses in all areas of the economy. Government's inability to align itself to a particular policy direction can ultimately lead to economic policy uncertainty (hereinafter known as EPU) which can culminate in a loss of productivity. Political events like general elections between two parties with different standpoints on economic policy, wars, terrorist attacks and fiscal policy battles can also precipitate EPU (Baker *et al.*, 2016).The underlying transmission mechanism of this phenomenon stems from the fact that EPU creates an unfavorable investment climate which increases the risk premium of financial assets and potential investment decisions (Chi and Li, 2017; Gilchrist *et al.*, 2014). An increased risk premium increases the opportunity cost of investment which can reflect in the interest rates of financial institutions. This can result in the instigation of "put options" and or "wait and see" decisions in real options valuations by firms (Cerda *et al.*, 2018). These developments can have negative implications for productivity as well as economic growth. As such, it becomes important to empirically determine the predictive power of EPU for GDP growth rates in order to make well informed policy decisions at the macro-economic level.

In this regard, the main objective of the present study is to determine the causal relationship between EPU and the GDP growth rates of selected emerging market economies. To avoid misspecification due to omitted variables, the causal effects of interest rates, consumer prices and domestic currency denominated oil prices are also controlled for. Due to differences in sampling frequencies between GDP which is sampled at quarterly frequency and the other control variables which are all sampled at monthly frequencies, the mixed frequency Granger causality test (MFGCT) of Ghysels *et al*. (2016) is employed. The usual practice of empirical analysis with studies that employ data of mixed frequencies is to apply temporal aggregation to the higher frequency data in order to bring it to the same frequency as the lower frequency ones. This is usually achieved with aggregation or skipped sampling. Both these methods constitute several drawbacks most pertinent of which are, the loss of viable information through the smoothening of data points by temporal aggregation. As such, Granger causality analysis with temporally aggregated data may uncover spurious inferences. The MFGCT technique circumvents the potential spurious (non-)rejection of the causal null which may arise due to temporal aggregation of time series data. The countries investigated in the present study are: Brazil, Chile, China, Colombia, India, Mexico and Russia. The choice of countries is based on the premise that empirical studies on the causal nexus between EPU and GDP growth rates for these countries are to the best of the authors' knowledge, quite scarce in the literature. Also the application of mixed data sampling techniques to empirically ascertain the predictive content of EPU for GDP for these set of countries are, as at the time of writing, non-existent in the literature. As such the present study fills a veritable gap.

There has been an influx of studies relating EPU with microeconomic as well as macroeconomic indicators (Aizenman and Marion, 1993; Kang *et al.*, 2014; Wang *et al.*, 2014; Colombo, 2013; Antonakakis *et al.*, 2014; Krol, 2014; Caggiano *et al.*, 2017). Recent studies that analyzed the macroeconomic implications of EPU have employed the news-based variant of the EPU measure in order to uncover the nature of the underlying relationship that may exist between EPU and industrial production, unemployment, interest rates (Colombo,2013; Baker *et al.*, 2016;Caggiano *et al.*, 2017), exchange rates (Beckmann and Czudaj, 2017; Krol, 2014; Balcilar *et al.*, 2016a),and stock markets (Arouri *et al.,* 2016; Wu *et al.*, 2016; Li *et al.*, 2016; Sum, 2012; Karnizova and Li, 2014). The news-based variant of the EPU was originally employed by Baker *et al.* (2016). The index was constructed by observing the frequency of occurrence of the terms: 'economy', 'uncertainty' and one of 'congress', 'deficit', 'legislation', 'Federal Reserve', 'regulation' or 'White House' in 10 leading U.S newspapers. This system has also been applied to a few other countries and the constructed EPU indices has consistently shown in various studies to be inversely related to corporate investment (Wang *et al.*, 2014; Kang *et al.*, 2014), aggregate investment level, index of industrial production and employment (Baker *et al.*, 2016; Caggiano *et al.*, 2017; Colombo 2013). A more detailed and broader review is given by Redl (2018) as well as Istiak and Serletis (2018).

However, focusing on research which lean towards the spectrum of real output and economic growth, a few studies have empirically assessed the relationship between EPU and real output whilst employing the index of industrial production (IIP) as a proxy for real output because of its synchronized monthly frequency with the EPU index. Baker *et al.* (2016) finds that EPU helps in predicting declines in the IIP of the US. Colombo (2013) also uncovers a negative spillover effect of US-EPU on Euro area macro-economic aggregates, notably the IIP and aggregate prices. Istiak and Serletis (2018) employ monthly data to access the asymmetric relationship between EPU and IIP. Their findings show that while the EPU index is largely countercyclical, its relationship with most of the G7 countries is however symmetric. Employing the synchronized IIP monthly index may not capture economic growth the same way the GDP proxy can because the IIP covers only the industrial sector which may not totally reflect overall economic activity. Also, studies by OECD (2012) have shown that in recent times, sufficient synchronization between the cyclical components of the IIP and the GDP has been lost. This is because of the simultaneous reduction and growth of the industry and services sector value added respectively in most advanced economies. This alludes to the possibility that these two variables may not be identical in capturing growth dynamics. It however brings about an empirical dilemma because the IIP and the EPU indexes are both measured at monthly frequencies, but the GDP series are conventionally measured at quarterly frequencies. The next best option is temporal aggregation as was applied by Sahinoz and Cosar (2018) who construct a monthly EPU index for Turkey and employ structural vector autoregressive (SVAR) models to identify the relationship between EPU, the Turkish real GDP and other macroeconomic variables. They uncover a countercyclical relationship between the two variables. Stockhammar and Österholm (2016) go a bit further by using both monthly and quarterly data to empirically uncover the spillover effect of the US-EPU index on Swedish economic variables notably the IIP and GDP growth. However, aggregating the EPU series to a lower quarterly frequency may bring about a loss of information within the data which might result to misleading empirical relationships between the EPU index and the GDP series. This drawback has been pointed out in studies by Granger (1980, 1988) and Granger and Lin (1995) wherein the distorting effects of temporal aggregation is extensively discussed. Temporal aggregation can induce spuriously hidden or generated causality in even the simplest models, like for instance a bivariate vector autoregression of order one (VAR(1)). The original causal patterns of models with datasets that have undergone these types of modifications are always nearly impossible to recover (Ghysels *et al.*, 2016).

In order to circumvent this potential empirical inconsistency, we employ the mixed frequency Granger causality test (MFGCT) of Ghysels *et al*., (2016). MFGCT as earlier discussed has the intuitive advantage of mitigating potential spurious (non-)rejection of the causal null that may arise as a result of temporal aggregation of high frequency data in Granger causality tests. Furthermore, the multi-horizon nature of the MFGCT approach allows it to isolate causal chains in multivariate VAR systems. As such, our study will not only uncover the latent causal dynamics between EPU and GDP growth but would also isolate the indirect causal pathways from which EPU may affect GDP growth through other auxiliary variables in the multivariate VAR system. This is achieved by exploiting the multi-horizon nature of the MFGCT. Apart from Balcilar *et al*., (2016b) that analyzed how EPU aids the prediction of US recessions, to the best of our knowledge no other study has analyzed any type of empirical relationship between GDP growth and EPU whilst employing mixed frequency data sampling (MIDAS) techniques. Nor has any study isolated the direct and indirect causal relationship between EPU and GDP for emerging economies within a multivariate mixed frequency framework. Also, empirical studies on emerging market economies as regards to EPU and macroeconomic indicators are quite scarce implying that these economies have not really been given much attention. There have however been studies on the Chinese EPU relationship with regards to capital structure (Zhang *et al.*, 2015), stock markets (Li *et al.*, 2016; Yang and Jiang, 2016 Li and Peng, 2017; Chen *et al.*, 2017; Yu *et al*., 2018) as well as credit risks (Chi and Li, 2017). As regard to studies analyzing the impact of EPU on economic activity in emerging market economies, Han *et al.*, (2016) employ a global VAR (GVAR) approach to ascertain the spillover effect of Japanese, UK, US and EU EPU on Chinese macroeconomic variables namely, the IIP, equity prices, export and exchange rates. They discover that the US EPU shocks had the most significant negative effect on these variables. Studies have also been undertaken to analyze the Chilean economic uncertainty macroeconomic variables relationship (Cerda *et al.*, 2018) with empirical inferences alluding to a negative relationship between EPU and GDP. Redl (2018) develops a new index of economic uncertainty for the South African economy. He employs a structural VAR model to ascertain the relationship between the South African EPU, GDP, investment, industrial production, private sector employment and prices. He finds that an unanticipated increase in EPU coincides with a reduction in GDP. A major issue with all the aforementioned studies is that none of their specified models incorporated variables that could capture economic growth within a much broader sense *viz*. the GDP growth rate. When they do however, they employ temporal aggregation which has the potential of instigating spurious (non-)rejection of the causal null as earlier explained. This brings about a need to specify models that will not only incorporate overall economic activity but would also circumvent the potential distorting effects of temporal aggregation. The present study is intended to fill this gap by employing the MFGCT procedure of Ghysels *et al*., (2016) as well as incorporating interest rates, CPI and oil prices, variables that are known to influence the GDP growth path in the mixed frequency VAR system. Also as earlier mentioned, the present study is motivated by a dearth of literature in the EPU and GDP growth nexus as regards to emerging market economies. As a result, we contribute to the literature by first uncovering the causal relationship between EPU and the GDP growth rates of seven emerging market economies. Secondly, by also employing low frequency granger causality tests (LFGCT), we show through comparative assessments how temporal aggregation can influence the (non-)rejection of the causal null. We also reveal how mixed frequency data follow very different patterns from low frequency data in recovering causal relationships. Finally, by incorporating multiple horizons in both multivariate VAR frameworks we are able to uncover the indirect causal pathways through which EPU can affect the growth rate of GDP via auxiliary variables.

The rest of the study is structured as follows: Section 2 outlines the data and methodology, section 3 presents the empirical results while section 4 concludes.

2. Methodology and Data

2.1. Mixed frequency Granger causality test

Following Ghysels *et al*., (2016) we construct an MF-VAR(p) model such that high frequency (HF) series $\{\{\boldsymbol{X}_H(\tau_L, k)\}_{k=1}^{m}\}_{\tau_L}$ and low frequency (LF) $\{\{\boldsymbol{X}_L(\tau_L, k)\}_{k=1}^{m}\}_{\tau_L}$ are contained in a partially latent underlying high frequency process. The LF time index (quarterly) in this process is denoted as $\tau_L \in \{0, \dots, T_L\}$, while the HF time index (monthly) is indicated by $k \in \{1, \dots, m\}$. m is indicative of the number of HF time periods in one LF time period which in the present study equals three since one quarter contains three months. Observations $\boldsymbol{X}_H\left(\tau_{Lq}, k\right) \in$

$\mathbb{R}^{K_H \times 1}, K_H \geq 1$, are high Frequency variables. Whilst $\boldsymbol{X}_L(\tau_L, k) \in \mathbb{R}^{K_L \times 1}, K_L \geq 1$, are low frequency variables. $\boldsymbol{X}_L(\tau_L, k)$ are latent LF variables because they are not observed in high frequencies and only some temporal aggregated, denoted $\boldsymbol{X}_L(\tau_L)$, are available in a high frequency analysis.

A mixed frequency VAR (MF-VAR) model stacks all observables in a mixed frequency $K \times 1$vector of the form:

$$\boldsymbol{X}(\tau_L) = [\boldsymbol{X}_H(\tau_L, 1)', \ldots, \boldsymbol{X}_H(\tau_L, m)', \boldsymbol{X}_L(\tau_L, 1)']' \tag{1}$$

The dimension of the mixed frequency vector $\boldsymbol{X}(\tau_L)$is $K = K_L + mK_H$. In our case, the MF-VAR combined monthly HF and quarterly LF observables. Since there are four high frequency variables and one low frequency variable employed for this study. The mixed frequency vector$\boldsymbol{X}$ defined in Eq. (1) with sampling frequency ratio $m = 3$ becomes a 13×1 vector which contains the following endogenous variables:

$$\begin{aligned} \boldsymbol{X}(\tau_L) = [&EPU_H(\tau_L, 1)', \ldots, EPU_H(\tau_L, 3)', OIL_H(\tau_L, 1)', \ldots, OIL_H(\tau_L, 3)', CPI_H(\tau_L, 1)', \ldots, \\ &CPI_H(\tau_L, 3)', RATE_H(\tau_L, 1)', \ldots, RATE_H(\tau_L, 3)', GDP_L(\tau_L)']' \end{aligned} \tag{2}$$

where $EPU_H(\tau_L, 1)$, $OIL_H(\tau_L, 1)$, $CPI_H(\tau_L, 1)$ and $RATE_H(\tau_L, 1)$ are high frequency variables which denotes, respectively, the index of economic policy uncertainty and the year on year growth rates of domestic currency denominated oil prices, consumer price index and interest rates at the $1st$ month of the τ-th quarter. $GDP_L(\tau_L)$ is a low frequency variable which denotes the year on year growth rate of *GDP* at quarter τ.

From Eq. (2) $\boldsymbol{X}(\tau_L)$ follows a MF-VAR(p) process for some $p \geq 1$ of the form:

$$\boldsymbol{X}(\tau_L) = \sum_{k=1}^{p} \boldsymbol{A}_k \boldsymbol{X}(\tau_L - k) + \boldsymbol{\varepsilon}(\tau_L) \tag{3}$$

Iterating Eq. (3) over the employed test horizon h would allow the deduction of simple testable parameter restrictions for non-causality at horizon h. Following Dufour *et al.*, (2006) we employ the (p,h)-autoregression which enables Eq.(3) to take the form:

$$\boldsymbol{X}(\tau_L + h) = \sum_{k=1}^{p} \boldsymbol{A}_k^{(h)} \boldsymbol{X}(\tau_L + 1 - k) + \boldsymbol{e}^{(h)}(\tau_L) \tag{4}$$

where

$$\begin{gathered} \boldsymbol{A}_k^{(i)} = \boldsymbol{A}_{k+i-1} + \sum_{l=1}^{i-1} \boldsymbol{A}_{i-l} \boldsymbol{A}_k^{(l)} \text{ for } i \geq 2 \\ \boldsymbol{e}^{(h)}(\tau_L) = \sum_{k=0}^{h-1} \boldsymbol{\psi}_k \, \boldsymbol{\varepsilon} \end{gathered} \tag{5}$$

with $\boldsymbol{A}_k^{(1)} = \boldsymbol{A}_k$, and conventionally $\boldsymbol{A}_k = \boldsymbol{0}_{K \times K}$ when $k > p$. In the (*p*,*h*)-autoregression model defined in Eqs. (3)-(5), h is the low frequency prediction horizon.

MFGCT test exploit the Wald statistics from the ordinary least squares (OLS) estimator of the (*p,h*)-autoregression parameter set:

$$\boldsymbol{B}(h) = \left[\boldsymbol{A}_1^{(h)}, \dots, \boldsymbol{A}_p^{(h)}\right]' \tag{6}$$

In order to test for causality in the mixed frequency sense, from Eq. (2) the mixed frequency vector is partitioned into 5 sub vectors of low frequency variables

$$\widetilde{EPU}_H(\tau_L) = [EPU(\tau_L, 1), EPU(\tau_L, 2), EPU(\tau_L, 3)] \tag{7a}$$
$$\widetilde{OIL}_H(\tau_L) = [OIL(\tau_L, 1), OIL(\tau_L, 2), OIL(\tau_L, 3)], \tag{7b}$$
$$\widetilde{CPI}_H(\tau_L) = [CPI(\tau_L, 1), CPI(\tau_L, 2), CPI(\tau_L, 3)], \tag{7c}$$
$$\widetilde{RATE}_H(\tau_L) = [RATE(\tau_L, 1), RATE(\tau_L, 2), RATE(\tau_L, 3)] \tag{7d}$$

and a high frequency variable, $GDP(\tau_L)$

From Eq. (7) we obtain the "mixed frequency reference information set" in period τ_L as:

$$\begin{gathered} \ell(\tau_L) = \widetilde{EPU}_H(-\infty, \tau_L] + \widetilde{OIL}_H(-\infty, \tau_L] + \widetilde{CPI}_H(-\infty, \tau_L] \\ + \widetilde{RATE}_H(-\infty, \tau_L] + GDP_L(-\infty, \tau_L] \end{gathered} \tag{8}$$

From Eq.(8), *EPU_H* does not cause *GDP_L* at horizon h given ℓ, denoted $\ell\left(EPU \nrightarrow_h GDP \middle| \ell(\tau_L)\right)$,if:

$$\begin{gathered} P[GDP_L(\tau_L + h) | \widetilde{OIL}_H(-\infty, \tau_L] + \widetilde{CPI}_H(-\infty, \tau_L] + \widetilde{RATE}_H(-\infty, \tau_L] + GDP_L(-\infty, \tau_L] \\ = P[GDP_L(\tau_L + h) | \ell(\tau_L)] \qquad \forall \, \tau_L \quad \#(9) \end{gathered}$$

Eq. (9) implies that the availability or non-availability of the past and present values of EPU in the mixed frequency information set does not alter the h-step ahead prediction of *GDP*. The null hypothesis of interest is thus linear restrictions:

$$H_0(h): \boldsymbol{R}\ \mathrm{vec}[\boldsymbol{B}(h\ )] = \mathbf{r} \tag{10}$$

which can be tested with the following Wald statistic:

$$W_{T_L^*}[H_0(h)] \equiv T_L^*(\boldsymbol{R}\mathrm{vec}[\widehat{\boldsymbol{B}}(h)] - \mathbf{r})' \times (\boldsymbol{R}\widehat{\boldsymbol{\Sigma}}_p(h)\boldsymbol{R}') \times (\boldsymbol{R}\mathrm{vec}[\widehat{\boldsymbol{B}}(h)] - \mathbf{r}) \tag{11}$$

From Eqs. (10-11) $\boldsymbol{R}$ is a $q \times pK^2$selection matrix of full row rank q. $T_L^* = T_L - h + 1$ denotes the effective sample size of the (p,h)-autoregression model while $\widehat{\boldsymbol{B}}(h)$ indicates the least squares estimator of the parameters of the (p,h)-autoregression model and $\widehat{\boldsymbol{\Sigma}}_p(h)$ is a positive-definite covariance matrix of the $\widehat{\boldsymbol{B}}(h)$. Under $H_0(h)$, $W_{T_L^*}[H_0(h)]$ follows a χ_q^2 distribution.

2.2. Data

We employ monthly frequency data for economic policy uncertainty (EPU), consumer price index (CPI), interest rates (RATE) and domestic currency denominated oil prices (OIL) for Brazil, China, India, Russia, Mexico, Chile and Colombia. Also, GDP is sampled at quarterly periods. The variables are sampled at different time periods for each country because data availability is not uniform across countries. All the variables except EPU are transformed to year-on-year growth rates to smooth out seasonal fluctuations and abate the effects of seasonality. Except for EPU, data for all the variables for all countries were obtained from Datastream while data for EPU was obtained from http://www.policyuncertainty.com (Baker *et al*., 2016). Figure 1 displays time plots of the year on year growth rates of all the variables for each country except the EPU which is captured in its level. It can be observed that in some of the countries notably, India, Chile, Colombia and Brazil, major spikes (upswings) in EPU closely correspond to major troughs (downswings) in GDP. Table1 displays the descriptive statistics for all the variables in all countries as well as their respective sample periods.

What can immediately be perceived from the table is that in all countries the OIL (year-on-year growth rate of the oil price) variable seems to be the most volatile of all the variables employed in the model. The volatility of the EPU variable varies across the countries, but it is generally the third or fourth most volatile series following CPI or GDP. More so, Mexico's EPU seems to be the most volatile of all the selected countries followed by China, which is ironic because China's GDP growth turns out to be the least volatile. Policy uncertainty may not have a spillover effect on investment and productivity based decisions in China because a majority of these decisions lie with the government rather than the private sector. GDP growth for all countries appears to be negatively skewed except for China which has a positively skewed GDP growth. Russia has the most volatile GDP growth. This may not be unconnected with its high dependence on crude oil exports which makes it prone to highly volatile oil demand and supply shocks. All in all, only a few of the variables follow a normal distribution as inferred by the Jarque-Bera test.

Visual inspection of Figure 1 indicates that all the variables show evidence of mean reversion which is a core requirement for Granger causality tests however in order not to be entirely subjective in our assumptions on the stationarity of the untransformed variables we employ formal unit root test procedures with the aim of coming to more objective conclusions as to their integration orders and to further justify transforming the other variables to year on year growth rates while leaving the EPU at levels prior to undertaking the estimation tests.

INSERT FIGURE 1 HERE

INSERT TABLE 1 HERE

3. Estimation results

Before commencing with the MFGCT and the LFGCT test results we first of all elaborate more on the unit root and stationarity test results. To give a more robust inference as to their stationarity properties we employ four different unit root and stationarity test procedures namely, the Augmented Dickey Fuller (ADF; Dicky and Fuller 1979, 1981), the Elliot-Rothenberg-Stock (ERS; *Elliot et al*., 1996) and the Phillips-Perron (PP; Phillips and Perron, 1988) unit root tests as well as the Kwiatkowski-Phillips-Schmidt-Shin (KPSS; Kwiatkowski*et al*., 1992) stationarity test. All tests allow for an intercept (Model A) and both intercept and trend (Model B) in the test regression. The implication of non-rejection of the null of a unit root in the ADF, PP and ERS unit root test is that the variables follow a nonstationary process at their levels while that of the KPSS implies that the variables follow a stationary process when the null cannot be rejected. The ADF test is parametric while the PP test is semi-parametric and the ERS test is an efficient unit root test based on generalized least squares estimation of the deterministic component.

All tests follow different dynamics in their underlying structure and have different power and size properties as such there may be scenarios where they all infer conflicting results based on the null. In light of all these, we follow a majority rule when taking decisions based on different inferences obtained from different test results and when no clear majority can be construed in light of the different tests, we go with the KPSS test results. Looking at the results from Table 2, what can be accurately inferred when our rule is applied is that all the variables except the EPU variables for each country are nonstationary at levels. The EPU variables on the other hand are stationary at levels. In light of all these the decision to apply year-on-year growth transformations to all the other variables apart from EPU are empirically justified. It is now appropriate to proceed with the MFGCT and the LFGCT tests.

INSERT TABLE 2 HERE

3.1. Mixed Frequency and Low frequency Granger causality test results

The results for the MFGCT and the LFGCT tests are outlined in Tables 3 to 9. The most noteworthy observation from the results in Tables 3-9 for the EPU-GDP nexus, the primary focus of our study, is the rejection of direct Granger non-causality from EPU to GDP for all countries, except China. Moreover, this result holds for both mixed frequency and low frequency cases. Although direct causality from EPU to GDP is not observed for China, indirect causality occurs through CPI and RATE variables in the MF case while it occurs through CPI in the LF case. Although, the causality from EPU to GDP occurs at different steps across countries, generally low frequency causality is observed in the first quarter while mixed frequency causality is observed later than the first quarter. This result is due to the spurious causality introduced by temporal aggregation in the LF case.

One general observation that can easily be inferred from the results as outlined in the tables is that they both follow very different causal patterns. However as regards to the rejection of the causal null in the EPU $\nrightarrow$ GDP relationship what tends to be the general pattern is that where the MFGCT rejects(does not reject) the null of no Granger causality, the LFGCT is consistent in upholding the inference. When this inference specifically constitutes the rejection of the null, the LFGCT is also consistent in upholding the inference even though this may occur on a different horizon at a different statistical level of significance. At this point, one may arrive at the conclusion that the EPU-GDP multi-horizon causal nexus is robust to temporal aggregation of the type that has been applied in the present study. This, however, does not hold for all the other causal interactions when comparing both multivariate VAR frameworks. However, one particular observation is noteworthy which happens to be the significance of the LFGCT in rejecting the non-causality null occurring at a higher statistical level than the MFGCT in both the Brazilian and Russian cases. This may have occurred due to the smoothing by temporal aggregation of certain data points which hitherto strengthened the evidence for rejecting the non-causal null in the quarterly VAR. Nevertheless, the empirical investigations uncovered more economically meaningful causal relationships in the MFGCT specification for both the Brazilian and Russian cases.

In the MFGCT specification for the Brazilian case as seen in Table 3, EPU causes GDP directly ($h = 2$) and indirectly through the auxiliary variables OIL and RATE. In the LFGCT specification however, EPU causes GDP directly ($h = 2,3$) and indirectly through the price channel (CPI). Moreover, a non-rejection of the causal null for RATE $\nrightarrow$ CPI in the LFGCT specification spuriously implies a neutrality of monetary policy in the Brazilian economy. Going by the MFGCT specification, a strong monetary policy transmission mechanism is also observed for the Brazilian economy as RATE is seen to Granger cause all the other auxiliary variables. The result, thus, alludes to a scenario wherein economic policy uncertainty passes through the monetary policy transmission mechanism to the overall economy. This may be as a result of its adoption of an inflation targeting monetary policy in the 1990's and its shift from a semi-fixed to a managed floating exchange rate system. In effect, this gave the Central bank back the control of monetary policy under a macroeconomic stabilization program termed the Real Plan which was implemented following a period of hyperinflation in the Brazilian economy (Afonso and Fajardo, 2016).

In Russia in Table 9, EPU Granger causes GDP both in the MF ($h = 5$) and LF ($h = 3,4,5$)cases. For Russia, even though the LFGCT uncovered more causal relationships than the MFGCT it is noteworthy to know that it however could not uncover an important causal effect between OIL and GDP. Considering the peculiarities of the Russian economy which are its high dependence on crude oil extraction and its status as the second highest exporter of crude oil, the deduction that OIL should have a significant predictive content for GDP is not entirely subjective and is also consistent with previous studies (Ito, 2008; Algieri, 2011).

In the case of Chile in Table 4, we see what most likely resembles a direct causality flowing from EPU to GDP because the EPU variable has no predictive content for the other auxiliary variables in the MF-VAR system. The same can be said for the LFGCT specification. Even though EPU has predictive content for RATE at the 4th and 5th horizon in the LF-VAR system, this, however, does not constitute indirect causality from EPU to GDP because causality from RATE to GDP and also from EPU to GDP precedes it. The result for the Chilean case is consistent with Cerda *et al.*, (2018) which employed impulse response functions from a low frequency VAR.

We uncover a very peculiar setup in Table 5 for the Chinese case because in both the MFGCT and LFGCT specifications, EPU does not have direct predictive content for GDP at all horizons. As pointed out before, indirect causality from EPU to GDP works through CPI (MF and LF cases) and RATE (MF case) variables. Also, as implied earlier in the data section, the idiosyncrasies of the Chinese economy may bring about a scenario wherein policy uncertainty would have minimal effects on its growth path. This may stem from its status as a socialist market economy where a significant portion of the productive sectors are state controlled. The state also influences the price mechanism and to a reasonable extent, information dissemination (Huang and Dai, 2015; Lim, 2018).

In Table 6 for Colombia, it is observed in the MFGCT specification that EPU has direct causality at the 4th horizon and also indirect causality for GDP at the 4th horizon through its causal effect on RATE which has predictive content for GDP at all horizons. It is also observed that statistical evidence for EPU's causal effect on GDP is established at the exact same horizon its causal effect on RATE was uncovered albeit with a weaker statistical evidence. This is, however, not the case for the LFGCT specification of the same country. In the LFGCT specification however causality flows from EPU to GDP at both the 1st and 3rd horizons with no clear indication of indirect causality at the 1st horizon. Similar to Brazil and going by the MFGCT specification, this implies that economic policy uncertainty is 'filtered' to the Colombian economy via monetary policy effects. RATE also Granger causes all the other auxiliary variables in the MFVAR system which is parallel to the Brazilian case. Another noteworthy similarity is the adoption of inflation targeting monetary policy by the Colombian monetary authorities in late 1999 following the Russian crises and the resultant floating of the exchange rates (Vargas, 2008).

In Table 7 for the Indian case we observe a strong direct Granger causality from EPU to GDP for both MF and LF cases at all horizons. For India, we also observe a high level of interconnectedness between the auxiliary variables and GDP in the MFGCT specification. All the auxiliary variables have strong predictive content for GDP in the first horizon. OIL's predictive content extends to the second horizon although with lesser statistical evidence. EPU's predictive content for GDP is observed throughout all the horizons. This is robust to temporal aggregation as can be observed from the LFGCT specification wherein EPU's predictive content for GDP is statistically significant for all horizons. However, the MFGCT specification uncovers a more economically meaningful causal pattern. Since EPU Granger causes GDP at all horizons, it should be expected that its predictive content for some of the auxiliary variables which can also affect GDP would have some statistical evidence. This is the case for the MFGCT specification as EPU is found to have predictive content for all auxiliary variables except OIL. No statistical evidence of such was found for the LFGCT specification.

Finally moving on to Table 8 for the Mexican case both MF and LF specifications yield strong statistical evidence to reject the EPU $\nrightarrow$ GDP null in the 2nd and 3rd horizon for the MFGCT specification but only in the 1st horizon for the LFGCT case. We observe a very surprising scenario for Mexico wherein the LFGCT specification uncovers more causal relations than that of the MFGCT. This may also be because of the spurious causality by temporal aggregation of data points that strengthen statistical evidence for rejecting the causal null.

INSERT TABLES 3-9 HERE

4. Summary and Conclusions

We employ mixed frequency and low frequency Granger causality tests within a multivariate multi-horizon VAR framework to uncover the direct and/or indirect causal relationship between economic policy uncertainty (EPU) and the GDP of seven emerging market economies namely, Brazil, Russia, India, China, Mexico, Colombia and Chile. With the MFGCT specification we uncover strong statistical evidence for direct causality flowing from EPU to GDP in Chile, India and Mexico while weak statistical evidence for direct causality was found for Brazil, Colombia and Russia. With the LFGCT specification however strong statistical evidence of direct causality flowing from EPU to GDP for Brazil, Chile, India, Mexico and Russia is uncovered. Nonetheless, the causal patterns uncovered in the LFGCT specifications are less intuitively appealing than those that are obtained in the MFGCT specification. In China however, no statistical evidence of EPU's direct predictive content for GDP is uncovered. This may be due to China's socialist market economy which places a lot of investment decisions in state hands. Also, the Chinese authorities influences, to a considerable extent the dissemination of information and thus news based EPU may originate endogenously. In summary, indirect causality from EPU to GDP is found for all countries both in MF and LF cases, with stronger evidence in the LF case. In the LF case, temporal aggregation is likely to introduce spurious (non-)causality, which explains the stronger LF causality in our case. This points out that the sampling frequency may have considerable effects on the Granger causality tests in empirical applications.

In a recent line of research, growing number of studies have also conducted out-of-sample forecasting analysis of industrial production or GDP, as well as recessions, using EPU (or variants of uncertainty measures) based on same frequency models for advanced economies (see for example, Aye *et al*., 2019; Pierdzioch and Gupta, 2019). Given that in-sample predictability, i.e., causality does not guarantee forecasting gains, and also the fact that mixed-frequency models are less likely to be spurious, as part of future analysis, it would be interesting to extend our analysis to a full-fledged out-of-sample forecasting exercise for emerging economies, as has been done for the US as in Segnon *et al*., (2018).

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Table 1. Descriptive statistics

	n	Mean	S.D.	Min	Max	Skewness	Kurtosis	JB	Q(1)	Q(4)	ARCH(1)	ARCH(4)	Sample Period
Panel A: Brazil													
OIL	252	10.833	31.983	-60.048	125.719	0.520	0.892	20.451***	218.216***	606.854***	194.658***	196.310***	1997M10-2018M09
CPI	252	6.176	3.014	1.547	18.596	1.698	4.055	300.063***	245.359***	844.493***	236.189***	241.898***	1997M10-2018M09
RATE	252	-6.099	30.800	-96.257	70.834	-0.332	-0.276	5.362*	225.085***	690.020***	156.270***	166.745***	1997M10-2018M09
EPU	252	143.230	91.203	22.296	676.955	2.162	6.662	675.460***	129.182***	366.653***	83.837***	93.353***	1997M10-2018M09
GDP	84	2.210	3.046	-5.681	8.809	-0.321	-0.272	1.645	61.182***	107.666***	50.501***	49.556***	1997Q4-2018Q3
Panel B: Chile													
OIL	264	6.939	29.079	-67.841	93.975	-0.031	0.306	1.250	212.959***	590.949***	166.340***	164.634***	1997M01-2018M12
CPI	264	3.365	1.942	-3.437	9.401	0.138	2.195	55.772***	247.922***	803.481***	233.185***	238.801***	1997M01-2018M12
RATE	264	-6.434	39.973	-161.170	94.112	-0.821	2.139	82.150***	224.583***	677.014***	207.734***	212.765***	1997M01-2018M12
EPU	264	108.164	47.639	30.231	345.395	1.017	1.766	81.751***	96.498***	247.822***	1.267	7.122	1997M01-2018M12
GDP	88	3.795	2.696	-3.653	8.902	-0.653	0.354	7.160**	62.478***	91.813***	38.699***	46.454***	1997Q1-2018Q4
Panel C: China													
OIL	258	3.662	34.595	-93.847	89.422	-0.472	0.186	10.166***	229.727***	664.543***	199.324***	199.777***	1997M04-2018M09
CPI	258	1.849	2.105	-2.225	8.438	0.603	0.481	18.609***	240.542***	833.817***	224.834***	224.720***	1997M04-2018M09
RATE	258	-6.872	41.174	-121.599	115.991	-0.074	0.118	0.454	192.687***	552.082***	118.677***	120.625***	1997M04-2018M09
EPU	258	146.606	116.389	9.067	694.849	1.925	4.265	362.012***	171.320***	515.764***	129.350***	137.082***	1997M04-2018M09
GDP	86	8.680	1.916	6.196	14.020	0.823	-0.130	10.065***	68.969***	186.711***	53.776***	54.015***	1997Q2-2018Q3
Panel D: Colombia													
OIL	264	10.122	29.560	-65.753	112.760	0.315	0.824	12.410***	214.789***	601.407***	167.774***	169.181***	1995M01-2016M12
CPI	264	7.670	5.363	1.742	19.789	1.136	-0.033	57.479***	260.721***	999.501***	259.114***	257.194***	1995M01-2016M12
RATE	264	-4.612	22.917	-85.362	40.121	-0.808	1.016	41.094***	245.394***	791.477***	219.578***	219.898***	1995M01-2016M12
EPU	264	102.398	57.615	0.000	324.655	1.000	1.197	61.136***	72.727***	191.186***	4.793**	8.453*	1995M01-2016M12
GDP	88	3.385	2.567	-5.718	7.787	-1.109	2.155	37.617***	71.227***	143.587***	57.190***	66.504***	1995Q1-2016Q4
Panel E: India													
OIL	180	7.450	31.274	-72.511	74.105	-0.692	0.037	14.636***	152.761***	412.655***	131.489***	133.186***	2004M01-2018M12
CPI	180	6.691	2.821	1.450	14.940	0.509	-0.448	9.219***	166.491***	579.706***	142.373***	142.534***	2004M01-2018M12
RATE	180	2.123	12.273	-38.770	37.869	-0.006	0.466	1.915	133.360***	328.336***	52.157***	54.371***	2004M01-2018M12
EPU	180	96.081	52.980	24.940	283.689	1.181	1.244	55.060***	92.430***	308.306***	30.104***	47.144***	2004M01-2018M12
GDP	60	7.400	2.040	0.269	12.491	-0.797	1.811	16.440***	33.324***	49.632***	9.172***	17.183***	2004Q1-2018Q4
Panel F: Mexico													
OIL	264	9.171	30.717	-65.954	84.603	-0.170	-0.213	1.689	212.377***	595.537***	149.854***	149.475***	1997M01-2018M12
CPI	264	6.137	4.401	2.108	23.462	1.963	2.911	267.664***	249.302***	899.560***	259.908***	257.791***	1997M01-2018M12
RATE	264	-6.318	31.808	-92.775	78.826	-0.062	-0.020	0.172	234.501***	727.831***	187.867***	188.018***	1997M01-2018M12
EPU	264	95.582	70.066	8.509	428.725	1.925	4.851	430.072***	164.264***	450.727***	77.287***	77.665***	1997M01-2018M12
GDP	88	2.505	2.661	-9.350	8.508	-1.349	4.597	111.168***	54.317***	80.543***	34.354***	37.449***	1997Q1-2018Q4
Panel G: Russia													
OIL	249	16.774	38.238	-66.659	175.380	1.432	3.471	214.907***	220.750***	676.653***	204.884***	204.523***	1998M01-2018M09
CPI	249	13.353	13.861	2.152	81.713	3.382	11.880	1974.300***	238.230***	813.096***	223.910***	224.655***	1998M01-2018M09
RATE	249	-5.725	43.884	-135.621	152.771	-0.056	0.504	3.073	172.446***	495.336***	129.304***	128.622***	1998M01-2018M09
EPU	249	120.610	77.298	12.399	400.017	1.138	0.965	64.713***	76.221***	250.875***	31.205***	43.838***	1998M01-2018M09

GDP	83	3.212	4.877	-11.823	11.404	-0.941	0.926	16.313***	63.712***	105.932***	36.838***	55.369***	1998Q1-2018Q3

Note: The table shows descriptive statistics for the OIL, CPI, RATE, EPU, and GDP series. The OIL, CPI, RATE, and GDP variables are in year-on-year growth rates while the EPU series are in levels. In addition to number of observations (*n*), the mean, standard deviation (S.D.), minimum (Min), maximum (Max), skewness, and kurtosis, the table also displays Jarque-Bera normality test (JB), the firs- [Q(1)] and fourth-order [Q(4)] Ljung-Box test for autocorrelation, the first [ARCH(1)] and fourth-order [ARCH(4)] test for autoregressive conditional heteroskedasticity. Superscripts *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. See the note to Figure 1 for variable definitions.

Table 2. Unit root tests

	ADF Test		ERS Test		KPSS Test		PP Test	
	Model A	**Model B**	**Model A**	**Model B**	**Model A**	**Model B**	**Model A**	**Model B**
				Panel A: Brazil				
OIL	-1.969	-2.495	48.074	11.308	1.352***	0.334***	-1.427	-2.006
CPI	-0.707	-1.735	1597.002	12.821	1.727***	0.208**	-0.823	-0.791
RATE	-1.502	-2.951	14.087	5.171**	1.330***	0.135*	-1.227	-2.506
EPU	-4.328***	-5.751***	0.977***	2.254***	1.099***	0.108	-7.210***	-9.946***
GDP	-1.802	-0.610	208.991	24.515	0.794***	0.142*	-1.446	-0.140
				Panel B: Chile				
OIL	-1.833	-1.943	33.140	12.978	1.400***	0.380***	-2.048	-1.941
CPI	-1.205	-3.195*	1564.667	20.674	1.823***	0.068	-1.921	-2.983
RATE	-1.970	-2.567	8.616	6.349*	0.940***	0.139*	-1.930	-2.741
EPU	-3.806***	-3.786**	3.442*	7.638	0.186	0.180**	-7.842***	-7.862***
GDP	-0.458	-2.110	614.934	9.693	0.874***	0.139*	-1.320	-1.522
				Panel C: China				
OIL	-1.811	-2.210	9.202	8.802	1.029***	0.325***	-1.622	-1.920
CPI	1.741	-2.673	681.393	103.648	1.729***	0.327***	1.760	-1.960
RATE	-3.409**	-3.223*	22.146	18.122	0.549**	0.292***	-3.160**	-3.001
EPU	-2.294	-4.846***	4.638	4.751**	1.202***	0.097	-6.246***	-9.642***
GDP	-1.443	-1.582	4660.080	27.280	0.859***	0.145*	-2.133	1.105
				Panel D: Colombia				
OIL	-1.862	-1.900	79.740	17.730	1.572***	0.406***	-1.971	-1.882
CPI	-5.891***	-5.662***	8183.645	1159.402	1.688***	0.400***	-19.493***	-10.698***
RATE	-1.900	-1.985	55.638	20.648	1.484***	0.300***	-1.366	-0.861
EPU	-9.040***	-9.229***	0.507***	1.146***	0.198	0.102	-12.877***	-12.972***
GDP	0.970	-2.205	545.894	34.124	0.855***	0.183**	1.135	-1.314
				Panel E: India				
OIL	-3.124**	-2.888	11.838	10.046	0.708**	0.235***	-2.320	-2.142
CPI	-1.235	0.312	2743.413	64.855	1.377***	0.188**	-0.831	-0.052
RATE	-3.060**	-2.776	5.623	7.817	0.526**	0.222***	-2.459	-2.539
EPU	-2.800*	-2.765	2.930**	7.017	0.310	0.253***	-5.108***	-5.137***
GDP	-0.966	-2.918	3477.260	17.688	0.702**	0.145*	-1.373	-2.710
				Panel F: Mexico				
OIL	-1.416	-2.043	46.376	10.198	1.587***	0.337***	-1.611	-2.149
CPI	-4.948***	-7.366***	3740.162	504.500	1.733***	0.325***	-11.054***	-14.523***
RATE	-2.088	-1.004	69.544	31.308	1.374***	0.256***	-2.330	-1.063
EPU	-3.175**	-4.830***	3.769*	2.805***	1.357***	0.105	-5.360***	-8.327***
GDP	-0.314	-3.107	279.978	12.670	0.879***	0.080	-1.515	-3.073
				Panel G: Russia				
OIL	-2.745*	-2.998	111.385	23.994	1.413***	0.291***	-2.042	-2.103
CPI	-3.506***	-3.522**	1053.872	131.186	1.606***	0.321***	-4.642***	-2.493
RATE	-2.394	-2.421	17.591	14.379	0.579**	0.283***	-3.264**	-3.329*
EPU	-4.191***	-10.495***	6.994	22.135	1.503***	0.078	-10.091***	-13.330***
GDP	-2.516	-1.111	319.232	50.677	0.760***	0.202**	-1.537	-0.589

Note: The table reports the Dickey-Fuller (DF), Elliot-Rothenberg-Stock (ERS), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Phillips-Perron (PP) unit root tests. Model A includes only a constant as a deterministic component in the tests regression while Model B includes both a constant and a linear time trend. The null hypothesis for the DF, ERS, and PP tests is that the series is nonstationary while it is stationary for the KPSS test. Superscripts *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. See the note to Figure 1 for variable definitions.

Table 3. Granger causality tests for Brazil

h	1	2	3	4	5
			Panel A: Mixed frequency VAR (MF-VAR)		
CPI ↛ OIL	0.3138	0.2234	0.4008	0.0785	0.7196
RATE ↛ OIL	**0.0005**	**0.0125**	**0.0145**	**0.0010**	**0.0040**
EPU ↛ OIL	0.1014	0.8026	**0.0485**	0.8636	0.7706
GDP ↛ OIL	0.0725	0.3198	0.2714	0.6692	0.5187
OIL ↛ CPI	0.1869	0.1164	0.7836	0.6752	0.6857
RATE ↛ CPI	**0.0060**	0.2574	0.1174	0.4483	**0.0025**
EPU ↛ CPI	0.4768	0.7191	0.7006	0.1369	**0.0355**
GDP ↛ CPI	0.1554	0.9185	0.1629	0.6202	0.1614
OIL ↛ RATE	0.6152	0.2414	0.2019	0.1974	0.6762
CPI ↛ RATE	0.2199	0.2789	0.3418	0.3468	0.3908
EPU ↛ RATE	0.6202	0.2414	0.0805	0.0925	0.2284
GDP ↛ RATE	0.2529	0.1289	0.4623	0.5312	0.1249
OIL ↛ EPU	0.7256	0.9405	0.9440	0.8681	0.8726
CPI ↛ EPU	**0.0225**	0.1944	0.0835	0.7551	0.6002
RATE ↛ EPU	0.2044	**0.0020**	0.0745	0.7361	0.5392
GDP ↛ EPU	0.2754	**0.0470**	0.8801	0.9270	0.8141
OIL ↛ GDP	**0.0040**	0.1009	0.0855	0.4703	0.8716
CPI ↛ GDP	0.0930	0.0625	0.1124	0.4268	0.7821
RATE ↛ GDP	**0.0005**	**0.0025**	**0.0155**	**0.0185**	0.1329
EPU ↛ GDP	0.8621	0.4193	0.0770	0.2944	0.4443
			Panel B: Low frequency standard VAR		
CPI ↛ OIL	0.4393	0.6562	0.8686	0.8211	0.7266
RATE ↛ OIL	**0.0080**	**0.0180**	0.1789	0.9545	0.5472
EPU ↛ OIL	0.1214	0.1489	0.2904	0.4863	0.4358
GDP ↛ OIL	0.3103	0.2169	0.1644	0.1824	0.0950
OIL ↛ CPI	0.1544	0.4038	0.7711	0.4383	0.7106
RATE ↛ CPI	0.1959	0.4053	0.8206	0.9540	0.7776
EPU ↛ CPI	0.4188	0.1604	0.0665	**0.0270**	**0.0495**
GDP ↛ CPI	0.8561	0.9450	0.8261	0.4893	0.3738
OIL ↛ RATE	0.8356	0.2849	**0.0360**	**0.0135**	0.0660
CPI ↛ RATE	0.7046	0.6307	0.6172	0.4878	0.3178
EPU ↛ RATE	0.9880	0.4558	0.2054	0.1659	0.2484
GDP ↛ RATE	**0.0115**	**0.0120**	0.1544	0.4998	0.9640
OIL ↛ EPU	0.7421	0.9905	0.9310	0.9800	0.7816
CPI ↛ EPU	0.1469	0.2364	0.5657	0.8096	0.9370
RATE ↛ EPU	0.6857	0.2434	0.2859	0.5212	0.7511
GDP ↛ EPU	0.1584	0.1019	0.2809	0.4773	0.6362
OIL ↛ GDP	0.0555	**0.0205**	0.1269	0.3188	0.6972
CPI ↛ GDP	0.1394	0.0610	0.2684	0.3518	0.4258
RATE ↛ GDP	**0.0005**	**0.0005**	**0.0005**	0.0535	0.4503
EPU ↛ GDP	0.1064	**0.0435**	**0.0450**	0.1299	0.3053

Note: The table reports *p*-values of the mixed frequency Granger causality tests (MFGCT) and low frequency Granger causality (LFGCT) for the low frequency (quarterly) horizons (*h*) from 1 to 5. Panel A reports the *p*-values for the MFGCT based on the mixed frequency VAR (MF-VAR) model with monthly data on OIL, CPI, RATE, and EPU, and quarterly data on GDP. Panel B reports the *p*-values for the LFGCT based on a standard VAR model with quarterly data on all variables. The *p*-values are obtained based the covariance matrix estimates using Newey and West (1987) kernel-based heteroskedasticity and autocorrelation consistent (HAC) estimator with Newey and West (1994) automatic lag selection, and bootstrap approach of GonçavlesandKilian(2004) with 2,000 replications. X ↛ Y means the variable X does not Granger cause the variable Y. The *p*-values less than 10% are donated with a shaded background, while the *p*-values less than 5% are in bold characters. The lag orders of the MF-VAR and VAR models are selected with the Schwarz (Bayesian) Information Criterion (SIC). The selected lag order is 1 for the MF-VAR model and 2 for the VAR model. See the note to Figure 1 for variable definitions.

Table 4. Granger causality tests for Chile

h	1	2	3	4	5
			Panel A: Mixed frequency VAR (MF-VAR)		
CPI ↛ OIL	**0.0210**	**0.0035**	0.0555	**0.0440**	0.1719
RATE ↛ OIL	**0.0145**	0.1149	0.7101	0.6187	0.2629
EPU ↛ OIL	0.5567	0.4918	0.7901	0.8236	0.6642
GDP ↛ OIL	0.3848	0.5297	0.3318	0.0970	0.0725
OIL ↛ CPI	**0.0015**	0.2694	0.2319	0.5732	0.5702
RATE ↛ CPI	0.2079	0.1084	0.1089	0.0660	0.4153
EPU ↛ CPI	0.1664	0.4908	0.8001	0.6787	0.9445
GDP ↛ CPI	**0.0005**	**0.0015**	**0.0225**	0.0570	0.5187
OIL ↛ RATE	0.0725	0.0830	0.1389	0.2714	0.7681
CPI ↛ RATE	**0.0175**	**0.0005**	**0.0400**	0.1459	0.2684
EPU ↛ RATE	0.7696	0.4608	0.5252	0.1094	0.4073
GDP ↛ RATE	**0.0005**	**0.0065**	**0.0015**	**0.0110**	**0.0165**
OIL ↛ EPU	0.9895	0.5977	0.6902	0.7326	0.1589
CPI ↛ EPU	**0.0335**	0.2814	0.3288	0.1709	0.2224
RATE ↛ EPU	0.1839	0.5257	0.8206	0.3158	0.4963
GDP ↛ EPU	0.9785	0.6387	0.3123	0.8411	0.1224
OIL ↛ GDP	0.4058	0.8951	0.3653	0.1599	0.1144
CPI ↛ GDP	**0.0490**	0.3983	0.3418	0.1269	**0.0070**
RATE ↛ GDP	**0.0005**	0.2239	0.5892	0.1789	0.0765
EPU ↛ GDP	**0.0135**	0.2869	0.1959	0.2254	0.4198
			Panel B: Low frequency standard VAR		
CPI ↛ OIL	**0.0335**	**0.0175**	**0.0125**	**0.0015**	**0.0410**
RATE ↛ OIL	0.6952	0.2954	0.1234	0.1129	0.2269
EPU ↛ OIL	0.2989	0.3803	0.4778	0.9155	0.3833
GDP ↛ OIL	0.5342	0.2519	0.1324	0.2174	0.5872
OIL ↛ CPI	0.0775	0.1929	0.5027	0.7266	0.3183
RATE ↛ CPI	0.1444	0.0620	0.0710	0.1339	0.4508
EPU ↛ CPI	0.8721	0.7216	0.4653	0.3558	0.4328
GDP ↛ CPI	**0.0425**	0.0940	0.1139	0.1754	0.2704
OIL ↛ RATE	0.0850	0.0925	0.1729	0.6257	0.3338
CPI ↛ RATE	0.3493	0.3163	0.9865	0.4793	0.1654
EPU ↛ RATE	0.8536	0.5467	0.3393	**0.0430**	0.0915
GDP ↛ RATE	**0.0010**	**0.0035**	**0.0105**	0.0890	0.4168
OIL ↛ EPU	0.8521	0.7991	0.6287	0.8981	0.9830
CPI ↛ EPU	**0.0230**	**0.0490**	0.2114	0.4398	0.4903
RATE ↛ EPU	0.2174	0.1954	0.2129	0.2824	0.1164
GDP ↛ EPU	0.8281	0.3398	0.0995	0.1904	0.3153
OIL ↛ GDP	0.1074	0.2499	0.4423	0.3418	0.2924
CPI ↛ GDP	0.7291	0.3493	0.1869	0.0880	**0.0140**
RATE ↛ GDP	**0.0460**	0.1389	0.3218	0.8906	0.1259
EPU ↛ GDP	**0.0340**	0.0570	0.0740	0.1314	0.4983

Note: The selected lag order for both the MF-VAR and VAR is 1. See the note to Table 3 for the table explanations.

Table 5. Granger causality tests for China

h	1	2	3	4	5
			Panel A: Mixed frequency VAR (MF-VAR)		
CPI ↛ OIL	**0.0455**	0.1299	0.6877	0.2394	0.3333
RATE ↛ OIL	0.2234	0.0655	0.2939	0.3368	0.2244
EPU ↛ OIL	0.0880	0.2324	0.2744	0.5022	0.5312
GDP ↛ OIL	0.3038	0.2714	0.2064	0.2054	0.2374
OIL ↛ CPI	0.7811	0.1719	0.2629	0.7376	0.6297
RATE ↛ CPI	**0.0195**	0.4558	0.2569	**0.0045**	0.1829
EPU ↛ CPI	0.1009	0.7196	0.0965	0.1934	0.1864
GDP ↛ CPI	0.0585	**0.0035**	**0.0025**	**0.0030**	**0.0085**
OIL ↛ RATE	0.5762	0.8781	0.7726	0.8241	0.8166
CPI ↛ RATE	0.6372	**0.0290**	0.0535	0.1134	0.7186
EPU ↛ RATE	0.4833	0.1174	0.1739	**0.0305**	0.1204
GDP ↛ RATE	0.0550	**0.0230**	0.0640	**0.0485**	0.2869
OIL ↛ EPU	0.1154	0.1099	0.3593	0.1914	0.8881
CPI ↛ EPU	0.3163	0.0905	0.1519	0.4068	0.1649
RATE ↛ EPU	0.8871	0.6507	**0.0375**	0.5797	0.5347
GDP ↛ EPU	0.1199	0.0505	0.0570	**0.0295**	0.1284
OIL ↛ GDP	0.2244	0.4123	0.5932	0.4003	0.3093
CPI ↛ GDP	0.1109	0.1494	0.0930	**0.0065**	0.1189
RATE ↛ GDP	0.9630	0.8836	0.6047	0.0905	0.2314
EPU ↛ GDP	0.3758	0.9235	0.8866	0.8756	0.8986
			Panel B: Low frequency standard VAR		
CPI ↛ OIL	0.3738	0.2524	0.1184	**0.0485**	**0.0300**
RATE ↛ OIL	0.3833	0.4143	0.7181	0.7521	0.3993
EPU ↛ OIL	0.2819	0.1794	0.1709	0.1564	0.1899
GDP ↛ OIL	0.0970	0.0625	**0.0420**	0.1044	0.1929
OIL ↛ CPI	0.8091	0.5302	0.5637	0.3028	0.3343
RATE ↛ CPI	0.2019	0.1499	0.1584	0.0790	0.1204
EPU ↛ CPI	0.4678	0.4358	0.1569	0.0975	0.0690
GDP ↛ CPI	**0.0105**	**0.0105**	**0.0115**	**0.0005**	**0.0055**
OIL ↛ RATE	0.0550	0.3068	0.9820	0.7906	0.7181
CPI ↛ RATE	0.6342	0.3343	0.2669	0.1524	0.0750
EPU ↛ RATE	0.1629	0.0915	0.0860	**0.0395**	0.0935
GDP ↛ RATE	**0.0300**	**0.0275**	**0.0075**	**0.0020**	0.0560
OIL ↛ EPU	0.9025	0.2609	0.2894	0.1849	0.3383
CPI ↛ EPU	**0.0085**	**0.0130**	**0.0360**	0.1499	0.3228
RATE ↛ EPU	0.4963	0.1809	0.3628	0.5952	0.5897
GDP ↛ EPU	**0.0255**	0.0645	0.2199	0.1509	0.3098
OIL ↛ GDP	0.4743	0.4708	0.6902	0.9450	0.6192
CPI ↛ GDP	**0.0185**	0.0610	0.0560	0.1000	0.3723
RATE ↛ GDP	0.7386	0.9560	0.8121	0.9485	0.7516
EPU ↛ GDP	0.7291	0.6422	0.6997	0.8506	0.6952

Note: The selected lag order for both the MF-VAR and VAR is 1. See the note to Table 3 for the table explanations.

Table 6. Granger causality tests for Colombia

h	1	2	3	4	5
Panel A: Mixed frequency VAR (MF-VAR)					
CPI ↛ OIL	0.9955	0.4193	0.2349	0.1224	0.2569
RATE ↛ OIL	**0.0050**	0.2319	0.1414	0.3123	0.1019
EPU ↛ OIL	0.9705	0.9885	0.7931	0.4693	0.6167
GDP ↛ OIL	0.1069	0.9275	0.4583	0.1859	0.1709
OIL ↛ CPI	**0.0315**	0.7981	0.5642	0.8241	0.2884
RATE ↛ CPI	**0.0400**	0.0800	0.0590	0.1104	0.0545
EPU ↛ CPI	0.3318	0.2544	0.7956	0.4003	**0.0055**
GDP ↛ CPI	0.0965	0.1369	**0.0375**	**0.0320**	0.1339
OIL ↛ RATE	**0.0005**	0.3763	0.4048	0.7381	0.1929
CPI ↛ RATE	**0.0465**	0.3063	0.2989	0.0970	0.2114
EPU ↛ RATE	0.7001	0.2474	0.2709	**0.0180**	0.8791
GDP ↛ RATE	**0.0475**	**0.0490**	**0.0025**	**0.0005**	**0.0020**
OIL ↛ EPU	0.5322	0.5512	0.8081	0.2789	0.6437
CPI ↛ EPU	0.3938	0.3818	0.2704	0.2649	0.2834
RATE ↛ EPU	0.2124	0.5912	0.9195	0.4478	0.4608
GDP ↛ EPU	0.1744	0.1784	0.0590	0.5842	0.2874
OIL ↛ GDP	0.3668	0.9825	0.7136	0.7316	0.1729
CPI ↛ GDP	**0.0295**	0.0560	**0.0285**	**0.0450**	**0.0315**
RATE ↛ GDP	**0.0015**	**0.0020**	**0.0005**	**0.0010**	**0.0225**
EPU ↛ GDP	0.2509	0.4178	0.2339	0.0600	0.1089
Panel B: Low frequency standard VAR					
CPI ↛ OIL	0.3018	0.8486	0.5097	0.3288	0.2569
RATE ↛ OIL	0.3643	0.3483	0.5942	0.9250	0.6102
EPU ↛ OIL	0.6027	0.8931	0.8106	0.8431	0.7911
GDP ↛ OIL	0.0805	0.2479	0.1914	0.1289	0.0750
OIL ↛ CPI	**0.0320**	0.1124	0.5007	0.9930	0.7236
RATE ↛ CPI	0.5357	0.2674	0.1684	0.0910	0.0570
EPU ↛ CPI	0.1944	**0.0260**	**0.0335**	**0.0395**	0.0560
GDP ↛ CPI	0.0725	0.0730	**0.0425**	**0.0310**	**0.0220**
OIL ↛ RATE	0.5002	0.4858	0.8766	0.8576	0.6832
CPI ↛ RATE	0.3833	0.4278	0.4363	0.5852	0.6082
EPU ↛ RATE	0.8506	0.1934	0.2614	0.1024	**0.0500**
GDP ↛ RATE	**0.0005**	**0.0010**	**0.0005**	**0.0005**	**0.0015**
OIL ↛ EPU	0.1119	0.4638	0.9185	0.4808	0.3888
CPI ↛ EPU	0.9350	0.5282	0.2569	0.1389	0.1139
RATE ↛ EPU	0.3983	0.2994	0.6327	0.8786	0.8816
GDP ↛ EPU	**0.0280**	0.0670	0.1794	0.6942	0.9930
OIL ↛ GDP	0.2624	0.6047	0.4623	0.6677	0.8186
CPI ↛ GDP	**0.0200**	**0.0150**	**0.0090**	**0.0200**	**0.0430**
RATE ↛ GDP	**0.0010**	**0.0035**	**0.0225**	0.0895	0.3543
EPU ↛ GDP	0.0860	0.1104	0.0805	0.1854	0.7811

Note: The selected lag order for both the MF-VAR and VAR is 1. See the note to Table 3 for the table explanations.

Table 7. Granger causality tests for India

h	1	2	3	4	5
			Panel A: Mixed frequency VAR (MF-VAR)		
CPI ↛ OIL	0.6827	0.5362	0.7576	0.4663	0.6617
RATE ↛ OIL	0.3578	0.3978	0.1784	0.4768	0.6722
EPU ↛ OIL	0.8376	0.8406	0.5252	0.2474	0.9695
GDP ↛ OIL	0.1864	0.1924	0.2584	0.5957	0.0795
OIL ↛ CPI	0.2124	**0.0175**	0.5532	0.8841	0.8791
RATE ↛ CPI	**0.0005**	**0.0300**	0.5457	**0.0450**	0.1089
EPU ↛ CPI	**0.0210**	0.1494	0.5577	0.5697	0.6852
GDP ↛ CPI	**0.0005**	0.8216	0.9850	0.7656	0.9005
OIL ↛ RATE	**0.0035**	0.6817	0.1479	0.0575	**0.0285**
CPI ↛ RATE	**0.0110**	0.8306	0.3373	0.4743	0.7426
EPU ↛ RATE	**0.0190**	0.3428	0.0590	0.1799	0.2374
GDP ↛ RATE	**0.0060**	0.2609	0.4683	0.2809	0.4623
OIL ↛ EPU	0.5157	0.2024	0.2879	0.6467	0.2529
CPI ↛ EPU	0.9840	0.4383	0.6137	0.7956	0.2384
RATE ↛ EPU	0.9940	0.8146	0.5537	0.6052	0.9485
GDP ↛ EPU	0.2499	0.1974	0.1574	0.3003	0.2444
OIL ↛ GDP	**0.0160**	0.0600	0.1419	0.2004	0.7986
CPI ↛ GDP	**0.0020**	0.1644	0.1589	0.1909	0.6952
RATE ↛ GDP	**0.0205**	0.3378	0.4918	0.4248	0.9020
EPU ↛ GDP	**0.0200**	0.0845	0.0540	**0.0065**	**0.0290**
			Panel B: Low frequency standard VAR		
CPI ↛ OIL	0.8966	0.9110	0.8741	0.9455	0.7091
RATE ↛ OIL	0.0835	0.2399	0.6602	0.9830	0.7916
EPU ↛ OIL	0.8676	0.7946	0.7656	0.7516	0.9565
GDP ↛ OIL	0.1184	0.1309	0.5512	0.9505	0.9555
OIL ↛ CPI	0.6017	0.5862	0.7921	0.7451	0.5782
RATE ↛ CPI	0.3818	0.2419	0.3808	0.6087	0.8416
EPU ↛ CPI	0.5562	0.5642	0.4173	0.5322	0.3978
GDP ↛ CPI	0.8726	0.5797	0.5162	0.4158	0.5632
OIL ↛ RATE	**0.0435**	0.4928	0.6767	0.6822	0.6617
CPI ↛ RATE	0.5712	0.9640	0.8671	0.6627	0.7891
EPU ↛ RATE	0.2764	0.4508	0.1724	0.1149	0.2884
GDP ↛ RATE	0.5067	0.3573	1.0000	0.5267	0.5187
OIL ↛ EPU	**0.0215**	0.2589	0.7736	0.7051	0.2474
CPI ↛ EPU	0.0830	0.1029	0.2369	0.1429	0.0740
RATE ↛ EPU	0.3473	0.8291	0.5302	0.6707	0.8411
GDP ↛ EPU	0.7316	0.5442	0.0945	0.0820	0.1584
OIL ↛ GDP	**0.0235**	**0.0340**	0.0650	0.2294	0.8231
CPI ↛ GDP	0.1289	0.1009	0.1464	0.2654	0.5217
RATE ↛ GDP	0.1529	0.2739	0.1594	0.3788	0.8046
EPU ↛ GDP	**0.0175**	**0.0035**	**0.0055**	**0.0035**	**0.0190**

Note: The selected lag order for both the MF-VAR and VAR is 1. See the note to Table 3 for the table explanations.

Table 8. Granger causality tests for Mexico

h	1	2	3	4	5
Panel A: Mixed frequency VAR (MF-VAR)					
CPI ↛ OIL	0.4393	0.6562	0.8686	0.8211	0.7266
RATE ↛ OIL	**0.0080**	**0.0180**	0.1789	0.9545	0.5472
EPU ↛ OIL	0.1214	0.1489	0.2904	0.4863	0.4358
GDP ↛ OIL	0.3103	0.2169	0.1644	0.1824	0.0950
OIL ↛ CPI	0.1544	0.4038	0.7711	0.4383	0.7106
RATE ↛ CPI	0.1959	0.4053	0.8206	0.9540	0.7776
EPU ↛ CPI	0.4188	0.1604	0.0665	**0.0270**	**0.0495**
GDP ↛ CPI	0.8561	0.9450	0.8261	0.4893	0.3738
OIL ↛ RATE	0.8356	0.2849	**0.0360**	**0.0135**	0.0660
CPI ↛ RATE	0.7046	0.6307	0.6172	0.4878	0.3178
EPU ↛ RATE	0.9880	0.4558	0.2054	0.1659	0.2484
GDP ↛ RATE	**0.0115**	**0.0120**	0.1544	0.4998	0.9640
OIL ↛ EPU	0.7421	0.9905	0.9310	0.9800	0.7816
CPI ↛ EPU	0.1469	0.2364	0.5657	0.8096	0.9370
RATE ↛ EPU	0.6857	0.2434	0.2859	0.5212	0.7511
GDP ↛ EPU	0.1584	0.1019	0.2809	0.4773	0.6362
OIL ↛ GDP	0.0555	**0.0205**	0.1269	0.3188	0.6972
CPI ↛ GDP	0.1394	0.0610	0.2684	0.3518	0.4258
RATE ↛ GDP	**0.0005**	**0.0005**	**0.0005**	0.0535	0.4503
EPU ↛ GDP	0.1064	**0.0435**	**0.0450**	0.1299	0.3053
Panel B: Low frequency standard VAR					
CPI ↛ OIL	0.8246	0.8681	0.8506	0.4488	0.2774
RATE ↛ OIL	0.6657	0.3253	0.0950	**0.0255**	0.1114
EPU ↛ OIL	0.6212	0.1314	0.0610	**0.0030**	**0.0050**
GDP ↛ OIL	0.0870	0.1244	0.2109	0.5467	0.6382
OIL ↛ CPI	0.4473	0.3518	0.1899	0.1379	0.1000
RATE ↛ CPI	0.0880	0.2484	0.6327	0.8616	0.8091
EPU ↛ CPI	0.4318	0.3438	0.2914	0.3728	0.9720
GDP ↛ CPI	0.0930	0.0800	0.0595	0.0660	0.0550
OIL ↛ RATE	0.4453	0.1269	**0.0275**	**0.0335**	0.1459
CPI ↛ RATE	**0.0185**	**0.0070**	0.0535	0.2444	0.6042
EPU ↛ RATE	0.8271	0.5317	0.0630	0.5932	0.8276
GDP ↛ RATE	**0.0020**	**0.0045**	**0.0065**	**0.0300**	0.2254
OIL ↛ EPU	0.8256	0.5317	0.5167	0.3068	0.7371
CPI ↛ EPU	**0.0120**	**0.0010**	**0.0045**	**0.0200**	**0.0085**
RATE ↛ EPU	0.1479	0.1319	**0.0475**	**0.0130**	**0.0075**
GDP ↛ EPU	0.9360	0.7851	0.9395	0.4618	0.9515
OIL ↛ GDP	0.5452	0.6697	0.4093	0.1814	0.1779
CPI ↛ GDP	**0.0105**	**0.0100**	0.0635	0.1799	0.2209
RATE ↛ GDP	**0.0220**	0.0725	0.9000	0.1629	0.0690
EPU ↛ GDP	**0.0075**	0.1174	0.6242	0.5627	0.4273

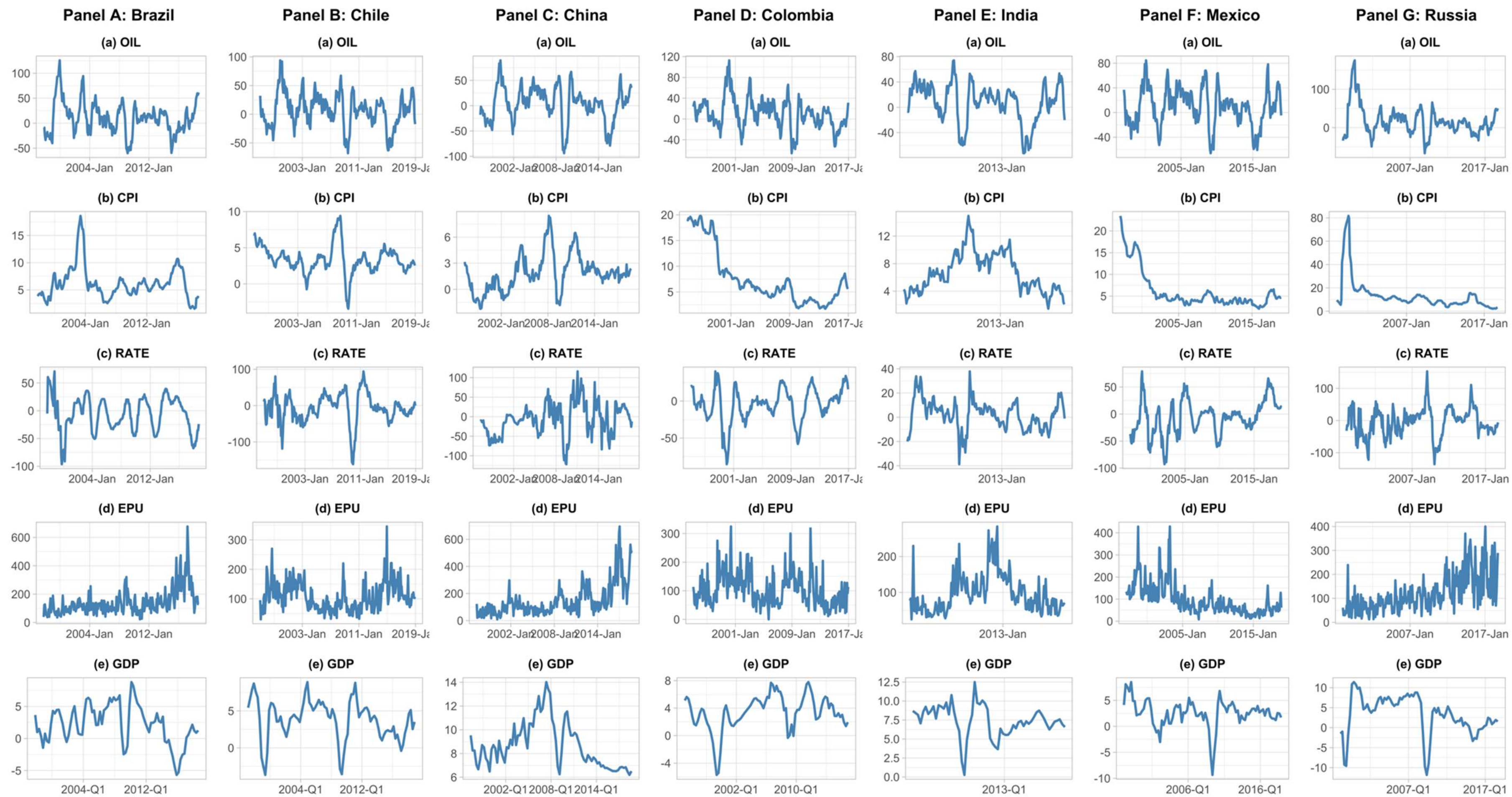
Note: The selected lag order is 1 for the MF-VAR model and 2 for the VAR model. See the note to Table 3 for the table explanations.

Table 9. Granger causality tests for Russia

h	1	2	3	4	5
Panel A: Mixed frequency VAR (MF-VAR)					
CPI ↛ OIL	**0.0160**	0.4463	0.5642	**0.0220**	0.1289
RATE ↛ OIL	**0.0005**	0.1204	0.6522	**0.0245**	0.3988
EPU ↛ OIL	0.6332	0.3738	0.4008	0.1109	0.4413
GDP ↛ OIL	0.1269	0.1389	0.2859	0.4533	0.4048
OIL ↛ CPI	0.5357	0.5722	0.2389	0.5802	0.9695
RATE ↛ CPI	0.1964	0.7921	0.7956	0.8801	0.9465
EPU ↛ CPI	0.7101	0.9940	0.8231	0.8466	0.7936
GDP ↛ CPI	0.5932	0.7866	0.4488	0.5652	0.6907
OIL ↛ RATE	**0.0090**	0.2974	0.1594	0.3418	0.5527
CPI ↛ RATE	**0.0060**	0.3118	0.0730	0.0535	**0.0105**
EPU ↛ RATE	0.6717	0.4988	0.4513	0.6957	0.6777
GDP ↛ RATE	0.0605	**0.0165**	**0.0005**	**0.0010**	**0.0225**
OIL ↛ EPU	0.1774	0.7866	0.6922	0.8256	0.9350
CPI ↛ EPU	0.0565	0.0610	0.2974	0.5512	0.5017
RATE ↛ EPU	**0.0335**	**0.0165**	0.7256	0.8701	0.7576
GDP ↛ EPU	0.0875	**0.0015**	**0.0040**	0.0555	0.2444
OIL ↛ GDP	0.0570	0.1039	0.5132	0.7056	0.6737
CPI ↛ GDP	0.1719	0.2074	0.2599	0.3578	0.2814
RATE ↛ GDP	0.2724	0.3843	0.5837	0.7671	0.8591
EPU ↛ GDP	0.6317	0.6037	0.4573	0.1589	0.0770
Panel B: Low frequency standard VAR					
CPI ↛ OIL	0.4228	0.3318	0.1154	**0.0435**	0.2904
RATE ↛ OIL	0.9385	0.8436	0.7056	0.4563	0.2864
EPU ↛ OIL	**0.0495**	**0.0240**	0.1174	0.3323	0.3923
GDP ↛ OIL	**0.0315**	**0.0330**	0.2549	0.3543	0.3283
OIL ↛ CPI	0.3183	0.4653	0.6417	0.9395	0.8851
RATE ↛ CPI	0.2444	0.3968	0.6697	0.9135	0.9125
EPU ↛ CPI	0.0560	0.0835	0.1859	0.1644	0.1914
GDP ↛ CPI	0.2444	0.3298	0.4718	0.6172	0.7736
OIL ↛ RATE	0.1589	0.3348	0.7516	0.5107	0.6027
CPI ↛ RATE	0.5147	0.7321	0.5767	0.0605	**0.0420**
EPU ↛ RATE	0.1454	0.0805	0.2034	0.5387	0.6952
GDP ↛ RATE	**0.0065**	**0.0070**	0.1004	0.2504	0.3188
OIL ↛ EPU	0.1044	0.0605	0.9290	0.6112	0.9790
CPI ↛ EPU	**0.0040**	**0.0090**	0.2769	0.4278	0.2194
RATE ↛ EPU	0.7486	0.8761	0.2884	0.4533	0.6127
GDP ↛ EPU	**0.0335**	**0.0105**	0.1339	0.3108	0.2494
OIL ↛ GDP	0.7891	0.8396	0.5277	0.3063	0.2664
CPI ↛ GDP	0.1009	0.0705	0.0940	0.1059	0.1424
RATE ↛ GDP	0.1679	0.2794	0.4288	0.4383	0.4623
EPU ↛ GDP	0.8651	0.1109	**0.0055**	**0.0055**	**0.0105**

Note: The selected lag order is 1 for the MF-VAR model and 2 for the VAR model. See the note to Table 3 for the table explanations.

Figure 1. Oil price, CPI, interest rate and GDP growth rates and economic policy uncertainty



Note: Figure plots the year-on-year growth rates of the oil price (OIL), consumer price index (CPI), interest rate (RATE), and gross domestic product (GDP) in percent as well as the level of economic policy uncertainty (EPU) index. The OIL, CPI, RATE, EPU series are at monthly frequency while the GDP series are at quarterly frequency.