3.

THE IMPACT OF GLOBAL UNCERTAINTIES ON ECONOMIC GROWTH: EVIDENCE FROM THE US ECONOMY (1996: Q1-2018: Q4)

Ömer YALÇINKAYA[1]
Ali Kemal ÇELİK[2]

Abstract

This paper econometrically examines the impact of uncertainties on the global economy caused by the recent economic, political, and geopolitical (EPG) events, and on the economic growth of the US using extended Cobb-Douglas production function and linear and nonlinear time series analysis for the sample period 1996: Q1-2018: Q4. In this regard, the paper mainly purposes to empirically determine whether or not the global EPG uncertainties have a contractionary impact on the economic growth of the US as previously predicted by the existing literature. The economic growth of the US takes part on the main axis of EPG events with its crucial position on global economic area. The linear and nonlinear time series analyses reveal that the EPG uncertainties have a statistically significant negative impact on the growth of the US on both short and long term during the sample period and that there is a unidimensional causality relationship from the EPG uncertainties to economic growth. The empirical findings also confirm that the EPG uncertainties have contractionary impact on the economic growth of the US during the sample period. Moreover, the EPG uncertainties may be considered as an important constraint of sustainability of the economic growth rates of the US at its potential level and permanent economic recovery.

Keywords: global uncertainties, sustainability of economic growth, Cobb-Douglas production function, linear and nonlinear time series

JEL Classification: C40, F43, O47

1. Introduction

Since the 2008 Global Economic Crisis, the decisive role of the EPG uncertainties on global economy has been widely accepted during the economic crisis and the post-economic crisis periods with high levels of economic recession (Chinn *et al*., 2018). Along with the impact of recent events that lead to uncertainties in terms of EPG aspects, the global economic growth

[1] *Atatürk University, Faculty of Economics and Administrative Sciences, Department of Economics, 25240, Erzurum, Turkey, oyalcinkaya@atauni.edu.tr.*
[2] *Ardahan University, Faculty of Economics and Administrative Sciences, Department of Quantitative Methods, 75002, Ardahan, Turkey, alikemalcelik@ardahan.edu.tr.*

rates do not show a widespread and balanced presence, with a slow pace below their actual potential since the 2008 Global Economic Crisis and, therefore, the desired permanent economic recovery was lagged. In such a context, the achievement and permanent economic recovery of sustainable economic growth rates at their potential levels before the 2008 Global Economic Crisis appear to be mainly dependent on solving the EPG uncertainties.

Recent events that cause uncertainties in terms of the EPG issues may lead to capital flows by increasing fluctuations in the financial and fiscal markets. Such events may increase the opportunity costs of financial and/or fiscal investments due to relatively limited access to internal and external funding sources and they may also significantly restrict consumption-investment decisions by decreasing the risk appetite of economic actors (Greig *et al*., 2018). In that sense, the contractionary impact of EPG-based uncertainties on the global economy is recognized by the operation of different channels that feed each other, including consumption, investment (employment), and risk premium (Lee, 2015). As the withdrawal or adjustment of consumption, investment, and relevant employment decisions require additional costs, uncertainties generally lead the economic actors to delay or cancel their decisions until the corresponding uncertainties are solved and more information about their decision is available. Similarly, as such uncertainties increase the level of risk premium on the financial markets, the economic actors which encounter relatively low financial asset prices endure relatively high financial costs and they tend to postpone their financial investments in the sense of a wait-and-see effect (Balta *et al*., 2013).

The empirical validity of theoretical explanations towards the impact of EPG-based uncertainties on the global economy was actually investigated since the last decade in parallel with recent events after the 2008 Global Economic Crisis. Both several difficulties on defining and on measuring the EPG uncertainties and the limitations on having representative indicators that more comprehensively measure such uncertainties are generally considered as potential obstacles to conduct additional empirical research in this field (Ferrara and Guérin, 2018). Along with the introduction of three prominent indices, including the economic and political uncertainty index (EPU), the world uncertainty index (WUI), and the geopolitical uncertainty index (GPU), more empirical research that concentrates on the impact of EPG uncertainties on economic growth was successfully carried out. The EPU index was proposed by Baker *et al.* (2013) and it is calculated over the frequency of news that include main words within the scope of economics, politics, and uncertainty in articles published in leading newspapers of individual countries. The WUI was proposed by Ahir *et al*. (2018) and it is measured with respect to the frequency of words within the scope of economics, politics, and uncertainty that come across country reports released by the Economist Intelligence Unit (EUI) for individual countries. The GPU index is calculated by counting the number of occurrences in leading English-language newspapers (in the US, the UK, and Canada) of articles discussing the geopolitical events and risks (Caldara and Iacoviello, 2018).

In most of the empirical studies conducted on various developed and developing countries whereby EPU, WUI and GPU indices are calculated, the direct and indirect (reflection) effects of the EPG uncertainties on economic growth are predominantly examined. Most of these studies are based on linear models within the scope of time series analysis. The findings of these studies reveal that the EPG uncertainties generally have negative effects on the economic growth of countries based on real options and / or risk aversion channels in the theoretical literature.

The purpose of this study, following similar methodology as those documented in the literature, is to empirically examine the indirect (reflection) effects of global EPG uncertainties on the economic growth of the US for the period 1996: Q1-2018: Q4 using various forms of EPU, WUI and GPU indices calculated for the global economy. Following this purpose, the effects of global EPG uncertainties, created using EPU, WUI and GPU indices and Principal Component Analysis (PCA), on the economic growth of the United States (simultaneous) were analysed econometrically within the scope of both linear and nonlinear analysis.

As a matter of fact, the US with its global economic position, is one of the main developed countries with developments that create uncertainty in terms of EPG and directs the course of such developments and, as a consequence, feels the associated effects on economic growth most. Considering the simultaneous effects of EPG uncertainties arising from the developments in the global economy, the findings of this study on the US economy is supposed to contribute to the ongoing theoretical discussions on the EPG uncertainties since the 2008 crisis, to help examining the reflection effects of the global EPG uncertainty indicators and to understand the econometric methods used in this emerging empirical literature.

The rest of the paper is organized as follows. In the second section, theoretical approaches regarding the channels through which EPG uncertainties affect economic growth are explained, summary of empirical studies on the subject matter in the literature are provided and the possible contributions of the study to the literature are also explained. The third section investigates the simultaneous impact of global EPG uncertainties on the economic growth of the US econometrically, using extended Cobb-Douglas production function and within the scope of linear and nonlinear time series analyses for the sample period 1996: Q1-2018: Q4. The paper concludes with the discussion of empirical results, recommendations for policy implications and future studies.

2. Literature Review

In the theoretical literature, the effects of uncertainties (EPG uncertainties) on economic growth are explained within the scope of real options, growth options and risk aversion theories based on the function of consumption, investment (employment) and risk premium channels. These three basic theories are shaped by the behavior of economic actors. While real options and risk aversion reveal channels that affect economic growth negatively, growth options indicate channels that affect economic growth positively (Bloom, 2014).

Through the real options channel, the negative effects of uncertainties on economic growth occur when the economic actors postpone consumption and investment (employment) decisions. In times of increased EPG uncertainties, the total demand of the household sector diminishes due to tendency to increase its savings and postpone consumption decisions on the motive of "caution" (Carroll, 1996), while the business sector does not want to undertake new investments and recruitments on the "wait and see" motive and postpones investment-employment decisions by reducing the total supply (Dixit and Pindyck, 1994) which adversely affects economic growth (Haddow *et al*., 2013). Through the risk aversion channel, the negative effects of uncertainties on economic growth are realized when economic actors delay investment and employment decisions and also increase risk premium in search of higher returns (Haddow *et al*., 2013). In times of increased EPG uncertainty, the increment in costs of debt due to increases in risk premium restricts the business sector's access to finance and decreases the business risk appetite. This, in turn, increases the opportunity cost of investment, decreasing the total supply and, hence, negatively affects the economic growth (Gilchrist *et al*., 2014).

The growth options channel states that uncertainties can increase the potential returns on investments and create a positive impact on economic growth. Since the economic actors take into account the worst possible scenario when evaluating the present and future returns of investments, EPG pushes investment decisions forward, due to the fact that the future returns will decrease more during periods of increased uncertainty. As this increases the present return on investments relatively, it encourages investment (employment) decisions and positively affects economic growth by increasing total supply (Bianchi *et al*., 2017).

Although the effects of EPG uncertainties on economic growth are explained in the theoretical literature based on positive and negative channels, findings in the empirical literature generally support the negative channels (Kisten, 2020). When the empirical literature is examined, it is noticed that the pioneering study using the EPU index was done by Baker *et al*. (2013) on the USA. Baker *et al*., (2013) examined the effects of economic and political uncertainties on the economic growth performance (industrial production index) of the USA with monthly data for the period 1985: M1-2014: M12 within the scope of time series analysis. The result of their analysis based on the Linear Vector Autoregression (VAR) model concluded that the USA EPU index has a negative effect on economic growth performance. After Baker *et al*., (2013) study, the relationship between economic and political uncertainties and economic growth was investigated for various developed and developing countries for which the EPU or WUI indices are calculated. The literature on this subject shows a significant development. Within the scope of time series analysis, the direct effects of economic and political uncertainties on the growth performance of countries are examined by using linear VAR or Structural (S) VAR models as in the study by Baker *et al*. (2013): US-VAR (Lee, 2015), US-VAR (Baker *et al*., 2016), India-VAR (Bhagat *et al*., 2016), Ireland-VAR (Zalla, 2017), Norway-SVAR (Larsen, 2017), Croatia-VAR (Sorić and Lolić, 2017), Japan-VAR (Arbatli *et al*., 2017), Hong Kong-VAR (Wong *et al*., 2017), Chile-VAR (Cerda *et al*., 2018), New Zealand-SVAR (Greig *et al*., 2018), Greece-VAR (Hardouvelis *et al*., 2018),Turkey-VAR (Sahinoz and Cosar, 2018), US-VAR (Ferrara and Guérin, 2018), Spain-SVAR (Ghirelli *et al*., 2019), cross-country analysis (Čižmešija *et al*., 2017; Peric´ and Soric, 2018).

In addition, there are studies investigating the direct effects of economic and political uncertainties on the growth performance of countries based on nonlinear Time-Varying Parameter-TVP (VAR), TVP Factor (FVAR) and Autoregressive Conditional Heteroscedasticity (ARCH) models, such as US- Nonlinear ARCH (Dima *et al*., 2017), South Africa-TVP-VAR (Kisten, 2020), China-TVP-FVAR (Ren *et al*., 2020). Without exception, all of these studies using the EPU or WUI indices of countries concluded that economic and political uncertainties have negative effects on the economic growth performance of countries based on real options and / or risk aversion channels. In some other studies, the direct effects of economic, political and geopolitical uncertainties calculated based on the EPU and GPU indices on economic growth performance of countries are examined within this scope. Caldara and Iacoviello (2018) examined the effects of economic and political and geopolitical uncertainties calculated on the basis of the EPU and GPU indices on the economic growth performance of the United States (industrial production index) within the scope of time series analysis with monthly data for the period 1985: M1-2016: M12. The result of their analysis based on the linear VAR model concluded that both economic, political and geopolitical uncertainties have a negative effect on the economic growth performance of the USA. This result is supported by Adedoyin *et al*. (2020) in their studies using annual data on Malaysia for the period 1980-2018 and the linear Autoregressive Distributed Lag (ARDL) model.

On the other hand, in a limited number of empirical studies on countries for which the EPU or WUI indices are calculated, the spill-over effects of economic and political uncertainties of developed and developing countries or global economic and political uncertainties on the growth performance of countries are investigated. In a related study, Stockhammar and Österholm (2016) examined the effects of economic and political uncertainties originating from the USA on Sweden's economic growth performance (Real Gross Domestic Product) with quarterly data for the period 1988: Q1-2013: Q2 within the scope of time series analysis. The result of their analysis based on the Linear Bayesian Vector Autoregression (BVAR) model demonstrated that economic and political uncertainty originating from the USA had a negative effect on Sweden's economic growth performance. Similarly, Ahir *et al*. (2018) analyzed the effects of global economic and political uncertainties calculated on the WUI index of 146 countries on the economic growth performance (Real Gross Domestic Product) of 46 developed and developing countries in the scope of panel data analysis using quarterly data. Their estimated linear panel (VAR) model showed that global economic and political uncertainties had a negative impact on the economic growth performance of the 46 countries.

Chen *et al*. (2019) analyzed the effects of global economic and political uncertainties (calculated on the EPU index of 20 countries) on China's industrial value added using monthly data for the period 2000: M1-2017: M12, within the scope of time series analysis. They found that the global economic and political uncertainty had a negative impact on China's economic growth performance. Similar results indicate that the economic and political uncertainties originating from the USA were determined by India-SVAR (Nyawo and Van Wyk, 2018), cross-country analysis-BVAR (Stockhammar and Österholm, 2017), Hong Kong-SVAR (Luk *et al*., 2018) and China. Economic and political uncertainties arising from USA-Smooth Transition (ST-VAR) (Fontaine *et al*., 2017), Hong Kong-SVAR (Luk *et al*., 2018) cross-country analysis-ST-VAR (Fontaine *et al*., 2018) also support the findings of their studies. All these studies reveal that the empirical literature, which has started to emerge since the work of Baker *et al*. (2013), has made a significant progress both in measuring the uncertainties arising from the EPG developments and in analyzing the effects on economic growth. In most of these studies on different developed and developing countries for which the EPU, WUI and GPU indices are calculated, the direct effects of the EPG uncertainties on economic growth and the indirect (reflection) effects in a limited part are examined.

Significant number of these studies which are based on linear models within the scope of time series analysis show that the EPG uncertainties generally have negative effects on the economic growth of countries based on real options and / or risk aversion channels in the theoretical literature. In this study, the indirect (reflection) effects of the uncertainties arising from the EPG developments in the global economy on the economic growth of the USA are examined empirically with both linear and nonlinear approaches using the forms of the EPU, WUI and GPU indices created within the scope of similar methodologies as observed in the literature. Considering the simultaneous effects of uncertainties arising from the EPG developments in the global economy, the findings of this study on the US economy are supposed to contribute to the empirical literature in terms of examining the global EPG uncertainty indicators and the econometric methods and the reflection effects of uncertainties.

3. Data Description

Table 1 introduces the description of the corresponding variables used in the econometric analyses and their main sources for the purpose of investigating the impact of global EPG uncertainties on the economic growth of the US (real Gross Domestic Product-GDP) for the sample period 1996: Q1-2018: Q4. The sample period of this study was selected based on the steady availability of the corresponding variables during the sample years. In this study, the quarterly growth rates (with respect to the same period of the previous year) of macroeconomic variables including RGDP, RGFI, EL, and TFP were utilized during the sample period, whereas the level values of GEPGU variable was used in the econometric analysis. The GEPGU index was considered as a proxy variable of global EPG uncertainties. The RGDP and RGFI variables represent economic growth and fixed capital investments, respectively, and they were extracted from the OECD data base (OECD, 2019) as seasonally adjusted real prices (base year 2010) in purchasing power parity (in US dollars). The EL variable represents the human capital investments and it was extracted from the OECD data base (OECD, 2019). The EL indicator is calculated as the labor force divided by the total working-age population (that refers to people aged between 15 and 64) per thousand persons. The TFP indicator usually represents the technological development level and it was extracted from the FRBSF data base (FRBSF, 2019). The corresponding indicator is calculated by considering quality and quantity differences for fixed and human capital investments using quarterly growth rates. The main reason for using the TFP indicator in this study relies on measuring the technological development level of the US with a single variable instead of representation of related indicators separately, such as research and development investments, education levels of labor force, trade openness, etc.

Table 1

Data Description

Abbreviation	Description	Data Source
RGDP	Real GDP (2010-USD).	OECD-Stat (Organization for Economic Cooperation and Development Statistics-2019)
RGFI	Real Fixed Capital Investments (2010-USD).	
EL	Employed Labor	
TFP	Total Factor Productivity	FRBSF-Stat (Federal Reserve Bank of San Francisco - Indicators and Data-2019)
GEPGU	Global EPG Uncertainties Index	Economic Policy Uncertainty (2019) Authors' Own Calculation

The GEPGU indicator was generated by a principal component analysis and obtaining relevant data for EPU, WUI, and GPU indices. The dataset for the EPU index was extracted for twenty countries (Australia, Brazil, Canada, Chile, France, Germany, Greece, India, Italy, Japan, Mexico, People's Republic of China, Republic of Ireland, Russian Federation, Spain, South Korea, Sweden, the Netherlands, the UK, and the US) that may represent the global economy. The final EPU index was obtained by calculating the mean values of the monthly EPU indices. The WUI and GPU indices are quarterly and monthly calculated, respectively, and these indices were incorporated in the econometric analyses. In order to generate the GEPGU index, monthly datasets of EPU and GPU indices were transformed into quarterly datasets by taking their three-month mean values for the sample period of 1996-2018. Later, the final GEPGU index was generated by transforming the quarterly values of the EPU, WUI, and GPU indices using a principal component analysis. The final shape of the calculated GEPGU index for the period of 1996 Q:1-2018: Q4 is illustrated in Figure 1. A principal component analysis provides to obtain a reduced new indicator from its linear components that reflect the explained structure of multiple correlated variables and observed variances (Hotelling, 1933). Using a principal component analysis, the simultaneous effects of the EPG uncertainties can be measured as a single GEPGU index, since the EPG uncertainties are strongly correlated.

Figure 1

The Progress of the GEPGU Index for the Sample Period of 1996: Q1-2018: Q4

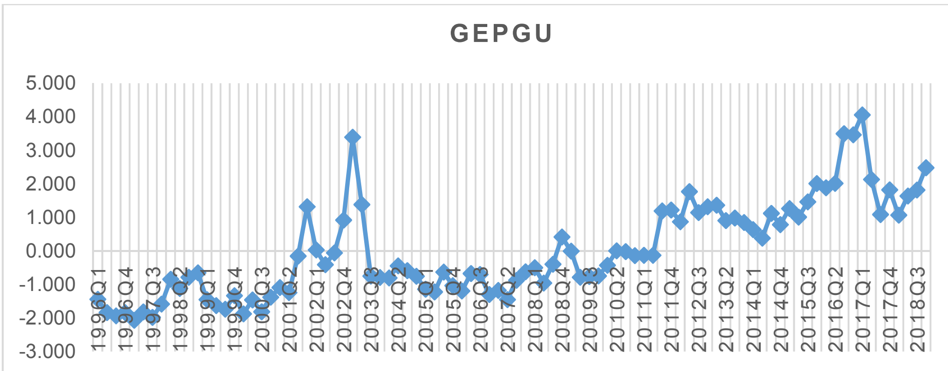

Table 2 presents the descriptive statistics of the aforementioned indicators that were used in the econometric analyses for the sample period of 1996: Q1-2018: Q4.

Table 2

Descriptive Statistics of Selected Variables

1996: Q1-2018: Q4	RGDP	RGFI	EL	TFP	GEPGU
Mean	2.47	3.30	0.97	1.01	1.09
Median	2.58	4.51	1.38	0.85	-0.42
Maximum	5.29	11.51	2.80	9.76	4.06
Minimum	-3.92	-15.16	-4.04	-4.85	-2.07
Standard Deviation	1.74	5.15	1.37	2.66	1.42
Skewness	-1.36	-1.39	-2.00	0.400	0.69
Kurtosis	6.08	5.45	7.38	3.16	2.84
Observations	92	92	92	92	92

4. Econometric Methods and Empirical Evidence

The econometric models utilized in this study are mainly the extension of Neo-Classical Cobb-Douglas total production function to be estimated on the determination of simultaneous impacts of global EPG uncertainties on the economic growth of the US. The determination of econometric models through the extension of Cobb-Douglas production function including other potential determinants of economic growth was frequently utilized in earlier empirical research (*i.e.*, Barro, 1991; Temple, 2000; Rodrik, 2012). The econometric model estimated to determine the simultaneous global EPG uncertainties on the economic growth of the US using linear and nonlinear times series analysis methodology for the sample period of 1996:Q1-2018:Q4 can be described as

$$RGDP_t = \alpha_t + \beta_1 RGFI_t + \beta_2 EL_t + \beta_3 TFP_t + \beta_4 GEPGU_t + \varepsilon_t \quad (1)$$

where: GDP denotes economic growth; TFP denotes technological development level; RGFI denotes fixed capital investments; EL denotes human capital investments; GEPGU denotes global EPG uncertainties; and α, β, ε, and t denote constant parameter, slope parameters, error terms, and time variable, respectively. The econometric analyses in this study were performed using EViews 10.0, WinRATS 9.1, Gauss 18.0 and C++ package programs.

In time series analyses, the stationarity condition of the selected variables is crucial, whereas using nonstationary variables may lead to biased test statistics and spurious regression phenomenon. Therefore, the stationarity condition should be primarily tested in order to obtain unbiased test statistics and to avoid the spurious regression issue in time series analysis (Gujarati, 2004). The stationarity condition in time series analysis can be examined using different linear and nonlinear unit root tests under a variety of assumptions considering symmetric and asymmetric features, deterministic or stochastic structure of time series. Particularly, the selected variables in the models for a certain sample period may show linear and nonlinear trends and unit root tests that do not take such trends into account may lead to biased results in terms of the stationarity of selected variables (Cuestas and Garrant, 2011). In order to obtain unbiased results and to avoid the spurious regression issue, the stationarity condition was separately examined using both linear (*i.e.,* Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP)) and nonlinear (*i.e.*, Kapetanios, Shin and Snell (KSS) and Sollis (SLS)) unit root tests with different features.

The ADF (Dickey and Fuller, 1979) and PP (Phillips and Perron, 1988) unit root tests are frequently used when the movement of time series shows linear trends for the sample period and they provide stationarity analysis under certain assumptions to overcome the autocorrelation issue among the selected variables**.** On the one hand, the ADF unit root test assumes that autocorrelation of error terms can be avoided by including lagged values of explanatory variables and the application of the corresponding unit root test requires the determination of correct degree of autocorrelation for the error terms. On the other hand, the PP unit root test provides a stationarity analysis using a nonparametric method to control high degrees of correlation for time series and, thus, improves the assumption in the ADF unit root test associated with the distribution of random shocks. In this aspect, the PP unit root test is widely adopted as the complement of the ADF unit root test and the PP unit root test introduces a Newey-West coefficient estimator instead of including lagged values of explanatory variables to avoid autocorrelation issue (Phillips and Perron, 1988). In addition, the stationarity condition for both the ADF and PP unit root tests is examined by the alternative hypothesis stating “there is a unit root among series” and this hypothesis is rejected when the absolute value of test statistics with constant and trend form is higher than critical table values.

Both the KSS (Kapetanios, Shin and Snell, 2003) and the SLS (Sollis, 2009) unit root tests can be used when the movement of time series show nonlinear trends during the selected sample period and they provide stationarity analysis under certain assumptions with respect to symmetric and asymmetric features of the selected variables. The KSS unit root test assumes that the asymmetric time series follow an exponential and smooth transition autoregressive process, whereas the SLS unit root test assumes that the symmetric or asymmetric time series follow an exponential or a logistic smooth transition autoregressive process.

Table 3 presents the unit root test results for linear ADF and PP and nonlinear KSS and SLS that seek the stationarity conditions of the selected variables with constant and trend and demeaned and detrended form.

Table 3

Linear and Nonlinear Unit Root Test Results

		ADF			PP			I
Variables		LV	FD	L	LV	FD	L	
RGDP		-3.12	-6.45^{a}	1	-2.86	-7.29^{a}	4	I(1)
RGFI		-2.84	-3.80^{b}	5	-2.46	-5.86^{a}	4	I(1)
EL		-2.13	-6.11^{a}	4	-2.52	-6.39^{a}	5	I(1)
TFP		-10.03^{a}	–	0	-10.01^{a}	–	3	I(0)
GEPGU		-3.87^{b}	–	0	-3.79^{b}	–	4	I(0)
Critical Value	*%1*	*-4.06*			*-4.06*			
	%5	*-3.46*			*-3.46*			
		KSS			SLS			I
Variables		LV	FD	L	LV	FD	L	
RGDP		-2.72	-3.77^{b}	1	5.91	8.21^{b}	1	I(1)
RGFI		-3.47^{b}		2	7.13^{b}	–	2	I(0)
EL		-2.68	-3.44^{b}	2	4.09	7.15^{b}	2	I(1)
TFP		-3.32	-4.74^{a}	1	6.29	14.94^{a}	1	I(1)
GEPGU		-4.03^{a}	–	2	10.09^{a}	–	2	I(0)
Critical Value	*%1*	*-3.93*			*8.53*			
	%5	*-3.40*			*6.46*			

Note: ^{a} and ^{b} denote the variable is stationary at 1% and 5% significance levels, respectively. L denotes optimal lag length determined by Schwarz Information Criterion for ADF, KSS, and SLS unit root tests and Bartlett Kernel method for the PP unit root test. The critical table values are adopted from MacKinnon (1996) for both ADF and PP unit root tests and Kapetanios et al. (2003) and Sollis (2009) for KSS and SLS unit root tests, respectively.

For the ADF and PP unit root tests, Table 3 indicates that the TFP and GEPGU indicators were stationary at 1% and 5% significance levels at their level values, whereas the RGDP, RGFI, and EL indicators were found as stationary at their first differences. Similarly, the RGFI and GEPGU were found as stationary at their level values, while the RGDP, EL, and TFP indicators were stationary at their first differences for the KSS and SLS unit root tests. Since both linear and nonlinear unit root test results reveal that some variables were stationary at $I(0)$, while some other variables were stationary at $I(1)$, the model to be estimated involves integrated variables of different levels and at most $I(1)$ levels, long-term potential cointegrated relationships among selected variables should be sought using the Autoregressive Distrubuted Lag (ARDL) model. Furthermore, the long-term cointegrated relationships are examined using linear ARDL (L-ARDL) and nonlinear ARDL (NL-ARDL), respectively, for linear and nonlinear models involving integrated variables with different levels.

The L-ARDL model, proposed by Pesaran *et al*. (2001), provides to investigate the symmetric dimension of long-term relationships among integrated variables at different levels, namely, $I(0)$ or $I(1)$. The L-ARDL model utilizes lagged values of both dependent and explanatory variables in model estimation. It is assumed that the model overcomes some autocorrelation- and endogeneity-based issues and the model can provide consistent empirical evidence for even small samples. The L-ARDL model mainly bases on Unrestricted Error Correction Model (UECM) and in L-ARDL (p,q) model, the short- and long-term symmetric relationships between two time series variables (*i.e.*, x_t and y_t) are examined using the regression model defined as

$$y_t = \sum_{i=1}^{p} \lambda_i y_{t-j} + \sum_{i=0}^{q} \delta_i^{*\prime} x_{t-i} + \varepsilon_t \tag{2}$$

where: y_t denotes dependent variable; x_t denotes $k\times 1$ dimension exogenous variables vector; (p,q) denotes distributed lagged values of y_t and x_t variables, respectively. Furthermore, $\delta_i^{*\prime}$ denotes $k\times 1$ dimension coefficients vector of exogenous variables; λ_i denotes scalars vector, and finally ε_t denotes error term with zero mean and finite variance. A symmetric form of Equation (2) in regard to UECM can be re-written as follows:

$$\Delta y = \phi y_{t-1} + \beta_i^{'} x_t + \sum_{i=1}^{p-1} \lambda_i^{*} \Delta y_{t-1} + \sum_{i=0}^{q-1} \delta_i^{*\prime} \Delta y_{t-1} + \varepsilon_t \tag{3}$$

Since $\phi = -1\left(1 - \sum_{j=1}^{p} \lambda_j\right)$; $\beta_i = \sum_{i=0}^{q} \delta_i$; $\lambda_i^{*} = \sum_{m=i+1}^{p} \lambda_m$ for $i = 1,2,...,p-1$; $\delta_i^{*} = \sum_{m=i+1}^{q} \delta_m$ for $i = 1,2,...,q-1$, Equation (3) can be finally written as

$$\Delta y_t = \phi(y_{t-1} - \theta_i^{\prime} x_t) + \sum_{i=1}^{p-1} \lambda_i^{*} \Delta y_{t-1} + \sum_{i=1}^{q-1} \delta_i^{*\prime} \Delta x_{t-1} + \varepsilon_t \tag{4}$$

In Equation (4), $\theta = -\left(\frac{\beta}{\phi}\right)$ denotes calculated coefficients for long-term equilibrium relationships between x_t and y_t, while λ_i^{*} and δ_i^{*} denote short-term coefficients calculated for lagged values of potential changes on y_t and x_t, respectively. Additionally, ϕ denotes symmetric error correction coefficient that shows speed of convergence for y_t explanatory variable to the equilibrium in long-term relationship due to changes on x_t (Pesaran *et al*., 2001).

The N-ARDL approach was proposed by Shin *et al*. (2014) and it is the extension of the L-ARDL model to enable better understanding of the asymmetric dimension of long-term relationships among integrated variables at different levels. In that aspect, the N-ARDL model explores the long-term nonlinear relationships among dependent variable and explanatory variables. Hence, the N-ARDL model is the extension of Equation (3) that involves asymmetric relationships, as follows:

$$y_t = \beta^{+} x_t^{+} + \beta^{-} x_t^{-} + u_t \tag{5}$$

$$x_t = x_0 + x_t^{+} + x_t^{-} \tag{6}$$

In Equation (5), β^{+} and β^{-} denote long-term asymmetric parameters associated with x_t^{+} and x_t^{-} variables, respectively, and u_t denotes the deviation from long-term equilibrium. In Equation (6), x_t^{+} and x_t^{-} are two components of x_t and they denote partial sums of positive or negative changes on x_t variable. Equation (6) can be decomposed as in the following in order to explain the positive and negative changes on partial sum process in detail (Shin *et al.*, 2014):

$$x_t^{+} = \sum_{j=1}^{t} \Delta x_j^{+} = \sum_{j=1}^{t} Max(\Delta x_j, 0) \tag{7}$$

$$x_t^{-} = \sum_{j=1}^{t} \Delta x_j^{-} = \sum_{j=1}^{t} Min(\Delta x_j, 0) \tag{8}$$

In that context, the NL-ARDL (p, q) model in UECM form that explores short- and long-term asymmetric relationships between two time series variables (*i.e.*, y_t and x_t) can be described as follows:

$$\Delta y_t = \phi(y_{t-1} - \theta_1' x_t^{+} - \theta_2' x_t^{-}) + \sum_{i=1}^{p-1} \lambda_i \Delta y_{t-i} + \sum_{i=0}^{q-1} \delta_{1i}^{*\prime} \Delta x_{t-i}^{+} + \sum_{i=0}^{q-1} \delta_{2i}^{*\prime} \Delta x_{t-i}^{-} + \varepsilon_t \tag{9}$$

There are four consecutive phases of estimation for both L-ARDL and NL-ARDL models as described in Equation (3) and Equation (9), respectively. In the first phase, appropriate specifications (optimal lag length) of L-ARDL and NL-ARDL models are determined with respect to Schwarz Information Criterion where dependent variable and explanatory variables are integrated at different levels and at most $I(1)$ level. In the second phase, long-term symmetric and asymmetric cointegration relationships between dependent variable and explanatory variables are explored by a bound test. When the bound test statistics calculated for L-ARDL and NL-ARDL models are higher than critical table values, the null hypothesis stating "there is no cointegration relationship among variables" is rejected. In the third phase, when there are long-term symmetric and asymmetric relationships among the selected variables of L-ARDL and NL-ARDL models, Equation (3) and Equation (9) are estimated by ordinal least squares and short- and long-term ARDL coefficients are calculated for the explanatory variables. In the final phase, diagnostic tests such as heteroscedasticity, autocorrelation, normality, etc., are performed for the estimated L-ARDL and NL-ARDL models and their stability condition is also explored.

Following the above-mentioned four phases, Table 4 indicates the estimated L-ARDL and NL-ARDL models to examine the simultaneous impact of global EPG uncertainties on the economic growth of the US. In Table 4, Panel A presents the FPSS bound test statistics for dependent variable (RGDP) and explanatory variables (RGFI, EL, TFP, and GEPGU) using the Schwarz Information Criterion and selecting the maximum lag length as five. The empirical evidence obtained from Panel A indicates that calculated FPSS bound test statistics for estimated L-ARDL and NL-ARDL models were higher than the lower and upper bounds of critical table values (adopted from Pesaran *et al*., 2001) at 1% significance level and the null hypothesis was rejected. Thus, there are both symmetric and asymmetric long-term cointegration relationships between the dependent variable and explanatory variables of L-ARDL (1, 2, 0, 5, 0) and NL-ARDL (1, 1, 2, 0, 5, 0) models.

Panel B results in Table 4 presents the diagnostic statistics including the specification error test (Ramsey Reset-RR), autocorrelation (Lagrange Multiplier-LM), heteroscedasticity (Autoregressive Conditional Heteroscedasticity-ARCH), normality (Jarque-Berra-JB), structural stability (Cusum-CS and Cusum of Squares-CS^2), F, and R^2. In that context, the R^2 value was relatively high and the F test statistic values were statistically significant and both estimated L-ARDL and NL-ARDL models satisfy stability conditions in diagnostic aspects. The diagnostic test results in Panel B indicate that calculated test statistics for RR, LM, ARCH, JB tests were statistically significant at 5% significance level and both CS and CS^2 test results were stable. Thus, there was no serious specification error, autocorrelation, and heteroscedasticity issues and residuals were normally distributed for the estimated L-ARDL and NL-ARDL models.

The calculated coefficients for the short- and long-term symmetric and asymmetric relationships for explanatory variables of estimated L-ARDL and NL-ARDL models are presented in Panel C and Panel D, respectively. As shown in Panel C, the short-term symmetric and asymmetric coefficients for RGFI, $RGFI^+$, $RGFI^-$, EL and TFP at their level values were statistically significant and positive as expected.

Table 4

Estimation Results for the L-ARDL and NL-ARDL Models

Panel A: Bound Test	**L-ARDL**	**NL-ARDL**
Selected Model	(1, 2, 0, 5, 0)	(1, 1, 2, 0, 5, 0)
FPSS	5.19*	6.36*
Critical Values (% 1)		
Lower Bound I(0)	3.29	3.06
Upper Bound I(1)	4.37	4.15
Panel B: Diagnostic Statistics	**L-ARDL**	**NL-ARDL**
Adjusted R^2	0.95	0.94
F	124.86 [0.000]	116.36[0.000]
RR	1.179 [0.314]	0.584 [0.561]
LM	0.673 [0.513]	0.204 [0.816]
ARCH	0.889 [0.415]	0.556 [0.575]
JB	2.62[0.271]	2.92 [0.232]
CS (CS^2)	S(S)	S(S)

Panel C: Short-Run Estimates	L-ARDL		NL-ARDL	
	Coefficient	Standard Error	Coefficient	Standard Error
$RGDP_{t-1}$	0.578[a]	0.087 [0.000]	0.545[a]	0.095[0.000]
$RGFI_t$	0.239[a]	0.031 [0.000]	—	—
$RGFI_{t-1}$	-0.074	0.053 [0.171]	—	—
$RGFI_{t-2}$	-0.104[a]	0.031 [0.001]	—	—
$RGFI_t^+$	—	—	0.192[a]	0.049[0.000]
$RGFI_{t-1}^+$	—	—	-0.123[b]	0.056[0.032]
$RGFI_t^-$	—	—	0.293[a]	0.058[0.000]
$RGFI_{t-1}^-$	—	—	-0.008	0.089[0.929]
$RGFI_{t-2}^-$	—	—	-0.234[a]	0.058[0.000]
EL_t	0.218[b]	0.085[0.012]	0.161[b]	0.078[0.042]
TFP_t	0.038[b]	0.018[0.039]	0.044[b]	0.019[0.028]
TFP_{t-1}	0.009	0.018[0.593]	-0.001	0.017[0.994]
TFP_{t-2}	0.053[a]	0.018[0.005]	0.055[a]	0.017[0.003]
TFP_{t-3}	0.073[a]	0.019[0.000]	0.079[a]	0.018[0.000]
TFP_{t-4}	-0.055[a]	0.020[0.006]	-0.037	0.019[0.061]
TFP_{t-5}	0.048[a]	0.017[0.007]	0.056[a]	0.017[0.002]
$GEPGU_t$	-0.111[b]	0.042[0.010]	-0.161[b]	0.051[0.023]
C	0.469[a]	0.132[0.000]	1.018[b]	0.386[0.010]
Panel D: Long-Run Estimates	**L-ARDL**		**NL-ARDL**	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
$RGFI$	0.145[a]	0.049 [0.004]		
$RGFI^+$	—	—	0.154[a]	0.042[0.001]
$RGFI^-$	—	—	0.147[a]	0.044[0.001]
EL	0.517[a]	0.175 [0.004]	0.352[b]	0.160[0.032]
TFP	0.392[a]	0.112 [0.001]	0.434[a]	0.133[0.002]
$GEPJU$	-0.264[a]	0.084 [0.003]	-0.353[a]	0.120[0.005]
C	1.111[a]	0.174 [0.000]	2.235[a]	0.555[0.000]
ECM_{t-1}	-0.422[a]	0.073 [0.000]	-0.455[a]	0.066[0.000]

Note: [a] and [b] denote *t* test statistic value for a variable is statistically significant at 1% and 5% significance levels, respectively; values in square brackets are probabilities; t denotes determined lag levels of coefficients by Schwarz Information Criterion for t = 0; * for FPSS test statistics denotes there exists a statistically significant cointegration relationship among variables of models at 1% significance level.

This result can be interpreted as symmetric and/or asymmetric increases/changes in fixed-human capital investments and technological development level in the US have an increasing impact on the economic growth of the US on short term. Additionally, short-term symmetric and asymmetric coefficients of the RGDP indicator and the RGFI, $RGFI^+$, $RGFI^-$, EL and TFP variables were also calculated with respect to their lags in the estimated L-ARDL and NL-ARDL models. This evidence can be interpreted as symmetric and/or asymmetric increases/changes in fixed-human capital investments and technological development level in the US have an increasing or decreasing impact on the economic growth of the US on short term with regards to lags.

Panel C results in Table 4 reveal that short-term symmetric and asymmetric coefficients for the GEPGU explanatory variable at its level values were calculated as –0.111 and –0.161, respectively. These statistically significant values imply that one-unit symmetric and asymmetric increase/change in the global EPG uncertainties level led to a –0.111 and –0.161 unit decrease in the economic growth of the US as expected. The empirical evidence gathered from Panel C is also consistent in terms of long-term effects as presented in Panel D. Particularly, calculated long-term symmetric and asymmetric coefficients of the RGFI, $RGFI^+$, $RGFI^-$, EL and TFP variables were found as positive and statistically significant. These expected results indicate that potential symmetric and/or asymmetric increases/changes in fixed-human capital investments and technological development level of the US have an increasing impact on the economic growth of the US on long term. When the magnitudes of coefficients of the RGFI, $RGFI^+$, $RGFI^-$, EL and TFP variables in the estimated L-ARDL and NL-ARDL models are considered, the most significant effects were observed for the EL and TFP variables. These findings highlight that the economic growth performance of the US was mostly affected by the human capital investments and technological development levels, whereas the fixed capital investments have the least significant effect on the economic growth performance of the US.

The empirical evidence gathered from Panel D in Table 4 indicates that long-term symmetric and asymmetric coefficients of the GEPGU dependent variable were found as –0.264 and –0.353, respectively. As expected, these statistically significant coefficients imply that one-unit symmetric and/or asymmetric increase/change in the global EPG uncertainty level led to –0.264 and –0.353 unit decreases in the economic growth of the US, respectively. Moreover, one may argue that increases/changes in the global EPG uncertainty level have a contractionary impact on the economic growth of the US during the sample period, as predicted by the theoretical literature.

In terms of error correction coefficients, statistically significant ECM_{t-1} coefficients, which show long-term convergence levels among variables in the estimated L-ARDL and NL-ARDL models, were calculated as –0.422 and –0.455. This implies that short-term symmetric and asymmetric shocks occurred among variables would be eliminated on long term and the selected variables would reach the equilibrium again.

After determining the short- and long-term impact of global EPG uncertainties on economic growth of the US through estimated L-ARDL and N-ARDL models, the long-term causality among the selected variables were explored using relevant causality tests. In this study, long-term causality among the global EPG uncertainties and economic growth variables were examined using the linear HHJ (Hacker and Hatemi-J, 2006) and nonlinear DP (Diks and Panchenko, 2006) tests. The HHJ test was developed on the basis of Toda and Yamamoto-TY (1995) linear causality test and the HHJ test explores the symmetric causality relationships among integrated variables at different levels, cointegrated variables or variables which are not cointegrated. In that aspect, the determination of using level values of integrated variables at different levels and maximum integration levels are crucial in HHJ test. By using bootstrap distribution instead of asymptotic chi-square distribution and by considering ARCH, the HHJ test purposes to decrease the deviations on test statistics. In the HHJ test, the causality relationships among integrated variables at y_t explanatory vector, Vector Autoregressive Model, namely, $\mathrm{VAR}(p, d_{\max})$ with lag p and $d_{\max}$ maximum integration degree can be described as:

$$y_t = v + A_1 y_{t-1} + A_p y_{t-p} + \ldots A_{p+d} y_{t-(p+d)} + \mu_t \tag{10}$$

where: v denotes vector of constant terms; μ_t denotes vector of error terms, and A denotes vector of parameters. Using Equation (10), the causality relationships among variables are explored with a MWALD test statistic (Hacker and Hatemi-J, 2006). As a result, when the MWALD test statistic value is higher than critical table values, calculated by Monte Carlo simulations using bootstrap distribution, then the null hypothesis stating "there are no causality relationships among variables" is rejected.

The DP test is based on the extension of nonlinear Hiemstra and Jones-HJ (1994) test that do not consider possible changes in the conditional distribution of variables leading to rejecting the null hypothesis extremely for large samples. To overcome this issue, the DP allows the adaption of bandwidth with an appropriate speed towards zero and this nonparametric adjustment is applied to the residuals of the VAR model. In the DP test, the null hypothesis explores the L_x and L_y causality relationships for the X and Y variables, respectively. This null hypothesis bases on

$$T_n(\varepsilon) = \frac{(n-1)}{n(n-2)} \sum_i \left(\hat{f}_{X,Y,Z}(X_i, Y_i, Z_i)\, \hat{f}_Y(Y_i) - \hat{f}_{Y,Z}(Y_i, Z_i) \right) \tag{11}$$

where: $\hat{f}_{X,Y,Z}(X_i, Y_i, Z_i)$ denotes local density estimators of random vector; ε_n denotes bandwidth; n denotes sample size, and $\varepsilon_n = C n^{-\beta} \left(C > 0, \frac{1}{4} < \beta < \frac{1}{3} \right)$. The null hypothesis in Equation (11) examines the causality relationships as $L_x = L_y = 1$ between L_x and L_y variables and it is assumed that the above-mentioned null hypothesis satisfied the conditions of $\sqrt{n}\,\frac{(T_n(\varepsilon_n) - q)}{S_n} \xrightarrow{d} N(0,1)$. Here, $\xrightarrow{d}$ denotes the convergence on the distribution and S_n denotes the estimator of asymptotic variance for $T_n(\varepsilon)$. In the DP test, the causality relationships among variables are explored using normally distributed T_n test statistic (Diks and Panchenko, 2006). When the calculated value of T_n test statistic is higher than 1.65, then the null hypothesis stating "there is no causality relationship among variables" is rejected at 5% significance level. Table 5 presents the linear HHJ and nonlinear DP causality test results to explore the long-term linear and nonlinear causality relationships among the global EPG uncertainties and economic growth.

As shown in Table 5, the calculated MWALD test statistic value for GEPGU $\nRightarrow$ RGDP was higher than the critical table value in the HHJ and DP tests and the probabilities for T_n test statistic were lower than 0.05. This implies that there was only unidimensional causality relationship from the global EPG uncertainties (GEPGU) towards economic growth (RGDP), but not vice versa. This evidence also puts forward that the movements of the GEPGU and RGDP variables in time were affected by each other when these movements show linear and nonlinear trends. Consequently, one may argue that increases/changes in the global EPG uncertainty level cause decreases/changes in the economic growth of the US, but not vice versa.

Table 5

Linear and Nonlinear Causality Test Results

HHJ Linear Causality Test		DP Nonlinear Causality Test	
Null Hypothesis	MWALD Test Statistic	T_n Test Statistic	L
RGDP $\nRightarrow$ GEPGU	0.109 [3.98]	1.250 [0.106]	1
	0.560 [6.35]	1.036 [0.150]	2
GEPGU $\nRightarrow$ RGDP	4.989^b [3.91]	1.949^b [0.026]	1
	6.345^b [6.02]	2.202^b [0.014]	2

Note: Both the HHJ and DP test statistics were calculated regarding $d_{\max} = 1$ and ε_n; ^{b} denotes there exists a causality relationship among variables at 5% significance level; numbers in column L show maximum lag length; $\nRightarrow$ denotes the direction of causality relationship; values in square brackets show critical table values at 5% significance level for the HHJ test and probabilities for DP test.

5. Conclusion

This study mainly envisaged to empirically investigate the simultaneous impact of the EPG-based uncertainties of global economy on the economic growth of the US using linear and nonlinear time series analyses. For this purpose, the present study examines whether the global EPG uncertainties have a contractionary impact on the economic growth of the US, since the US economy takes place on the main axis of uncertainties in terms of the EPG aspects. In this study, the EPG uncertainties were generated using the EPU, WUI, and GPU indices through a principal component analysis and their simultaneous effects on the economic growth of the US were econometrically explored within the scope of both linear and nonlinear time series analyses. The econometric model of the present study was fitted by the extension of Cobb-Douglas production function and it was estimated for the sample period of 1996: Q1-2018: Q4 using relevant linear and nonlinear time series analyses.
The estimation results reveal that both short- and long-term effects of fixed-human capital investments and technological development level on the economic growth of the US during the sample period were positive and statistically significant. These findings underline that increases/changes in fixed-human capital investments and technological development level on both short and long term have a statistically significant positive impact on the economic growth of the US. Particularly; the technological development level, fixed capital investments and human capital investments were found as the most effective indicators of the economic growth of the US, respectively. On the one hand, these results reveal that the short- and long-term effects of the uncertainties arising from the developments in the global economy on the economic growth of the US are negative / statistically significant. On the other hand, the magnitude of this effect has become more pronounced on long term. These results show that the changes/increases in the level of uncertainty of the global economy arising from the EPG developments cause changes/decreases in the economic growth of the US.

The empirical evidence of the present study puts forward that, the global EPG uncertainties have a statistically significant negative impact on the economic growth of the US on both short and long term. In other words, increases/changes in the global EPG uncertainty level on the short and long term has a statistically significant negative impact on the economic growth of the US. Furthermore, this negative impact of global EPG uncertainties on the economic growth of the US was found to be more significant on long term. The aforementioned empirical results were also confirmed in terms of direction of the causality relationships among the selected variables, since a unidimensional causality relationship was observed from the global EPG uncertainties towards the economic growth of the US. These results of the study coincide with the theoretical literature suggesting that the EPG uncertainties will have adverse effects on the economic growth performance of countries based on real options and / or risk aversion channels. However, the results showing that the direct effects of the EPG uncertainties on the economic growth performance of the US are linear (Baker *et al*., 2013; Ferrara and Guérin, 2018; Caldara and Iacoviello, 2018) and non-linear (Dima *et al*. 2017) support the results of investigated studies. In this context, in the study, it is determined that the indirect (reflection) effects of the global EPG uncertainties on the economic growth performance of the US are also negative, with both linear and nonlinear analyses.

The estimation results of linear and nonlinear models indicate that the global EPG uncertainties have a contractionary impact on the economic growth of the US during the sample period in parallel with the theoretical literature. Thus, the global EPG uncertainties can be considered as a crucial constraint on the sustainability of economic growth rate of the US at its potential level and permanent economic recovery. At that point, it is also crucial for the authorized policy-makers in the US to design policy precautions in the future by decreasing the restrictive effects of global EPG uncertainties on the sustainability of economic growth rate and permanent economic recovery. For this purpose, policy-makers in the US may tend to develop and implement long-term monetary and fiscal policies with an emphasis on decreasing the dependency of economic growth rates on external conditions and on sustaining the economic growth rates by mostly internal dynamics. Later, the corresponding macroeconomic precautions can be encouraged by solving the existing global EPG uncertainties in further conciliatory and peaceful footsteps and avoiding the occurrence of new global EPG uncertainties with proactive foreign policy. Future empirical studies that concentrate on the impact of global EPG uncertainties on the economic growth of different developed and developing countries may contribute to the evolution of a rapidly growing literature.

References

Adedoyin, F.F., Afolabi, J.O., Yalçiner, K. and Bekun, F.V., 2020. The export-led growth in Malaysia: Does economic policy uncertainty and geopolitical risks matter? *Journal of Public Affairs*, e2361, pp.1-12.

Ahir, H., Bloom, N. and Furceri, D., 2018. The World Uncertainty Index. pp.1-33. Available at: <http://www.policyuncertainty.com/media/WUI_mimeo_10_29.pdf> [Accessed April 2019].

Arbatli, E.C. Davis, S.J. Ito, A. Miake, N. and Saito, I., 2017. Policy Uncertainty in Japan”, International Monetary Fund, *IMF Working Paper No. WP/17/128*. pp.1-48. Available at: <https://www.imf.org/en/Publications/WP/Issues/2017/05/30/Policy-Uncertainty-in-Japan-44915> [Accessed April 2019].

Baker, S.R., Bloom, N. and Davis, S.J., 2013. Measuring Economic Policy Uncertainty. *Stanford University Centre for Economic Performance*. *CEPR Working Paper*, pp.1-55.

Baker, S.R. Bloom, N. and Davis, S.J., 2016. Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, 131(4), pp.1593-1636.

Balta, N. Fernández, I.V. and Ruscher, E., 2013. Assessing the Impact of Uncertainty on Consumption and Investment. *Quarterly Report on the Euro Area*, 12(2), pp.7-16.
Barro R.J., 1991. Economic Growth in a Cross Section of Countries. *The Quarterly Journal of Economics*, 106, pp.407-443.
Bhagat, S. Ghosh, P. and Rangan, S., 2016. Economic Policy Uncertainty and Growth in India. *Economic & Political Weekly*, 51(35), pp.72-81.
Bianchi, F., Ilut, C.L. and Schneider, M., 2017, Uncertainty shocks, asset supply and pricing over the business cycle, *Working Paper* 20081, National Bureau of Economic Research. Available at: <http://www.nber.org/papers/w20081> [Accessed 22 November 2020].
Bloom, N., 2014. Fluctuations in uncertainty. *Journal of Economic Perspectives,* 28(2), pp.153–176.
Caldara, D. and Iacoviello, M., 2018. Measuring Geopolitical Risk. *International Finance Discussion Papers No. 1222*. pp.1-66. Available at: <doi:10.17016/IFDP.2018.1222> [Accessed in April 2019].
Carroll, D. C., 1996. Buffer-stock saving and the life cycle/permanent income hypothesis. *NBER Working Paper Series, 5788.*
Cerda, R. Silva, Á. and Valente, J.T., 2018. Impact of Economic Uncertainty in a Small Open Economy: The Case of Chile. *Journal Applied Economics*, 50(26), pp.2894-2908.
Chen, J. *et al*., 2019. Oil price shocks, economic policy uncertainty and industrial economic growth in China. *Plos ONE* 14(5): e0215397. https://doi.org/10.1371/journal.pone.0215397, pp. 1-19.
Chinn, M., Ferrara, L. and Giacomini, R., 2018. Impact of Uncertainty Shocks on the Global Economy. *Journal of International Money and Finance*, 88, pp.209-211.
Čižmešija, M. Lolić, I. and Sorić, P., 2017. Economic Policy Uncertainty Index and Economic Activity: What Causes What?. *Croatian Operations Research Review*, 8(2), pp.563-575.
Cuestas J.C. and Garrant, D., 2011. Is Real GDP per Capita a Stationary Process? Smooth Transitions, Nonlinear Trends and Unit Root Testing. *Empirical Economics*, 41, pp.555-563.
Dickey, D.A. and Fuller, W.A., 1979. Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association,* 74, pp.427-431.
Diks, C. and Panchenko, V., 2006. A New Statistic and Practical Guidelines for Nonparametric Granger Causality Testing. *Journal of Economic Dynamics & Control*, 30(9–10), pp.1647-1669.
Dima, B., Dincă, M.S. Dima, S.M. and Dincă, G., 2017. Does Economic Policies Uncertainty Affect Economic Activity? Evidences from the United States of America. *Romanian Journal of Economic Forecasting*, 20(1), pp.60-74.
Dixit, A. and Pindyck, R., 1994. *Investment under Uncertainty*. Princeton: Princeton University Press
Economic Policy Uncertainty., 2019. *Economic Policy Uncertainty Index*. Available at: <http://www.policyuncertainty.com/> [Accessed in Februay 2019].
Federal Reserve Bank of San Francisco., 2019. Indicators and Data. Available at: <https://www.frbsf.org/> [Accessed in Februay 2019].
Ferrara, L. and Guérin, P., 2018. What are the Macroeconomic Effects of High-frequency Uncertainty Shocks?. *Journal of Applied Econometrics*, 33, pp.662-679.

Fontaine, I., Didier, L. and Razafindravaosolonirina, J., 2017. Foreign policy uncertainty shocks and US macroeconomic activity: Evidence from China. *Economics Letters*, 155, pp.121-125.

Fontaine, I., Razafindravaosolonirina, J., and Didier, L., 2018. Chinese policy uncertainty shocks and the world macroeconomy: Evidence from STVAR. *China Economic Review*, 51, pp.1-19.

Ghirelli, C., Gil, M., Pérez, J.J. and Urtasun, A., 2019. Measuring economic and economic policy uncertainty and their macroeconomic effects: the case of Spain. *Empirical Economics*, pp.1-24.

Gilchrist, S., Sim, J. and Zakrajsek, E., 2014. Uncertainty, financial frictions, and investment dynamics. *NBER Working Paper* No: 20038. Available at: <https://ssrn.com/abstract=2424609>.

Greig, L., Rice, A., Vehbi, T. and Wong, B., 2018. Measuring uncertainty and its impact on a small open economy. *Australian Economic Review*, 51(1), pp.87-98. https://doi.org/10.1111/1467-8462.12255.

Gujarati, D.N., 2004. *Basic Econometrics*. New Jersey: McGraw-Hill.

Hacker, R.S. and Hatemi-J, A., 2006. Tests for Causality between Integrated Variables: Using Asymptotic and Bootstrap Distributions: Theory and Application. *Applied Economics*, 38(13), pp.1489-1500.

Haddow, A., Hare, C., Hooley, J. and Shakir, T., 2013. Macroeconomic Uncertainty: What is it, how can We Measure It and Why Does it Matter? *Quarterly Bulletin*, 53(2), pp. 100-109.

Hardouvelis, G.A. Karalas, G. Karanastasis, D. and Samartzis, P., 2018. Economic Policy Uncertainty, Political Uncertainty and the Greek Economic Crisis. *SSRN Electronic Journal*, pp.1-130. doi:10.2139/ssrn.3155172.

Hotelling, H., 1933. Analysis of a complex of statistical variables into principal components. *Journal of Educational Psychology*, 24(6), pp.417-441.

Kapetanios G. Shin Y. and Snell A., 2003. Testing for a Unit Root in the Nonlinear STAR Framework. *Journal of Econometrics*, 112, pp.359-379.

Kisten, T., 2020. Macroeconomic implications of uncertainty in South Africa. *South African Journal of Economic and Management Sciences*, 23(1), pp.1-15.

Larsen, V.H., 2017. Components of Uncertainty. Centre for Applied Macro and Petroleum Economics, *CAMP Working Paper Series No. 4/2017*, pp.1-41. Available at: <https://static.norgesbank.no/contentassets/78c009376c6548e799c27b94c036d480/working_paper_5_17.pdf?v=04/18/2017123755&ft=.pdf> [Accessed in April 2019].

Lee, S., 2015. Macroeconomic Uncertainty and Its Impact on Economic Activity: Investigating Two Different Measures, Georgetown Center for Economic Research Biennial Conference, May 28-29, Available at: Georgetown University Washington, DC, pp.1-27. Available at: <http://archivo.alde.es/encuentros.alde.es/anteriores/xviiieea/trabajos/l/pdf/182.pdf> [Accessed in April 2019].

Luk, P., Cheng, M., Ng, P. and Wong, K., 2018. Economic policy uncertainty spillovers in small open economies: The case of Hong Kong. *Pacific Economic Review*, 25(1), pp.1-26.

MacKinnon, J.G. 1996. Numerical Distribution Functions for Unit Root and Cointegration Tests. *Journal of Econometrics*, 11, pp.601-618.

Nyawo, S.T. and Van Wyk, R.B., 2018. The impact of policy uncertainty on macro-economy of developed and developing countries. *Journal of Economics and Behavioral Studies*. 10(1), pp.33-41.

OECD., 2019, OECD Data, https://data.oecd.org/ [Accessed in Februay 2019].

Perić, B.Š. and Sorić, P., 2018. A note on the “Economic Policy Uncertainty Index”. *Social Indicators Research*, 137(2), pp.505-526.

Pesaran, M.H., Shin, Y. and Smith, R.J., 2001. Bounds Testing Approaches to the Analysis of Level Relationships. *Journal of Applied Econometrics*, 16(3), pp.289-326.

Phillips, P.C.B. and Perron, P., 1988. Testing for a Unit Root in Time Series Regression. *Biometrika*, 75(2), pp.335-346.

Raileanu Szeles, M. and Saman, C., 2020. Globalisation, Economic Growth and COVID-19. Insights from International Finance. *Romanian Journal of Economic Forecasting*, 23(3), pp.78-92.

Ren, Y., Guo, Q., Zhu, H. and Ying, W., 2020. The effects of economic policy uncertainty on China’s economy: evidence from time-varying parameter FAVAR. *Applied Economics*, 52(29), pp.3167-3185.

Rodrik, D. 2012. Why We Learn Nothing from Regressing Economic Growth on Policies. *Seoul Journal of Economics*, 25(2), pp.137-151.

Sahinoz, S. and Cosar, E.E., 2018. Economic Policy Uncertainty and Economic Activity in Turkey. *Applied Economics Letters*, 25(21), pp.1517-1520.

Shin, Y., Yu, B. and Greenwood-Nimmo, M.J., 2014 Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework.. In: R.C. Sickles and W.C. Horrace, eds., *Festschrift in Honor of Peter Schmidt Econometric Methods and Applications*. New York: Springer, pp.281-314.

Sollis, R. 2009. A Simple Unit Root Test against Asymmetric STAR Nonlinearity with an Application to Real Exchange Rates in Nordic Countries. *Economic Modelling*, 26, pp.118-125.

Solow, R.M., 1956. A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*, 70(1), pp.65-94.

Sorić, P. Lolić, I., 2017. Economic uncertainty and its impact on the Croatian economy. *Public Sector Economics*, 41(4), pp.443-477.

Stockhammar, P. and Osterholm, P., 2016. Effects of US policy uncertainty on Swedish GDP growth. *Empirical Economics* 50.2, 443-462.

Stockhammar, P. and Osterholm, P., 2017. The impact of US uncertainty shocks on small open economies. *Open Economies Review*, 28(2), pp. 347-368.

Temple, J., 2000. Growth Regressions and What the Textbooks Don’t Tell You. *Bulletin of Economic Research* 52(3), pp.181-205.

Wong, K., Ng, P. and Cheng, M., 2017. Measuring Economic Uncertainty and its Effect on the Hong Kong Economy. *Research Memorandum* 11, Hong Kong Monetary Authority. Available at: <https://www.hkma.gov.hk/media/eng/publication-and-research/research/research-memorandums/2017/RM11-2017.pdf> [Accessed in Februay 2019].

Zalla, R. 2017. Economic Policy Uncertainty in Ireland. *Atlantic Economic Journal* 45(2), pp.269-271.