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 specified. This model fully exploits the recently developed mixed frequency Granger causality test in order to circumvent the distorting effects of temporal aggregation. The empirical results show a strong statistical evidence for causality flowing from EPU to GDP in Brazil, Chile and India in the mixed frequency case while weak statistical evidence is found for Colombia, Mexico and Russia. For comparative analysis, the low frequency Granger causality test is also employed and strong statistical evidence of causality flowing from EPU to GDP in Brazil, Chile, India, Mexico 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 specifications. The results have empirical as well as policy implications which are discussed.

Keywords: Economic policy uncertainty (EPU), mixed frequency Granger causality tests (MFGCT), temporal aggregation, emerging market economies.

JEL Codes: E32, E37, C32

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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 (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. EPU can also affect economic output through its effect on leading macroeconomic indicators such as housing prices (Chow et al., 2017; Aye, 2018), industrial production (Colombo, 2013; Istiak and Serletis, 2018) and stock markets (Arouri et al., 2016; Li et al, 2016; Li and Peng, 2017)

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 employing the news based EPU variable of Baker *et al.* (2016). Various studies have investigated the relationship between EPU and a diverse array of macroeconomic variables (Aizenman and Marion, 1993; Kang *et al.*, 2014; Wang *et al.*, 2014; Colombo, 2013; Antonakakis *et al.*, 2014; Krol, 2014; Stockhammar and Österholm, 2016; Caggiano *et al.*,2017; Chi and Li, 2017; Xie et al., 2019; Shi et al., 2020; Hammoudeh et al., 2016; Chen et al., 2019). However, very few of these studies isolate a causal interpretation to these relationships. Since correlation does not imply causation, isolating causal relationships between EPU and GDP would be more amenable to macro-economic policy formulation. Several studies have unraveled causal relationships between EPU and various macroeconomic indicators (Balcilar *et al*., 2016b; Li *et al*., 2016; Wu *et al*; 2016; Wu and Wu, 2019; Chow *et al*., 2017; Aye, 2018; Olanipekun *et al*., 2019) however none of these studies isolated the EPU-output causal nexus. 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) would be employed alongside the low frequency Granger causality test (LFGCT). The Importance of employing the MFGCT technique lies in the fact that the usual practice of employing temporal aggregation to mixed frequency data constitutes several drawbacks. The most pertinent of these drawbacks are, the loss of viable information through the smoothening of data points by temporal aggregation, a practice which may lead to spurious inferences. 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 from stock or skipped sampling can induce spuriously hidden or generated causality in even the simplest models, like for instance a bivariate 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). This is easily circumvented by the MFGCT technique.

Some studies (Colombo, 2013; Istiak and Serletis, 2018) employ the synchronized IIP monthly index which 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; because of the simultaneous reduction and growth of the industry and services sector value added respectively in most advanced economies, sufficient synchronization between the cyclical components of the IIP and the GDP has been lost.

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. Furthermore, these are the only emerging economies as at the time of writing for which the EPU variable has been constructed. 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.

This study contributes 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 with relevant policy implications.

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 $\tau_L \in \{0, \ldots, T_L\}$, while the HF time index (monthly) is indicated by $k \in \{1, \ldots, m\}$. 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 $\boldsymbol{X}_H(\tau_{Lq}, k) \in \mathbb{R}^{K_H \times 1}, K_H \geq 1$, 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:

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

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:

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

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

$$
\boldsymbol{A}_k^{(i)} = \boldsymbol{A}_{k+i-1} + \sum_{l=1}^{i-1} \boldsymbol{A}_{i-l}\boldsymbol{A}_k^{(l)} \text{ for } i \geq 2
$$

$$
\boldsymbol{e}^{(h)}(\tau_L) = \sum_{k=0}^{h-1} \boldsymbol{\psi}_k\, \boldsymbol{\varepsilon} \tag{5}
$$

with $\boldsymbol{A}_k^{(1)} = \boldsymbol{A}_k$, and conventionally $\boldsymbol{A}_k = \mathbf{0}_{K\times K}$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 periodτ_L as:

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

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:

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

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:

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

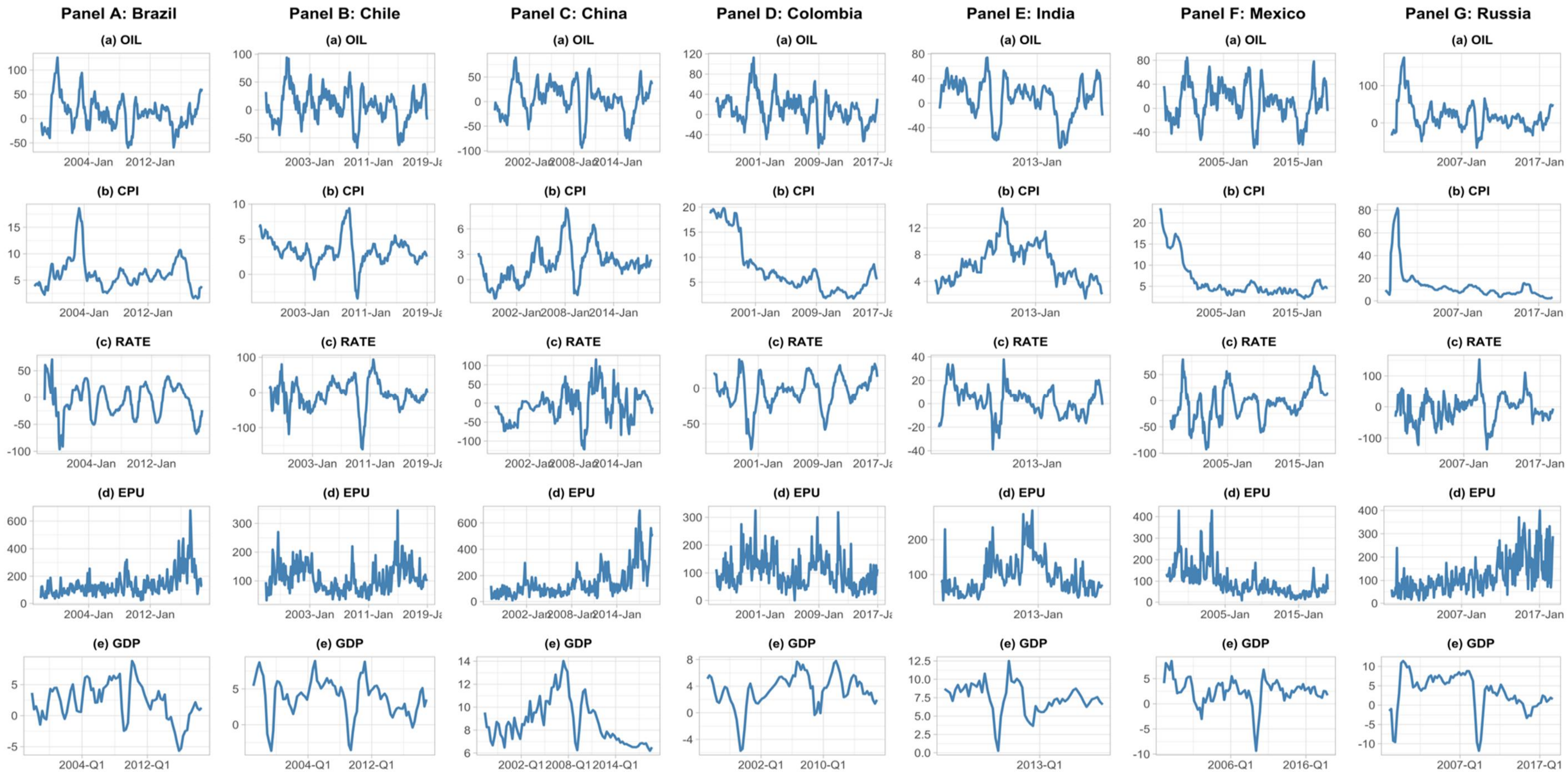
From Eqs. (10-11) $\boldsymbol{R}$ is a $q \times pK^2$selection matrix of full row rank q. $T_L^* = T_L - h + 1$ denotes the effective sample size of the (p,h)-autoregression model while $\widehat{\boldsymbol{B}}(h)$ indicates the least squares estimator of the parameters of the (p,h)-autoregression 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 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

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

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 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. 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.

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. Unit root tests are also augmented with the Narayan and Popp (2010) two endogenous structural break tests in order to circumvent potential inferential bias which may be instigated by incidences of structural breaks in the data.

Looking at the results from Table 2, what can be accurately inferred 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. Results of the

Table 2. Unit root and structural break tests

	ADF Test		ERS Test		KPSS Test		PP Test		NP Model 1			NP Model 2		
	Model A	**Model B**	**Model A**	**Model B**	**Model A**	**Model B**	**Model A**	**Model B**	Break 1	Break 2	Variance	Break 1	Break 2	Variance
Panel A: Brazil														
OIL	-1.969	-2.495	48.074	11.308	1.352***	0.334***	-1.427	-2.006	2003:M3	2008:M11	0.006676	2003:M3	2008:M10	0.006286
CPI	-0.707	-1.735	1597.002	12.821	1.727***	0.208**	-0.823	-0.791	2002:M5	2002:M10	0.000007	2002:M5	2002:M10	0.000007
RATE	-1.502	-2.951	14.087	5.171**	1.330***	0.135*	-1.227	-2.506	2002:M9	2003:M7	0.004054	2002:M9	2009:M2	0.003943
EPU	-4.328***	-5.751***	0.977***	2.254***	1.099***	0.108	-7.210***	-9.946***	2006:M1	2010:M9	0.158463	2010:M9	2011:M1	0.156592
GDP	-1.802	-0.610	208.991	24.515	0.794***	0.142*	-1.446	-0.140	2000:M10	2002:M8	0.000064	2000:M10	2002:M8	0.000059
Panel B: Chile														
OIL	-1.833	-1.943	33.140	12.978	1.400***	0.380***	-2.048	-1.941	2000:M11	2008:M10	0.007919	2000:M11	2003:M2	0.007573
CPI	-1.205	-3.195*	1564.667	20.674	1.823***	0.068	-1.921	-2.983	2008:M5	2008:M11	0.000008	2008:M5	2009:M8	0.000008
RATE	-1.970	-2.567	8.616	6.349*	0.940***	0.139*	-1.930	-2.741	2008:M9	2010:M7	0.011640	2001:M3	2008:M9	0.011603
EPU	-3.806***	-3.786**	3.442*	7.638	0.186	0.180**	-7.842***	-7.862***	2006:M12	2009:M3	0.096877	2006:M12	2009:M3	0.095389
GDP	-0.458	-2.110	614.934	9.693	0.874***	0.139*	-1.320	-1.522	1998:M9	2000:M10	0.000040	1998:M9	2000:M10	0.000041
Panel C: China														
OIL	-1.811	-2.210	9.202	8.802	1.029***	0.325***	-1.622	-1.920	2008:M9	2009:M2	0.006176	2008:M9	2009:M6	0.005694
CPI	1.741	-2.673	681.393	103.648	1.729***	0.327***	1.760	-1.960	2004:M1	2008:M1	0.000010	2004:M1	2012:M1	0.000009
RATE	-3.409**	-3.223*	22.146	18.122	0.549**	0.292***	-3.160**	-3.001	2008:M11	2013:M5	0.019412	2008:M11	2013:M5	0.019287
EPU	-2.294	-4.846***	4.638	4.751**	1.202***	0.097	-6.246***	-9.642***	2011:M4	2013:M5	0.205306	2002:M4	2011:M4	0.203716
GDP	-1.443	-1.582	4660.080	27.280	0.859***	0.145*	-2.133	1.105	1998:M9	2000:M8	0.000006	1998:M9	2000:M4	0.000005
Panel D: Colombia														
OIL	-1.862	-1.900	79.740	17.730	1.572***	0.406***	-1.971	-1.882	1999:M2	2008:M9	0.007554	1999:M2	2008:M9	0.007067
CPI	-5.891***	-5.662***	8183.645	1159.402	1.688***	0.400***	-19.493***	-10.698***	1999:M1	2000:M3	0.000003	1999:M1	2000:M3	0.000003
RATE	-1.900	-1.985	55.638	20.648	1.484***	0.300***	-1.366	-0.861	1998:M8	1999:M12	0.001562	1999:M12	2010:M12	0.001578
EPU	-9.040***	-9.229***	0.507***	1.146***	0.198	0.102	-12.877***	-12.972***	2005:M8	2006:M2	0.232113	2005:M8	2006:M3	0.222289
GDP	0.970	-2.205	545.894	34.124	0.855***	0.183**	1.135	-1.314	1998:M3	1998:M12	0.000044	1995:M12	1998:M12	0.000040
Panel E: India														
OIL	-3.124**	-2.888	11.838	10.046	0.708**	0.235***	-2.320	-2.142	2008:M9	2015:M6	0.006996	2008:M9	2015:M6	0.006848
CPI	-1.235	0.312	2743.413	64.855	1.377***	0.188**	-0.831	-0.052	2009:M6	2010:M11	0.000021	2009:M6	2010:M1	0.000020
RATE	-3.060**	-2.776	5.623	7.817	0.526**	0.222***	-2.459	-2.539	2008:M11	2009:M3	0.001132	2008:M9	2008:M11	0.001036
EPU	-2.800*	-2.765	2.930**	7.017	0.310	0.253***	-5.108***	-5.137***	2008:M2	2011:M7	0.110013	2008:M2	2011:M7	0.106759
GDP	-0.966	-2.918	3477.260	17.688	0.702**	0.145*	-1.373	-2.710	2004:M8	2004:M12	0.000047	2005:M2	2005:M11	0.000055
Panel F: Mexico														
OIL	-1.416	-2.043	46.376	10.198	1.587***	0.337***	-1.611	-2.149	2008:M10	2009:M2	0.009400	2003:M3	2008:M10	0.009011
CPI	-4.948***	-7.366***	3740.162	504.500	1.733***	0.325***	-11.054***	-14.523***	2000:M12	2002:M1	0.000003	2000:M12	2002:M1	0.000003
RATE	-2.088	-1.004	69.544	31.308	1.374***	0.256***	-2.330	-1.063	2001:M8	2003:M4	0.005026	2001:M8	2003:M4	0.004962
EPU	-3.175**	-4.830***	3.769*	2.805***	1.357***	0.105	-5.360***	-8.327***	2007:M3	2013:M11	0.143125	2001:M8	2007:M3	0.141654
GDP	-0.314	-3.107	279.978	12.670	0.879***	0.080	-1.515	-3.073	2000:M5	2000:M7	0.000036	2000:M5	2000:M8	0.000032
Panel G: Russia														
OIL	-2.745*	-2.998	111.385	23.994	1.413***	0.291***	-2.042	-2.103	2008:M9	2008:M11	0.007380	2008:M9	2008:M11	0.007287
CPI	-3.506***	-3.522**	1053.872	131.186	1.606***	0.321***	-4.642***	-2.493	2011:M12	2013:M12	0.000396	2001:M6	2011:M12	0.000387
RATE	-2.394	-2.421	17.591	14.379	0.579**	0.283***	-3.264**	-3.329*	2004:M11	2008:M9	0.027309	2004:M11	2008:M9	0.026107
EPU	-4.191***	-10.495***	6.994	22.135	1.503***	0.078	-10.091***	-13.330***	2002:M1	2008:M6	0.242348	2002:M1	2008:M6	0.243840
GDP	-2.516	-1.111	319.232	50.677	0.760***	0.202**	-1.537	-0.589	2000:M12	2001:M2	0.000036	2000:M11	2001:M6	0.000018

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. Narayan and Popp (2010) NP Model 1 allows two breaks in level while NP Model 2 allows two breaks both in level and trend. Variance is the residual variance of the estimated model given the optimal break dates. See the note to Figure 1 for variable definitions.

Narayan and Popp (2010) dual structural break tests are also presented in Table 2. Prior to undertaking the Granger causality tests, the dataset is further adjusted for the break effects by employing the results in NP Model. It is now appropriate to proceed with the MFGCT and the LFGCT tests.

3.1. Mixed Frequency and Low frequency Granger causality test results

Results for both tests are outlined in Tables 3 to 5. 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. The empirical investigations uncovered more economically meaningful causal relationships in the MFGCT specification for most of the cases.

In the MFGCT specification for the Brazilian case as seen in Table 3, EPU causes GDP directly ($h = 1$). In the LFGCT specification however, EPU also causes GDP directly ($h = 1,2,3,4,5$). Moreover, a weak rejection of the causal null for RATE $\nrightarrow$ CPI in the LFGCT specification spuriously diminishes the monetary policy transmission mechanism in the Brazilian economy. Going by the MFGCT specification, a strong monetary policy transmission mechanism is observed for the Brazilian economy as RATE is seen to Granger cause all the other auxiliary variables except GDP. 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).

At Russia in Table 5, EPU Granger causes GDP in the MF ($h = 4$) case but not in the LF case. For Russia, the LFGCT could not uncover an important causal effect between OIL and GDP which. 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).

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 Gonçavles and Kilian (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 Colombia, India and Chile

h	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Panel A: Mixed frequency VAR (MF-VAR)															
	Colombia					**India**					**Chile**				
CPI ↛ OIL	0.9955	0.4193	0.2349	0.1224	0.2569	0.6827	0.5362	0.7576	0.4663	0.6617	**0.0210**	**0.0035**	0.0555	**0.0440**	0.1719
RATE ↛ OIL	**0.0050**	0.2319	0.1414	0.3123	0.1019	0.3578	0.3978	0.1784	0.4768	0.6722	**0.0145**	0.1149	0.7101	0.6187	0.2629
EPU ↛ OIL	0.9705	0.9885	0.7931	0.4693	0.6167	0.8376	0.8406	0.5252	0.2474	0.9695	0.5567	0.4918	0.7901	0.8236	0.6642
GDP ↛ OIL	0.1069	0.9275	0.4583	0.1859	0.1709	0.1864	0.1924	0.2584	0.5957	0.0795	0.3848	0.5297	0.3318	0.0970	0.0725
OIL ↛ CPI	**0.0315**	0.7981	0.5642	0.8241	0.2884	0.2124	**0.0175**	0.5532	0.8841	0.8791	**0.0015**	0.2694	0.2319	0.5732	0.5702
RATE ↛ CPI	**0.0400**	0.0800	0.0590	0.1104	0.0545	**0.0005**	**0.0300**	0.5457	**0.0450**	0.1089	0.2079	0.1084	0.1089	0.0660	0.4153
EPU ↛ CPI	0.3318	0.2544	0.7956	0.4003	**0.0055**	**0.0210**	0.1494	0.5577	0.5697	0.6852	0.1664	0.4908	0.8001	0.6787	0.9445
GDP ↛ CPI	0.0965	0.1369	**0.0375**	**0.0320**	0.1339	**0.0005**	0.8216	0.9850	0.7656	0.9005	**0.0005**	**0.0015**	**0.0225**	0.0570	0.5187
OIL ↛ RATE	**0.0005**	0.3763	0.4048	0.7381	0.1929	**0.0035**	0.6817	0.1479	0.0575	**0.0285**	0.0725	0.0830	0.1389	0.2714	0.7681
CPI ↛ RATE	**0.0465**	0.3063	0.2989	0.0970	0.2114	**0.0110**	0.8306	0.3373	0.4743	0.7426	**0.0175**	**0.0005**	**0.0400**	0.1459	0.2684
EPU ↛ RATE	0.7001	0.2474	0.2709	**0.0180**	0.8791	**0.0190**	0.3428	0.0590	0.1799	0.2374	0.7696	0.4608	0.5252	0.1094	0.4073
GDP ↛ RATE	**0.0475**	**0.0490**	**0.0025**	**0.0005**	**0.0020**	**0.0060**	0.2609	0.4683	0.2809	0.4623	**0.0005**	**0.0065**	**0.0015**	**0.0110**	**0.0165**
OIL ↛ EPU	0.5322	0.5512	0.8081	0.2789	0.6437	0.5157	0.2024	0.2879	0.6467	0.2529	0.9895	0.5977	0.6902	0.7326	0.1589
CPI ↛ EPU	0.3938	0.3818	0.2704	0.2649	0.2834	0.9840	0.4383	0.6137	0.7956	0.2384	**0.0335**	0.2814	0.3288	0.1709	0.2224
RATE ↛ EPU	0.2124	0.5912	0.9195	0.4478	0.4608	0.9940	0.8146	0.5537	0.6052	0.9485	0.1839	0.5257	0.8206	0.3158	0.4963
GDP ↛ EPU	0.1744	0.1784	0.0590	0.5842	0.2874	0.2499	0.1974	0.1574	0.3003	0.2444	0.9785	0.6387	0.3123	0.8411	0.1224
OIL ↛ GDP	0.3668	0.9825	0.7136	0.7316	0.1729	**0.0160**	0.0600	0.1419	0.2004	0.7986	0.4058	0.8951	0.3653	0.1599	0.1144
CPI ↛ GDP	**0.0295**	0.0560	**0.0285**	**0.0450**	**0.0315**	**0.0020**	0.1644	0.1589	0.1909	0.6952	**0.0490**	0.3983	0.3418	0.1269	**0.0070**
RATE ↛ GDP	**0.0015**	**0.0020**	**0.0005**	**0.0010**	**0.0225**	**0.0205**	0.3378	0.4918	0.4248	0.9020	**0.0005**	0.2239	0.5892	0.1789	0.0765
EPU ↛ GDP	0.2509	0.4178	0.2339	0.0600	0.1089	**0.0200**	0.0845	0.0540	**0.0065**	**0.0290**	**0.0135**	0.2869	0.1959	0.2254	0.4198
h	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Panel B: Low frequency standard VAR															
	Colombia					**India**					**Chile**				
CPI ↛ OIL	0.3018	0.8486	0.5097	0.3288	0.2569	0.8966	0.9110	0.8741	0.9455	0.7091	**0.0335**	**0.0175**	**0.0125**	**0.0015**	**0.0410**
RATE ↛ OIL	0.3643	0.3483	0.5942	0.9250	0.6102	0.0835	0.2399	0.6602	0.9830	0.7916	0.6952	0.2954	0.1234	0.1129	0.2269
EPU ↛ OIL	0.6027	0.8931	0.8106	0.8431	0.7911	0.8676	0.7946	0.7656	0.7516	0.9565	0.2989	0.3803	0.4778	0.9155	0.3833
GDP ↛ OIL	0.0805	0.2479	0.1914	0.1289	0.0750	0.1184	0.1309	0.5512	0.9505	0.9555	0.5342	0.2519	0.1324	0.2174	0.5872
OIL ↛ CPI	**0.0320**	0.1124	0.5007	0.9930	0.7236	0.6017	0.5862	0.7921	0.7451	0.5782	0.0775	0.1929	0.5027	0.7266	0.3183
RATE ↛ CPI	0.5357	0.2674	0.1684	0.0910	0.0570	0.3818	0.2419	0.3808	0.6087	0.8416	0.1444	0.0620	0.0710	0.1339	0.4508
EPU ↛ CPI	0.1944	**0.0260**	**0.0335**	**0.0395**	0.0560	0.5562	0.5642	0.4173	0.5322	0.3978	0.8721	0.7216	0.4653	0.3558	0.4328
GDP ↛ CPI	0.0725	0.0730	**0.0425**	**0.0310**	**0.0220**	0.8726	0.5797	0.5162	0.4158	0.5632	**0.0425**	0.0940	0.1139	0.1754	0.2704
OIL ↛ RATE	0.5002	0.4858	0.8766	0.8576	0.6832	**0.0435**	0.4928	0.6767	0.6822	0.6617	0.0850	0.0925	0.1729	0.6257	0.3338
CPI ↛ RATE	0.3833	0.4278	0.4363	0.5852	0.6082	0.5712	0.9640	0.8671	0.6627	0.7891	0.3493	0.3163	0.9865	0.4793	0.1654
EPU ↛ RATE	0.8506	0.1934	0.2614	0.1024	**0.0500**	0.2764	0.4508	0.1724	0.1149	0.2884	0.8536	0.5467	0.3393	**0.0430**	0.0915
GDP ↛ RATE	**0.0005**	**0.0010**	**0.0005**	**0.0005**	**0.0015**	0.5067	0.3573	1.0000	0.5267	0.5187	**0.0010**	**0.0035**	**0.0105**	0.0890	0.4168
OIL ↛ EPU	0.1119	0.4638	0.9185	0.4808	0.3888	**0.0215**	0.2589	0.7736	0.7051	0.2474	0.8521	0.7991	0.6287	0.8981	0.9830
CPI ↛ EPU	0.9350	0.5282	0.2569	0.1389	0.1139	0.0830	0.1029	0.2369	0.1429	0.0740	**0.0230**	**0.0490**	0.2114	0.4398	0.4903
RATE ↛ EPU	0.3983	0.2994	0.6327	0.8786	0.8816	0.3473	0.8291	0.5302	0.6707	0.8411	0.2174	0.1954	0.2129	0.2824	0.1164
GDP ↛ EPU	**0.0280**	0.0670	0.1794	0.6942	0.9930	0.7316	0.5442	0.0945	0.0820	0.1584	0.8281	0.3398	0.0995	0.1904	0.3153
OIL ↛ GDP	0.2624	0.6047	0.4623	0.6677	0.8186	**0.0235**	**0.0340**	0.0650	0.2294	0.8231	0.1074	0.2499	0.4423	0.3418	0.2924
CPI ↛ GDP	**0.0200**	**0.0150**	**0.0090**	**0.0200**	**0.0430**	0.1289	0.1009	0.1464	0.2654	0.5217	0.7291	0.3493	0.1869	0.0880	**0.0140**
RATE ↛ GDP	**0.0010**	**0.0035**	**0.0225**	0.0895	0.3543	0.1529	0.2739	0.1594	0.3788	0.8046	**0.0460**	0.1389	0.3218	0.8906	0.1259
EPU ↛ GDP	0.0860	0.1104	0.0805	0.1854	0.7811	**0.0175**	**0.0035**	**0.0055**	**0.0035**	**0.0190**	**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 Mexico, Russia and China

h	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Panel A: Mixed frequency VAR (MF-VAR)															
	Mexico					**Russia**					**China**				
CPI $\nrightarrow$ OIL	0.4393	0.6562	0.8686	0.8211	0.7266	**0.0160**	0.4463	0.5642	**0.0220**	0.1289	**0.0455**	0.1299	0.6877	0.2394	0.3333
RATE $\nrightarrow$ OIL	**0.0080**	**0.0180**	0.1789	0.9545	0.5472	**0.0005**	0.1204	0.6522	**0.0245**	0.3988	0.2234	0.0655	0.2939	0.3368	0.2244
EPU $\nrightarrow$ OIL	0.1214	0.1489	0.2904	0.4863	0.4358	0.6332	0.3738	0.4008	0.1109	0.4413	0.0880	0.2324	0.2744	0.5022	0.5312
GDP $\nrightarrow$ OIL	0.3103	0.2169	0.1644	0.1824	0.0950	0.1269	0.1389	0.2859	0.4533	0.4048	0.3038	0.2714	0.2064	0.2054	0.2374
OIL $\nrightarrow$ CPI	0.1544	0.4038	0.7711	0.4383	0.7106	0.5357	0.5722	0.2389	0.5802	0.9695	0.7811	0.1719	0.2629	0.7376	0.6297
RATE $\nrightarrow$ CPI	0.1959	0.4053	0.8206	0.9540	0.7776	0.1964	0.7921	0.7956	0.8801	0.9465	**0.0195**	0.4558	0.2569	**0.0045**	0.1829
EPU $\nrightarrow$ CPI	0.4188	0.1604	0.0665	**0.0270**	**0.0495**	0.7101	0.9940	0.8231	0.8466	0.7936	0.1009	0.7196	0.0965	0.1934	0.1864
GDP $\nrightarrow$ CPI	0.8561	0.9450	0.8261	0.4893	0.3738	0.5932	0.7866	0.4488	0.5652	0.6907	0.0585	**0.0035**	**0.0025**	**0.0030**	**0.0085**
OIL $\nrightarrow$ RATE	0.8356	0.2849	**0.0360**	**0.0135**	0.0660	**0.0090**	0.2974	0.1594	0.3418	0.5527	0.5762	0.8781	0.7726	0.8241	0.8166
CPI $\nrightarrow$ RATE	0.7046	0.6307	0.6172	0.4878	0.3178	**0.0060**	0.3118	0.0730	0.0535	**0.0105**	0.6372	**0.0290**	0.0535	0.1134	0.7186
EPU $\nrightarrow$ RATE	0.9880	0.4558	0.2054	0.1659	0.2484	0.6717	0.4988	0.4513	0.6957	0.6777	0.4833	0.1174	0.1739	**0.0305**	0.1204
GDP $\nrightarrow$ RATE	**0.0115**	**0.0120**	0.1544	0.4998	0.9640	0.0605	**0.0165**	**0.0005**	**0.0010**	**0.0225**	0.0550	**0.0230**	0.0640	**0.0485**	0.2869
OIL $\nrightarrow$ EPU	0.7421	0.9905	0.9310	0.9800	0.7816	0.1774	0.7866	0.6922	0.8256	0.9350	0.1154	0.1099	0.3593	0.1914	0.8881
CPI $\nrightarrow$ EPU	0.1469	0.2364	0.5657	0.8096	0.9370	0.0565	0.0610	0.2974	0.5512	0.5017	0.3163	0.0905	0.1519	0.4068	0.1649
RATE $\nrightarrow$ EPU	0.6857	0.2434	0.2859	0.5212	0.7511	**0.0335**	**0.0165**	0.7256	0.8701	0.7576	0.8871	0.6507	**0.0375**	0.5797	0.5347
GDP $\nrightarrow$ EPU	0.1584	0.1019	0.2809	0.4773	0.6362	0.0875	**0.0015**	**0.0040**	0.0555	0.2444	0.1199	0.0505	0.0570	**0.0295**	0.1284
OIL $\nrightarrow$ GDP	0.0555	**0.0205**	0.1269	0.3188	0.6972	0.0570	0.1039	0.5132	0.7056	0.6737	0.2244	0.4123	0.5932	0.4003	0.3093
CPI $\nrightarrow$ GDP	0.1394	0.0610	0.2684	0.3518	0.4258	0.1719	0.2074	0.2599	0.3578	0.2814	0.1109	0.1494	0.0930	**0.0065**	0.1189
RATE $\nrightarrow$ GDP	**0.0005**	**0.0005**	**0.0005**	0.0535	0.4503	0.2724	0.3843	0.5837	0.7671	0.8591	0.9630	0.8836	0.6047	0.0905	0.2314
EPU $\nrightarrow$ GDP	0.1064	**0.0435**	**0.0450**	0.1299	0.3053	0.6317	0.6037	0.4573	0.1589	0.0770	0.3758	0.9235	0.8866	0.8756	0.8986
h	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Panel B: Low frequency standard VAR															
	Mexico					**Russia**					**China**				
CPI $\nrightarrow$ OIL	0.8246	0.8681	0.8506	0.4488	0.2774	0.4228	0.3318	0.1154	**0.0435**	0.2904	0.3738	0.2524	0.1184	**0.0485**	**0.0300**
RATE $\nrightarrow$ OIL	0.6657	0.3253	0.0950	**0.0255**	0.1114	0.9385	0.8436	0.7056	0.4563	0.2864	0.3833	0.4143	0.7181	0.7521	0.3993
EPU $\nrightarrow$ OIL	0.6212	0.1314	0.0610	**0.0030**	**0.0050**	**0.0495**	**0.0240**	0.1174	0.3323	0.3923	0.2819	0.1794	0.1709	0.1564	0.1899
GDP $\nrightarrow$ OIL	0.0870	0.1244	0.2109	0.5467	0.6382	**0.0315**	**0.0330**	0.2549	0.3543	0.3283	0.0970	0.0625	**0.0420**	0.1044	0.1929
OIL $\nrightarrow$ CPI	0.4473	0.3518	0.1899	0.1379	0.1000	0.3183	0.4653	0.6417	0.9395	0.8851	0.8091	0.5302	0.5637	0.3028	0.3343
RATE $\nrightarrow$ CPI	0.0880	0.2484	0.6327	0.8616	0.8091	0.2444	0.3968	0.6697	0.9135	0.9125	0.2019	0.1499	0.1584	0.0790	0.1204
EPU $\nrightarrow$ CPI	0.4318	0.3438	0.2914	0.3728	0.9720	0.0560	0.0835	0.1859	0.1644	0.1914	0.4678	0.4358	0.1569	0.0975	0.0690
GDP $\nrightarrow$ CPI	0.0930	0.0800	0.0595	0.0660	0.0550	0.2444	0.3298	0.4718	0.6172	0.7736	**0.0105**	**0.0105**	**0.0115**	**0.0005**	**0.0055**
OIL $\nrightarrow$ RATE	0.4453	0.1269	**0.0275**	**0.0335**	0.1459	0.1589	0.3348	0.7516	0.5107	0.6027	0.0550	0.3068	0.9820	0.7906	0.7181
CPI $\nrightarrow$ RATE	**0.0185**	**0.0070**	0.0535	0.2444	0.6042	0.5147	0.7321	0.5767	0.0605	**0.0420**	0.6342	0.3343	0.2669	0.1524	0.0750
EPU $\nrightarrow$ RATE	0.8271	0.5317	0.0630	0.5932	0.8276	0.1454	0.0805	0.2034	0.5387	0.6952	0.1629	0.0915	0.0860	**0.0395**	0.0935
GDP $\nrightarrow$ RATE	**0.0020**	**0.0045**	**0.0065**	**0.0300**	0.2254	**0.0065**	**0.0070**	0.1004	0.2504	0.3188	**0.0300**	**0.0275**	**0.0075**	**0.0020**	0.0560
OIL $\nrightarrow$ EPU	0.8256	0.5317	0.5167	0.3068	0.7371	0.1044	0.0605	0.9290	0.6112	0.9790	0.9025	0.2609	0.2894	0.1849	0.3383
CPI $\nrightarrow$ EPU	**0.0120**	**0.0010**	**0.0045**	**0.0200**	**0.0085**	**0.0040**	**0.0090**	0.2769	0.4278	0.2194	**0.0085**	**0.0130**	**0.0360**	0.1499	0.3228
RATE $\nrightarrow$ EPU	0.1479	0.1319	**0.0475**	**0.0130**	**0.0075**	0.7486	0.8761	0.2884	0.4533	0.6127	0.4963	0.1809	0.3628	0.5952	0.5897
GDP $\nrightarrow$ EPU	0.9360	0.7851	0.9395	0.4618	0.9515	**0.0335**	**0.0105**	0.1339	0.3108	0.2494	**0.0255**	0.0645	0.2199	0.1509	0.3098
OIL $\nrightarrow$ GDP	0.5452	0.6697	0.4093	0.1814	0.1779	0.7891	0.8396	0.5277	0.3063	0.2664	0.4743	0.4708	0.6902	0.9450	0.6192
CPI $\nrightarrow$ GDP	**0.0105**	**0.0100**	0.0635	0.1799	0.2209	0.1009	0.0705	0.0940	0.1059	0.1424	**0.0185**	0.0610	0.0560	0.1000	0.3723
RATE $\nrightarrow$ GDP	**0.0220**	0.0725	0.9000	0.1629	0.0690	0.1679	0.2794	0.4288	0.4383	0.4623	0.7386	0.9560	0.8121	0.9485	0.7516
EPU $\nrightarrow$ GDP	**0.0075**	0.1174	0.6242	0.5627	0.4273	0.8651	0.1109	**0.0055**	**0.0055**	**0.0105**	0.7291	0.6422	0.6997	0.8506	0.6952

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

In the case of Chile in Table 4, we see what most likely resembles a strong direct causality flowing from EPU to GDP at the first horizon. The EPU variable has no predictive content for the other auxiliary variables in the MF-VAR system at the first horizon. The same can be said for the LFGCT specification where EPU's predictive content is weaker at the initial horizon and stronger at the 3rd and 4th horizons. 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. Indirect causality from EPU to GDP works through RATE (MF case) at higher horizons in only the MF case. Also, 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 and news dissemination (Huang and Dai, 2015; Lim, 2018).

In Table 4 for Colombia, it is observed in the MFGCT specification that EPU has a weak direct causality for GDP at the 1st horizon. This is, however, not the case for the LFGCT specification of the same country. In the LFGCT specification we observe no direct causality from EPU to GDP but indirect causality through RATE. 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 almost 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 4 for the Indian case we observe a strong direct Granger causality from EPU to GDP for both MF and LF in the 2nd and 3rd horizons. EPU's predictive content for GDP is robust to temporal aggregation as can be observed from both specifications. However, the MFGCT specification uncovers a more economically meaningful causal pattern. Since EPU Granger causes GDP at multiple horizons, it should be expected that its predictive content for at least one 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 RATE. No statistical evidence of such was found for the LFGCT specification.

Finally moving on to Table 5 for the Mexican. The MF specification yields a weak statistical evidence to reject the EPU $\nrightarrow$ GDP null in the 2nd horizon. We observe a very surprising scenario for Mexico wherein the LFGCT specification uncovers more causal relations for the EPU-GDP causal nexus 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.

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. The differences in the empirical results may be due to differences in the monetary policy framework of the different economies as some economies have strong monetary policy interactions with EPU and GDP (Brazil, India, Mexico) while others do not. Since EPU affects the economy through various macro-economic indicators, it becomes expedient to stem the tidal wave of shocks emanating from it. A few policy implications can be deduced from the empirical results which are; firstly, Monetary and fiscal authorities should implement news-based rejoinders to counteract the purely speculative components of news based EPU. Secondly, monetary and fiscal authorities should re-assure investors and the general public through news-based media as to the policy direction they intend to take when this may not seem clear to all stakeholders. Finally, in the event an exogenous shock with potentials to change the direction of economic policy occurs, monetary and fiscal authorities should quickly map out ways to mitigate its effect. They should also immediately make their intended shock-induced policy framework public via news-based media so as to abate potential EPU shocks.

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