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The Causal Relationship between Economic Policy Uncertainty and Stock Market Returns

Merve KARACAER ULUSOY (*)
Burak PİRGAİP (**)

Abstract: *Given the substantially increased role of financial markets in the global economy, there is a various empirical evidence regarding how stock prices respond to changes in economic policy uncertainty (EPU). This study contributes to the literature by employing a bootstrap panel Granger causality approach on the relationship between EPU and stock market returns. The results, provide insight into the fact that it may indeed be the stock market that plays the triggering role in the context of emerging markets and for majority of developed markets there is no causal relationship between EPU and stock market returns.*

Keywords: *Economic policy uncertainty, stock market returns, Panel Granger causality, emerging markets, developed markets.*

Jel Codes: C23, G12, G18.

Ekonomik Politika Belirsizliği İle Borsa Getirileri Arasındaki Nedensellik İlişkisi

Öz: *Finansal piyasaların küresel ekonomideki önemli ölçüde artan rolü göz önüne alındığında, hisse senedi fiyatlarının ekonomik politika belirsizliğindeki (EPB) değişimlere nasıl tepki verdiğiyle ilgili çeşitli ampirik çalışmalar bulunmaktadır. Bu çalışma EPB ve borsa getirileri arasındaki ilişkiyi ölçmek için bootstrap panel Granger nedensellik yaklaşımı kullanarak literature katkıda bulunmaktadır. Sonuçlar, gelişmekte olan piyasalar bağlamında tetikleyici rolü borsaların belirlediğini, gelişmiş piyasaların çoğunda ise EPB ile borsa getirileri arasında herhangi bir nedensellik ilişkisi olmadığını ortaya koymuştur.*

Anahtar Kelimeler: *Ekonomik politika belirsizliği, borsa getirileri, Panel Granger nedensellik, gelişmekte olan piyasalar, gelişmiş piyasalar*

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I. Introduction

When uncertainty is high in the economy, firms (consumers) may start to delay their investment (consumption) decisions. Consequently, any monetary, fiscal or regulatory concern about economic policies may end up with recessions (Bernanke, 1983; Baum et

*) Dr.Öğr.Üyesi Ankara Yıldırım Beyazıt Üniversitesi İşletme Fakültesi Uluslararası Ticaret Ve İşletmecilik Bölümü (eposta: mkaracaer@ybu.edu.tr) ORCID ID.orcid.org/0000-0002-3108-8987

**) Dr.Öğr.Üyesi Hacettepe Üniversitesi/İktisadi Ve İdari Bilimler Fakültesi/İşletme Bölümü (eposta: burak.pirgaip@gmail.com) ORCID ID. orcid.org/0000-0001-8870-8502

al., 2006; Bloom, 2009; Bachman et al., 2013; Jones and Olson, 2013; Karnizova and Li, 2014).

Baker et al. (2012) have recently developed "economic policy uncertainty (EPU) index", which is built on several uncertainty metrics. Based on this novel index, they find negative impacts of EPU on investments. Kang et al. (2014), Wang et al. (2014), and Gulen and Ion (2016) similarly put that EPU and investments are inversely related. This general consensus is reflected in the stock market as well. On the "return" side, Sum (2012), Kang and Ratti (2013), Antonakakis et al. (2013), Koo and Lee (2015), Chang et al. (2015), Arouri et al. (2016), Christou et al. (2017) shed light on the negative relationship between stock returns and EPU. On the "volatility" side, the higher the EPU, the higher the stock market volatility (Pástor and Veronesi, 2013; Alexopoulos and Cohen, 2015; Liu and Zhang, 2015).

While previous research has mainly focused on the question of whether uncertainty about economic policies results in a downward or upward trend in the stock market, indeed, quite the opposite may be the case at least for some countries, since forward-looking nature of stock prices may act as a leading indicator for such uncertainties. This predictive power in itself may also imply a causal relationship that runs from stock returns to EPU as stock markets grow broader and deeper in both the developed and emerging economies and influence, even master, the behavior of all stakeholders including policymakers.

We therefore investigate the causality between EPU and stock market returns for 12 developed and 9 emerging countries between 2005.03 and 2019.03. We use bootstrap panel Granger causality methodology (Kónya, 2006), that enables us to consider not only cross-sectional dependency but also country-specific heterogeneity. To our knowledge, our study is one of the few to consider these issues in developed and emerging markets country-by-country.

Results reveal that Granger causality runs from stock returns to EPU in US, Canada, Sweden, South Korea, Brazil, India and Chile (*"stock price leading hypothesis"*). In Hong Kong, however, EPU Granger causes stock market returns ("*EPU leading hypothesis"*). No causality exists for Germany, UK, France, Italy, Australia, Spain, Netherlands, Ireland, Russia, and Mexico (*"neutrality hypothesis"*) and there is bidirectional causality in Singapore (*"feedback hypothesis"*). Japan and China have unique characteristics as the causality direction is subject to change when they interact with different markets.

The implications of our findings vary across countries since neither developed nor emerging countries provide any homogeneous structure. Further, the theory indicating that EPU affects stock market returns in negative terms may not hold. We believe that as markets become more converged; the primary indicator feature of stock prices provides a channel through which market confidence is considered in economic policy setting.

Our paper proceeds with the next section that explains the methodological foundations. Section 3 provides the data and the empirical findings. Section 4 ends the paper.

II. Methodology

In testing for Granger causality when working with panel, one concern is to figure out whether or not a cross-sectional dependence of error terms exists across countries due to globalization and integration in financial markets (E. De Hoyos and Sarafidis, 2006). As O'Connell (1998) and Pesaran (2006) suggest, ignoring cross-sectional dependence would cause potential bias and size distortions in making inferences about the relationship among two variables. If cross-sectional dependence prevails, Seemingly Unrelated Regression (SUR) would outweigh Ordinary Least Squares (OLS) since it estimates sets of equations rather than estimating them one by one (Zellner, 1962) and transforms the model so that the error terms become uncorrelated. Another concern is the heterogeneity of the slope coefficients of each panel member in order to impose restrictions for causality. Causality between one variable and the other by imposing the joint restriction for the panel as a whole is the strong null hypothesis (Granger, 2003) and the homogeneity assumption across panel parameters cannot capture cross-country heterogeneity due to unique properties of each country (Breitung, 2005).

In this regard, we employ tests for cross-sectional dependence and slope homogeneity as a prerequisite to select the appropriate estimator and to impose restrictions for causality. Then, we carry out a bootstrap panel Granger causality test which proves itself very attractive, presenting a number of advantages over other panel causality analyses[1] in that it can take both abovementioned issues into account and it removes the requirements of any preconditions for panel unit root and co-integration tests (Kónya, 2006).

A. Cross-Sectional Dependence Tests

We expect a spillover effect across countries due to the rapid globalization, trade internalization and financial integration. We look for cross-sectional dependence by using the Lagrange multiplier test *(LM test*) of Breusch and Pagan (1980) and various tests *(CD tests)* of Pesaran (2004) and Pesaran et al. (2008) based on the following panel data model:

$$y_{it} = \alpha_i + \beta'_i x_{it} + \varepsilon_{it} \ \forall i = 1,2,\ldots,N \text{ and } \forall t = 1,2,\ldots,T \quad (1)$$

where *i* denotes for the cross-section dimension, *t* denotes for the time-series dimension, y_{it} denotes for the dependent variable, x_{it} denotes for *1xk* vector of observations on the control variables, α_i (individual intercepts) and β_i (the slope coefficients) are, respectively, *1x1 and 1xk* vectors of parameters to be estimated on the explanatory variables that vary across *i* and *t*. For each *i*, ε_{it} are assumed to be identically and independently distributed error terms, while they may be correlated across cross sections.

In Eq. (1), cross-sectional dependence tests are performed under the null hypothesis (H_0) against the alternative hypothesis (H_1) as follows:

[1] See Kar et al. (2011) and Wolde-Rufael (2014) and references therein.

H_0: $Cov(\varepsilon_{it}, \varepsilon_{jt}) = 0$, $\forall t$ and $i \neq j$ (cross-sectional dependence does not exist)

H_1: $Cov(\varepsilon_{it}, \varepsilon_{jt}) \neq 0$ for at least one pair of $i \neq j$ (cross-sectional dependence exists)

In this regard, we make use of the *LM* test in the context of SUR estimation as follows:

$$LM = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^{2} \quad (2)$$

where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals in Eq. (1). *LM* test statistic is asymptotically distributed as $\chi^2$with *N(N-1)/2* degrees of freedom under H_0. However, as it is not appropriate where *N>T*, Pesaran (2004) offers the following scaled version of the *LM* test, which is applicable even when *N* and *T* are both large:

$$CD_1 = \sqrt{\left(\frac{1}{N(N-1)}\right)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(T\hat{\rho}_{ij}^{2} - 1\right) \quad (3)$$

Under H_0 with $T \rightarrow \infty$ and $N \rightarrow \infty$, *in this order*, CD_1 converges to the standard normal distribution. On the other hand, Pesaran (2004) proposes another test statistic presented in Eq. (4) lest *LM* and CD_1, tests should produce substantial size distortions when large *N* and small *T* are considered:

$$CD_2 = \sqrt{\left(\frac{2T}{N(N-1)}\right)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij} \quad (4)$$

Under H_0 with $T \rightarrow \infty$ and $N \rightarrow \infty$, *in any order*, the CD_2 test exhibits an asymptotic standard normal distribution and has filled the gap in the empirical literature that is to be applied where *N* is large and *T* is small, Pesaran (2004) indicates that this test has mean at exactly zero for fixed values of *T* and *N* and is robust for various panel data models be it a homogeneous/heterogeneous dynamic one or a non-stationary one. Yet, the CD_2 test would be less powerful in specific situations where pair-wise correlations of the average of the population are zero, although pair-wise correlations of the underlying individual population are not zero (Pesaran et al., 2008). Thus, Pesaran et al. (2008) propose the following bias-adjusted normal approximation to the *LM* test by using the exact mean and variance of the *LM* test statistic:

$$CD_3 = \sqrt{\left(\frac{2}{N(N-1)}\right)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\,\frac{(T-k-1)\hat{\rho}_{ij}^{2} - \mu_{Tij}}{\nu_{Tij}} \quad (5)$$

where μ_{Tij} and ν_{Tij} are, respectively, the exact mean and standard deviation of $(T-k-1)\hat{\rho}_{ij}^{2}$[2]. Under H_0 with $T \rightarrow \infty$ and $N \rightarrow \infty$, *in this order*, CD_3 test is asymptotically distributed as standard normal as well.

B. Slope Homogeneity Tests

It is vital as well to account for cross-sectional heterogeneity since each panel member has its own dynamics. In Eq. (1), slope homogeneity tests are performed under the null hypothesis (H_0) against the alternative hypothesis (H_1) as follows:

H_0: $\beta_i = \beta$, *for* $\forall i$ (slope coefficients are homogeneous)

H_1: $\beta i \neq \beta j$, *for some* $i \neq j$ (slope coefficients are heterogeneous)

In order to test for H_0, we employ the Wald principle where the *F* statistic is asymptotically distributed as χ^2 with *N-1* degrees of freedom (Mark et al., 2005). The Wald principle applies when $N<T$; independent variables are stringently exogenous; and error variances are not heteroscedastic (Pesaran and Yamagata, 2008). Swamy (1970) relaxes the latter assumption in the Wald test and derives the following test on the dispersion of individual slope estimates from a suitable pooled estimator:

$$\tilde{S} = \sum_{i=1}^{N} \left(\hat{\beta}_i - \hat{\beta}_{WFE}\right)' \frac{x_i' M_\tau x_i}{\hat{\sigma}_i^2} \left(\hat{\beta}_i - \hat{\beta}_{WFE}\right) \quad (6)$$

where $\hat{\beta}_i$ is the pooled OLS estimator, $\hat{\beta}_{WFE}$ is the weighted fixed effect pooled estimator, $M_\tau = I_T - Z_i(Z_i'Z_i)^{-1}Z_i'$ and $Z_i = (\tau_T, X_i)$, where τ_T is a *1xT* vector of ones, and $\hat{\sigma}_i^2$ is the estimator of error variance, σ_i^2[3]. When *N* is fixed and $T \rightarrow \infty$, Swamy test has an asymptotic χ^2 with *k(N-1)* degrees of freedom.

However, having considered that Swamy test requires panel data models in case of *N* is small when compared to *T*, Pesaran and Yamagata (2008) offer a modification for it with the following standardized dispersion statistic *($\hat{\Delta}$ test)* where *N* is large:

$$\hat{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right) \quad (7)$$

Under H_0, with $(N, T) \rightarrow \infty$ provided that $\sqrt{N}/T \rightarrow \infty$ and with the error terms normally distributed, the $\hat{\Delta}$ test statistic asymptotically follows the standard normal distribution.

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[2] We refer to Pesaran et al. (2008) for further details.

[3] We refer to Pesaran and Yamagata (2008) for further details of Swamy test and its estimators.

A mean and variance bias-adjusted version of the $\hat{\Delta}$ test statistic is improved by Pesaran and Yamagata (2008) so as to be valid for small samples as well. This statistic is:

$$\hat{\Delta}_{adj}=\sqrt{N}\left(\frac{N^{-1}\tilde{S}-E(\tilde{z}_{it})}{\sqrt{var(\tilde{z}_{it})}}\right) \tag{8}$$

where the mean $E(\tilde{z}_{it})$ = k and the variance $var(\tilde{z}_{it})$ = *2k(T-k-1)/T+1*.

C. Bootstrap Panel Granger Causality Test

Our approach enables us to handle both cross-section dependency and country-specific heterogeneity in analysing the causality between two variables in a simultaneous manner. This approach relies on SUR estimation of two sets of equations that can be embodied as follows and the Wald tests with bootstrap critical values assigned to each country of interest:

$$\begin{aligned}
y_{1,t} &= \alpha_{1,1} + \sum_{i=1}^{ly_1}\beta_{1,1,i}y_{1,t-i} + \sum_{i=1}^{lx_1}\delta_{1,1,i}x_{1,t-i} + \varepsilon_{1,1,t} \\
y_{2,t} &= \alpha_{1,2} + \sum_{i=1}^{ly_1}\beta_{1,2,i}y_{2,t-i} + \sum_{i=1}^{lx_1}\delta_{1,2,i}x_{2,t-i} + \varepsilon_{1,2,t} \\
y_{N,t} &= \alpha_{1,N} + \sum_{i=1}^{ly_1}\beta_{1,N,i}y_{N,t-i} + \sum_{i=1}^{lx_1}\delta_{1,N,i}x_{N,t-i} + \varepsilon_{1,N,t}
\end{aligned} \tag{9}$$

and

$$\begin{aligned}
x_{1,t} &= \alpha_{2,1} + \sum_{i=1}^{ly_2}\beta_{2,1,i}y_{1,t-i} + \sum_{i=1}^{lx_2}\delta_{2,1,i}x_{1,t-i} + \varepsilon_{2,1,t} \\
x_{2,t} &= \alpha_{2,2} + \sum_{i=1}^{ly_2}\beta_{2,2,i}y_{2,t-i} + \sum_{i=1}^{lx_2}\delta_{2,2,i}x_{2,t-i} + \varepsilon_{2,2,t} \\
x_{N,t} &= \alpha_{2,N} + \sum_{i=1}^{ly_2}\beta_{2,N,i}y_{N,t-i} + \sum_{i=1}^{lx_2}\delta_{2,N,i}x_{N,t-i} + \varepsilon_{2,N,t}
\end{aligned} \tag{10}$$

where y denotes the monthly change in the EPU index, x refers to monthly stock market return, *l* stands for the lag length. Both *y* and *x* have a natural logarithm transformation. Eq. (9) and Eq. (10) are estimated by the SUR system, since error terms might be contemporaneously correlated revealing the existence of possible links among individual regressions.

To test for Granger causality in this system, alternative causations are intended to be found for country j: (1) Stock price leading hypothesis holds if not all $\delta_{1,j,i}$s are zero, but all $\beta_{2,j,i}$s are zero (2) EPU leading hypothesis holds if all $\delta_{1,j,i}$s are zero, but not all $\beta_{2,j,i}$s are zero (3) Feedback hypothesis holds if neither $\delta_{1,j,i}$s nor $\beta_{2,j,i}$s are zero. (4) Neutrality hypothesis holds if all $\delta_{1,j,i}$s and $\beta_{2,j,i}$s are zero. Wald statistics for Granger causality are compared with the country-specific critical values, which are retrieved from the bootstrap sampling procedure[4]. Since the robustness of the test results mainly depend on the lag structure, following Kónya's (2006) procedure, we estimate the system by assuming from 1 to 4 lags and then select the combinations minimizing the Schwarz Bayesian Criterion[5].

III. Data and Findings

We use monthly data throughout the period of 2005.03 to 2019.03 for 21 countries. The sample reflects all of the countries that have their own EPU index, and the sample period is determined in consideration with the availability of the data to work with a balanced panel structure.

Table 1 contains summary statistics for both changes in country EPU and corresponding stock index returns in absolute and monthly terms. It suggests that the average monthly change in EPU indices is the highest (lowest) in Australia (Chile), while Russia (India) EPU index data prove to be the most (least) variable one. When monthly stock market return data are considered, respective countries are Japan (Ireland) and Australia (Canada). On the other hand, stock return data have a more negatively skewed and heavy-tailed distribution when compared to that of EPU.

Table 1: Descriptive statistics

Country	Mean	SD.	Skew.	Kurt.	JB.	Mean	SD.	Skew.	Kurt.	JB.
	Monthly Change in EPU Index					Monthly Stock Index Returns				
US	0,0074	0,2935	0,3453	4,2338	14,08***	0,0051	0,0407	-1,0265	5,7707	83,74***
Japan	-0,0024	0,3561	0,0614	2,8785	6,429**	0,0101	0,0648	-0,7043	6,8196	77,96***
Germany	0,0099	0,2808	0,0985	2,9017	1,589	0,0023	0,0376	-0,6327	3,8683	53,32***
UK	0,0071	0,3954	-0,1896	4,5882	0,3413	0,0024	0,0380	-0,7300	3,3463	16,58***
France	0,0030	0,4928	0,1360	3,2150	0,4569	0,0072	0,0639	-0,4874	4,5957	10,52***
Italy	0,0031	0,1978	-0,2982	3,7466	7,168**	0,0035	0,0563	-0,9883	5,6766	5,19*
Canada	0,0108	0,2705	0,2875	3,1619	2,513	0,0030	0,0372	-1,3106	7,8798	216,1***
Australia	0,0186	0,4913	-0,1058	3,9717	18,77***	0,0051	0,0834	-0,6092	4,6651	15,86***

[4] We refer to Kónya (2006) for further details of the bootstrap sampling procedure.
[5] Lag selection procedure are available upon request.

Spain	0,0057	0,3593	-0,0829	3,1935	0,62	0,0017	0,0470	-0,5747	3,4162	10,51***
Netherlands	0,0091	0,3937	0,2374	3,0165	0,4797	0,0058	0,0517	-0,8176	5,2133	150,8***
Sweden	0,0074	0,3098	0,4105	4,2709	3,803	0,0044	0,0519	-0,8968	7,0737	66,41***
Ireland	0,0043	0,4074	0,1309	2,8603	15,09***	-0,0001	0,0553	-0,3932	3,9351	71,99***
South Korea	0,0035	0,5996	-0,0059	2,8389	16,12***	0,0081	0,0731	-1,0159	6,7417	139,5***
Russia	-0,0030	0,6052	0,1609	4,4282	0,1838	0,0005	0,0576	-0,9731	5,5368	127,7***
Brazil	0,0023	0,3669	-0,0323	3,2529	0,8463	0,0023	0,0500	-1,2917	6,8395	24,62***
India	0,0026	0,1857	0,3518	3,2118	0,21	0,0042	0,0460	-0,8296	5,5843	116,7***
Singapore	0,0106	0,2073	0,0822	3,5761	2,527	0,0027	0,0503	-1,0435	9,1668	298,5***
China	0,0029	0,3375	-0,0502	3,0622	6,964**	0,0063	0,0393	0,0981	3,5133	29,98***
Chile	0,0011	0,3266	0,1088	3,9852	0,0981	-0,0024	0,0599	-0,3527	3,4893	2,126
Hong Kong	0,0019	0,4840	0,1756	3,1758	1,086	0,0042	0,0602	-0,7034	5,1246	45,72***
Mexico	0,0017	0,5012	0,4775	4,8239	29,85***	0,0068	0,0474	-0,5840	4,6827	29,55***

***, ** and * stand for for significance levels at 0.01, 0.05, and 0,10 respectively.

As is seen from Table 2, by and large, our test statistics are significant at 1% level to reject the null hypothesis of both cross-sectional independence and slope homogeneity. These results uncover the fact that uncertainty possesses a spillover potential among intertwined financial markets and that causal relationship between these markets has its own dynamics. An interesting finding, however, is that we cannot reject the null hypothesis of slope homogeneity in case of emerging markets. We believe that these figures may be interpreted as evidence that while shocks are easily transmitted, direction of causal linkages between EPU and stock market returns may not differ across emerging markets. As emerging market economies are more vulnerable to external shocks than their developed counterparts, they may be responding these shocks in the same way.

Table 2: Cross-sectional dependency and slope homogeneity

Test	Statistic		
Cross-sectional dependency	Developed	Emerging	Overall
LM	334,59***	28,50***	1.106,53***
CD_1	23,38***	178,73***	43,75***
CD_2	-3,14***	-1,48*	-2,64***
CD_3	5,43***	3,39***	10,72***
Slope homogeneity			
Swamy	65,46***	4,57	31,32*
$\hat{\Delta}$	14,35***	2,34***	13,10***
$\hat{\Delta}_{adj}$	14,48***	2,36***	13,21***

*** and * stand for significance levels at 0.01 and 0.1, respectively.

Bootstrap panel Granger causality test results are displayed in Table 3. On the whole, stock price leading hypothesis is 4 out of 12 in developed and 5 out of 9 in emerging markets, whereas neutrality hypothesis (12 out of 21) is the dominant one when both markets are considered simultaneously. Hypotheses at the individual level are summarized in Table 4.

Table 3: Bootstrap panel Granger causality test results

	Granger causality running from EPU to stock returns											
	Developed	Emerging	Overall	Developed			Emerging			Overall		
				Bootstrap critical values								
Country		Wald Statistics		1%	5%	10%	1%	5%	10%	1%	5%	10%
US	2,7792		2,9758	7,6841	4,3470	3,1055				8,5686	4,8918	3,4437
Japan	0,4105		0,5024	7,5167	4,3762	3,0606				8,4783	4,8778	3,4161
Germany	0,2264		0,3690	7,4316	4,4114	3,0444				9,0260	5,0144	3,5452
UK	1,2140		1,2528	7,5314	4,3650	3,0360				8,7975	4,9039	3,4776
France	0,3592		0,8116	7,5536	4,2009	2,9928				9,7063	5,4223	3,8290
Italy	0,5417		0,1507	7,4118	4,2793	3,0432				8,8219	4,9799	3,5663
Canada	2,3423		2,5136	7,3645	4,5108	3,0452				8,7907	4,9607	3,4735
Australia	0,1001		0,6885	7,5829	4,3941	3,0116				8,9303	5,0508	3,5380
Spain	0,3084		0,7869	7,3858	4,3186	3,0218				8,7110	5,0226	3,5292
Netherlands	0,7410		0,4891	8,0062	4,4420	3,0545				8,4448	5,1381	3,6061
Sweden	1,4728		2,3885	8,0187	4,4387	3,0760				8,9315	4,9109	3,5518
Ireland	0,1702		0,1366	7,4388	4,3561	3,1306				8,7199	5,0655	3,5452
South Korea		2,4456	3,0989				7,6734	4,2566	2,9292	8,3496	4,6815	3,4030
Russia		0,8736	0,2520				7,6506	4,2458	3,0047	8,2203	4,8957	3,4682
Brazil		0,2263	0,6168				7,4183	4,3477	3,0428	8,4976	4,9424	3,4215
India		0,5786	0,4580				7,3991	4,3968	3,0636	8,2043	4,9032	3,4196
Singapore		5,4259**	7,5063**				7,0485	4,1760	2,9544	8,5921	5,0075	3,5378
China		0,1011	0,9075				6,9404	4,1327	2,9313	8,5656	4,8418	3,4348
Chile		2,0999	2,1550				7,4115	4,3199	3,0444	8,4745	4,8933	3,5031
Hong Kong		6,5960**	5,0662**				7,3091	4,3569	3,0958	8,4756	4,8860	3,3970
Mexico		1,5261	0,6050				7,5380	4,2919	2,9659	8,2690	4,8305	3,4138
US	9,1584***		9,0001***	7,6812	4,3335	3,0411				7,8446	4,5309	3,1573
Japan	3,0736*		2,1399	7,5900	4,3365	2,9805				7,9217	4,7137	3,2973
Germany	2,7327		1,1997	7,4542	4,3407	3,0484				8,2462	4,5923	3,2332
UK	0,1552		0,2672	7,4001	4,3182	3,0684				7,6025	4,4283	3,1283
France	1,5495		0,7642	6,9381	4,1317	2,9042				7,7355	4,5602	3,1640
Italy	1,5619		1,7555	7,3303	4,2846	3,0230				8,1640	4,7439	3,2615
Canada	9,7866***		7,6632**	7,5535	4,3615	2,9662				8,4115	4,5907	3,2771
Australia	2,2389		0,1987	7,5326	4,2627	3,0194				8,1325	4,8656	3,2749
Spain	1,1498		1,9953	7,0837	4,2529	2,9541				8,5637	4,8646	3,3717
Netherlands	0,1053		0,2033	7,6502	4,2845	3,0148				7,8671	4,5921	3,1812
Sweden	10,9396***		10,1624***	7,0714	4,3704	2,9830				8,4530	4,8311	3,3406
Ireland	0,3951		0,7545	7,3442	4,2943	3,0361				8,5110	4,9655	3,4585
South Korea		6,0438**	5,4861**				7,1630	4,1308	2,9092	8,3474	4,7712	3,2971
Russia		0,1188	0,5338				7,2469	4,2262	2,9552	7,8819	4,7234	3,3652
Brazil		6,0541**	7,3467**				7,2097	4,2834	3,0514	8,2175	4,6212	3,2615
India		7,5122***	8,1218**				7,0899	4,1180	2,9001	8,1930	4,6988	3,2696
Singapore		6,8914**	7,8131**				7,3973	4,0345	2,9279	8,6941	4,8829	3,3803
China		3,8249*	1,1126				7,5449	4,2627	2,9633	8,4522	4,7121	3,3368
Chile		6,3665**	5,7309**				7,7325	4,3731	2,9953	8,7620	4,8079	3,3370
Hong Kong		0,6478	0,1614				7,0922	4,2295	2,9568	7,9265	4,6065	3,2181
Mexico		1,1704	0,9123				7,4904	4,2033	2,9903	7,9617	4,5308	3,2490

***, ** and * stand for significance levels at 0.01, 0.05 and 0.1, respectively. Bootstrap critical values are obtained from 10,000 replications

There are several outcomes that can be derived from the data set. First, stock markets lead in US, Canada, Sweden, South Korea, Brazil, India and Chile; second EPU leads only in Hong Kong, while bidirectional causality is found in Singapore alone. The rest of the countries show neutral causality namely; Japan, Germany, UK, France, Italy, Australia, Spain, Netherlands, Ireland, Russia, China and Mexico. On the other hand, China and Japan have somewhat controversial results but as the change is marginal with

10% of significance level, the existing causal link in their respective country groups disappears in the overall analyses.

Table 4: Countries and Holding Hypotheses

	Developed	Emerging	Overall
US	Stock Price Leading		Stock Price Leading
Japan	Stock Price Leading		Neutrality
Germany	Neutrality		Neutrality
UK	Neutrality		Neutrality
France	Neutrality		Neutrality
Italy	Neutrality		Neutrality
Canada	Stock Price Leading		Stock Price Leading
Australia	Neutrality		Neutrality
Spain	Neutrality		Neutrality
Netherlands	Neutrality		Neutrality
Sweden	Stock Price Leading		Stock Price Leading
Ireland	Neutrality		Neutrality
South Korea		Stock Price Leading	Stock Price Leading
Russia		Neutrality	Neutrality
Brazil		Stock Price Leading	Stock Price Leading
India		Stock Price Leading	Stock Price Leading

IV. Conclusion

We examine the causal relationship between EPU and stock market returns by carrying out bootstrap panel Granger causality tests for 12 developed and 9 emerging markets.

We find significant support for stock price leading hypothesis in US, Canada, Sweden, South Korea, Brazil, India and Chile while our results support neutrality hypothesis for the majority of the countries. Hong Kong and Singapore are the only countries that EPU leading and feedback hypothesis are supported, respectively.

Policymakers should be aware of country dynamics in developing economic policies. For countries where stock prices lead EPU, market participant behaviour may require policy actions, which in turn may lead to uncertainty if not taken timely and appropriately. For countries, as is the case with Hong Kong, where EPU leads stock prices, it is important to remove uncertainty to overcome possible stock market fluctuations. The lack of a causal link between EPU and stock markets may be implying that countries can feel more confident in applying their economic policies without being exposed to potential damages in stock markets since changes in economic policy uncertainty will not be expected to cause changes in stock market returns. On the other hand, stock price leading behavior of markets may find its roots in research for a structural break in time. We leave this possibility for future studies.

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References

Alexopoulos, M., and Cohen, J. (2015). "The power of print: Uncertainty shocks, markets, and the economy". *International Review of Economics & Finance, 40,* 8-28.

Antonakakis, N., Chatziantoniou, I., and Filis, G. (2013). "Dynamic co-movements of stock market returns, implied volatility and policy uncertainty". *Economics Letters, 120*(1), 87-92.

Arouri, M., Estay, C., Rault, C., and Roubaud, D. (2016). "Economic policy uncertainty and stock markets: Long-run evidence from the US". *Finance Research Letters, 18,* 136-141.

Bachmann, R., Elstner, S., and Sims, E. R. (2013)." Uncertainty and economic activity: Evidence from business survey data". *American Economic Journal: Macroeconomics, 5*(2), 217-249.

Baker, S., Bloom, N. and Davis, S. (2012). "Measuring economic policy uncertainty". Working Paper Series, Stanford University.

Baum, C. F., Caglayan, M., Ozkan, N., and Talavera, O. (2006). "The impact of macroeconomic uncertainty on non-financial firms' demand for liquidity". *Review of Financial Economics, 15*(4), 289-304.

Bernanke, B.S., (1983). "Irreversibility, uncertainty, and cyclical investment". *The Quarterly J. Econ.* 98, 85–106

Bloom, N. (2009). "The impact of uncertainty shocks". *Econometrica, 77*(3), 623-685.

Breitung, J. (2005). "A parametric approach to the estimation of cointegration vectors in panel data". *Econometric Reviews 24*(2), 151–173.

Breusch, T. S., and Pagan, A. R. (1980). "The Lagrange multiplier test and its application to model specifications in econometrics". Reviews of Economics Studies 47, 239–253.

Chang, T., Chen, W. Y., Gupta, R., & Nguyen, D. K. (2015). "Are stock prices related to the political uncertainty index in OECD countries? Evidence from the bootstrap panel causality test". *Economic Systems,* 39(2), 288-300.

Christou, C., Cunado, J., Gupta, R., and Hassapis, C. (2017). "Economic policy uncertainty and stock market returns in pacific-rim countries: Evidence based on a

Bayesian Panel VAR Mode"l. *Journal of Multinational Financial Management*, https://doi.org/10.1016/j.mulfin.2017.03.001.

E. De Hoyos, R., and Sarafidis, V. (2006). "Testing for cross-sectional dependence in panel-data models". *Stata Journal*, *6*(4), 482-496.

Granger, C.W.J. (2003). "Some aspects of causal relationships". *Journal of Econometrics 112*, 69–71.

Gulen, H., and Ion, M. (2016). "Policy uncertainty and corporate investmen"t. *Review of Financial Studies*, *29*(3), 523-564.

Jones, P. M., and Olson, E. (2013). "The time-varying correlation between uncertainty, output, and inflation: Evidence from a DCC-GARCH model". *Economics Letters*, *118*(1), 33-37.

Kang, W., and Ratti, R. A. (2013). "Structural oil price shocks and policy uncertainty". *Economic Modelling*, *35*, 314-319.

Kar, M., Nazlioglu S. and Agir, H. (2011). "Financial development and economic growth nexus in the MENA countries: Bootstrap panel granger causality analysis". *Economic Modelling, 28,* 685-693.

Karnizova, L., and Li, J. C. (2014)." Economic policy uncertainty, financial markets and probability of US recessions". *Economics Letters*, *125*(2), 261-265.

Ko, J. H., and Lee, C. M. (2015). "International economic policy uncertainty and stock prices: Wavelet approach". *Economics Letters*, *134*, 118-122.

Kónya, L. (2006). "Exports and growth: Granger causality analysis on OECD Countries with a panel data approach". *Economic Modelling 23*, 978–992.

Liu, L., and Zhang, T. (2015). "Economic policy uncertainty and stock market volatility". *Finance Research Letters, 15*, 99-105.

Mark, N.C., Ogaki, M. and Sul, D. (2005). "Dynamic seemingly unrelated cointegrating regression". *Review of Economic Studies 72*, 797–820.

O'Connell, Paul G.J. (1998). "The overvaluation of purchasing power parity". *Journal of International Economics 44*(1), 1-19.

Pástor, Ľ., anf Veronesi, P. (2013). "Political uncertainty and risk premia". *Journal of Financial Economics*, *110*(3), 520-545.

Pesaran, M.H. (2004). "General Diagnostic Tests for Cross Section Dependence in Panel"s. CESifo Working Paper 1229; IZA Discussion Paper 1240.[970].

Pesaran, M.H. (2006). "Estimation and inference in large heterogeneous panel with a multifactor error structure". *Econometrica 74*(4), 967–1012.

Pesaran, M.H., Ullah, A. and Yamagata, T. (2008). "A bias-adjusted LM test of error cross-section independence". *Econometrics Journal 11*, 105-127.

Pesaran, M.H. and Yamagata, T. (2008). “Testing slope homogeneity in large panels”. *Journal of Econometrics 142*, 50-93.

Sum, V. (2012). “The impulse response function of economic policy uncertainty and stock market returns: a look at the Eurozone”. *Journal of International Finance Studies,* 12(3), 100-105.

Swamy, P.A. (1970). “Efficient inference in a random coefficient regression model”. *Econometrica 38,* 311-323.

Wang, Y., Chen, C.R., and Huang, Y.S. (2014). “Economic policy uncertainty and corporate investment: Evidence from China”. *Pacific-Basin Finance Journal, 26,* 227-243.

Wolde-Rufael, Y. (2014). “Electricity consumption and economic growth in transition countries: A revisit using bootstrap panel Granger causality analysis”. *Energy Economics 44,* 325-330.

Zellner, A. (1962). “An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias”. *Journal of the American Statistical Association 57*, 348–368.