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CAUSALITY BETWEEN US ECONOMIC POLICY AND EQUITY MARKET UNCERTAINTIES: EVIDENCE FROM LINEAR AND NONLINEAR TESTS

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This paper examines the causal relationship between economic policy uncertainty (*EPU*) and equity market uncertainty (*EMU*) in the US. We use daily data on the newly developed indexes by Baker et al. (2013a) covering 1985:01:01 to 2013:06:14. Results from the linear causality tests indicate strong bidirectional causality. However, the parameters stability tests show strong evidence of short-run parameter instability, thus invalidating any conclusion from the full sample linear estimations. Therefore we turn to nonlinear tests and observe a stronger predictive power from *EMU* to *EPU* than from *EPU* to *EMU*. Using sub-sample bootstrap rolling window causality tests to fully account for the existence of structural breaks, we find evidence that *EPU* can help predict the movements in *EMU* only around 1993, 2004 and, 2006. However, we find strong evidence that *EMU* can help predict the movements in *EPU* throughout the sample period barring around 1998, 2003 and 2005.

JEL classification codes: C32, E61, G12, G18
Key words: economic policy uncertainty, equity market uncertainty, Granger causality

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I. Introduction

Over the past thirty years, a number of researches have focused on the effect of economic policy uncertainty on macroeconomic variables: economic growth, inflation, investment and employment (Bernanke 1983; Rodrik 1991; Bloom 2009; Bachmann et al. 2013; Jones and Olson 2013, among others). The general consensus is that policy uncertainty has a negative effect on economic growth and investment but a less clear-cut effect on inflation. The recent global financial crisis with the accompanying volatility in the equity market has kindled a protracted and high-profile debate over the role of key economic policies. This has primarily surrounded the European debt crisis and the US fiscal cliff and debt ceiling concerns, but also includes debate over such other policies as healthcare and financial services regulation (Fishman et al. 2012). It is believed that the recent increasing focus on economic policy uncertainty undoubtedly suggests the role it plays in economic growth and the equity market (Fishman et al. 2012).

Further, many investors argue that recent equity volatility levels are as much about policy as economics and corporate earnings. According to Li et al. (2013), "stock markets usually move swiftly and sharply in response to policy changes. Tax cuts, monetary easing or financial deregulation would send the stock markets soaring. On the contrary, quantitative easing withdrawal would send the stock markets crashing." However, Li et al. (2013) note that the extent to which the stock market would be impacted by policy changes (whether good or bad) depends on the certainty about such policy changes. Taylor (2010) and Hoshi (2011) suggest that high policy uncertainty in relation to the resolution of large bankrupt financial institutions has worsened or prolonged the recent financial crisis in the United States. Hatzius et al. (2012) argue that the economy's poor performance has been caused by an exogenous increase in US policy uncertainty.

This study intends to contribute towards the study of the effects of economic policy uncertainty, focusing on its effect on the US equity market performance. Specifically, we examine the causal link between two interesting new indexes, the US economic policy uncertainty index and the equity market uncertainty index developed by Baker et al. (2013a). We consider both the direction and magnitude of the causal and reverse causal effects. The choice for the US is justified because it is the only country with these indexes. A number of studies have investigated the relationship between economic policy uncertainty and equity market uncertainty or volatility.[1] This is particularly so since Baker et al. (2013a) constructed the respective two new indexes. For instance, Gregory and Rangel (2012) find a strong positive correlation between the US economic policy uncertainty and the level of S&P 500 variance (equity volatility) across different maturities. Using their own estimate of the market's implied earnings growth and the economic policy uncertainty index, Mezrich and Ishikawa (2013) find that the current US economic policy uncertainty index is far higher than before 2007, and that implied long-term earnings growth in equities could be pushed down to around 0.2 percent due to substantial existence of economic policy uncertainty. Baker et al. (2013b) also observed that the greater frequency (40 percent) of the US policy-driven equity market jumps is triggered by higher economic policy uncertainty.

Antonakakis et al. (2013) examine the time-varying correlations between the US stock market returns (and volatility) and policy uncertainty, and find that increased stock market volatility increases policy uncertainty and dampens stock markets returns while increases in the volatility of policy uncertainty lead to negative stock market returns and increased uncertainty. Pástor and Veronesi (2012; 2013) also show that the uncertainty about government policy increases stock volatility and risk premia, especially in a weak economy. Lam and Zhang (2014) use the economic policy uncertainty index of Baker et al. (2013a) and find that it has little explanatory power for international equity returns. They also construct two new measures of global policy uncertainty based on the ratings from International Country Risk Guide, which captures the potential policy shock from government changes and the bureaucratic ability to reduce policy shocks, and find that both factors significantly affect equity returns in 49 countries from 1995 to 2006.

The majority of these studies consider the relationship between the two series simply using correlation analysis or visual plots. Further, none of the studies account for structural breaks which are evident in the data. More importantly, there is a complete absence of studies examining the causality between the two newly developed indexes. Existence of a correlation or relationship may neither imply causality nor can reverse causality be inferred. Therefore, this study fills these gaps by considering the causal link between these two series.

[1] We do not provide references to the literature on the relationship between the economic policy uncertainty index and equity market returns. Interested readers may consult Li et al. (2013) for a review.

This paper makes two contributions to the existing literature. To the best of our knowledge, it is the first study to investigate the causal link between the Baker et al. (2013a) economic policy uncertainty and equity market uncertainty indexes. Furthermore, it takes potential structural breaks into account by using nonlinear and time varying causality methods instead of limiting the analysis to full-sample data that assumes that the same causality pattern holds over the whole period. We confront the data with a wide range of causality tests. First we consider different versions of the linear Granger causality tests. Results from full-sample causality tests may be misleading if structural changes exists. Therefore, we perform parameter stability tests on the estimated full sample VAR. Subsequently, we test for causality using the nonlinear methods of Hiemstra and Jones (1994), Diks and Panchenko (2006), and Kyrtsou and Labys (2006), the Sato et al. (2007) time-varying causality and the Balcilar et al. (2010) sub-sample rolling window bootstrap causality tests.

The majority of the studies reviewed above implicitly assume that policy uncertainty is exogenous and hence attempt to find the effect of policy uncertainty on equity market uncertainty, measured by realized volatility (squared returns) of an index of US stock prices. However, policy uncertainty is likely to be endogenous to other factors that affect equity market uncertainty. For instance, policy uncertainty has been found to be higher during elections and hence financial and economic variables also tend to change more during these periods (Rodrik 1991; Boutchkova et al. 2012; Julio and Yook, 2013). Moreover, the Baker et al. (2013a) economic policy uncertainty index spikes upward around US presidential elections. Other exogenous influences include debates over the stimulus package, the debt ceiling dispute, wars and financial crashes (Gulen and Ion 2013). This means that political decisions and other economic news may affect existing policies or introduction of new ones, hence providing some exogenous variation in policy risk over time. This potential endogeneity has implications for statistical analysis and result interpretations based on correlations and regressions that do not isolate the impact of policy uncertainty on economic activity from confounding variables, i.e., separating first moment shocks from second moment shocks. This might lead to a case of omitted variable bias which arises if increases in policy uncertainty tend to occur at the same time as increases in national election or other economic news. To address this endogeneity concerns, some studies have found proxies as instrumental variables for policy uncertainty while others have included several other variables that capture expectations about future economic conditions (Gulen and Ion 2013; Julio and Yook 2013). Therefore, in order not to fall prey of ignoring the endogeneity of policy uncertainty, this study analyses both causal and reverse causal effects, testing whether causality runs from policy uncertainty to equity market uncertainty as well as whether causality runs from the latter to the former.

The rest of the paper is organized as follows: the data and preliminary analysis is represented in section II. Section III presents the empirical models and results. Section IV concludes.

II. Data and preliminary analysis

To examine the causality between economic policy uncertainty (*EPU*) and equity market uncertainty (*EMU*) in the United States, this study draws on the daily *EPU* and *EMU* indexes from the Economic Policy Uncertainty Index website (http://www.policyuncertainty.com), newly introduced by Baker et al. (2013a). The data covers the 1985:01:01 to 2013:06:14 period. The end-point is pragmatic and was the final data point available at the time of writing. To measure policy-related economic uncertainty for the US, Baker et al. (2013a) construct an *EPU* index from three underlying components, namely, newspaper coverage of policy-related economic uncertainty, the number and projected revenue effects of federal tax code provisions set to expire in future years, and disagreement among economic forecasters about policy relevant variables. To measure equity market uncertainty, Baker et al. (2013a) construct a news-based index which is based on the count of articles that reference 'economy' or 'economic', and 'uncertain' or 'uncertainty" and one of 'stock price', 'equity price', or 'stock market' in 10 major U.S. newspapers, scaled by the number of articles in each month and paper. This news-based equity index is highly correlated with the widely used market-based equity volatility index (VIX) (Baker et al. 2013a). All the original data is processed by taking natural logarithms, to correct for potential heteroscedasticity and dimensional difference between series.

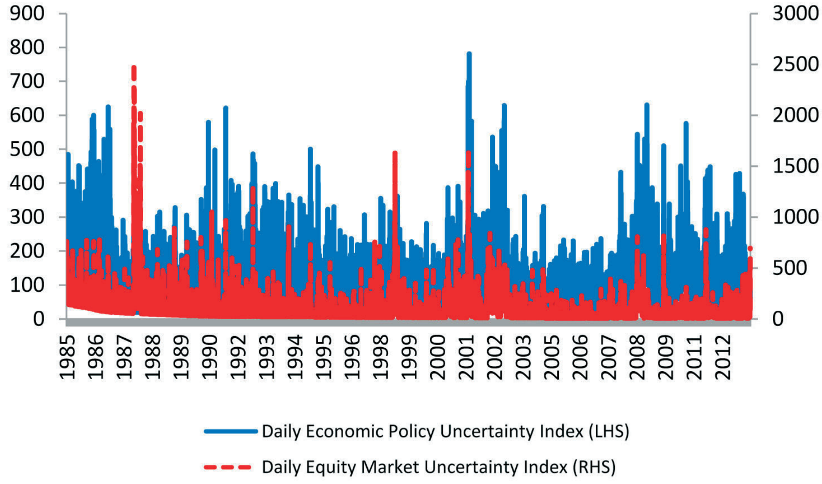
Figure 1A shows the plot of the original series. The scale on the left axis pertains to the policy uncertainty index while the scale on the right axis pertains to the equity market uncertainty. Although, the two series exhibit high volatility as expected, they look quite stationary. The figure shows *EPU* and *EMU* jumps corresponding to several prominent events, and much elevated levels of policy uncertainty since the 2007-09 recession. In particular, there are spikes associated with the 1987 and 1998 stock market crashes, tight presidential elections, wars, 2001 September 11 attacks, contentious budget battles, and major policy decisions and battles during and after the recent global recession. Overall, there seems to be some co-movement between the series.[2] To examine whether there is lead-lag relationship between *EPU* and *EMU*, we plot the corresponding 365-day moving average as shown in Figure 1B. From this figure there is no apparent way to decipher which variable is leading which. The figures may be used to make inferences about the lead-lag relationship; however they cannot provide a scientific proof of causality. Research in general is often based on statistical evidence. Hence, there is need for formal causality tests. This study therefore proceeds with formal causality testing using various approaches as stated earlier.

Prior to investigating Granger causality, in Table 1 we test for the stationarity of *EPU* and *EMU* using the using the Z_α unit root test of Phillips (1987) and Philips and Perron (1988) (PP), Augmented Dickey Fuller (ADF) test and the MZ_α test of Ng and Perron (NP) (2001). We conduct the test with two specifications: intercept only and both trend and intercept. The results show that the two series are I(0), meaning they are stationary. Hence, for subsequent analysis, we use the series in their natural logs.

[2] We find a positive but low correlation (0.26) between *EPU* and *EMU*. Correlation simply shows whether there is a positive or negative association or co-movement between two series, without showing which series leads the other, Moreover, any evidence of correlation may be due to other confounding factors. Therefore correlations are not sufficient to make causal inferences.

Figure 1. Economic policy uncertainty and equity market unceratinty

A. Daily index



B. Moving average

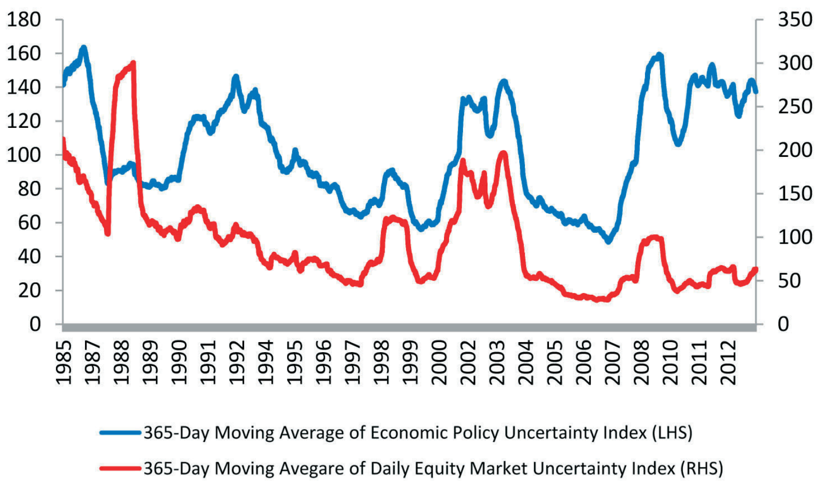


Table 1. Unit root testing

		Trend and intercept	Intercept	Conclusion
EPU	ADF	-13.705***	-12.899***	I(0)
	PP	-97.716***	-97.656***	
	NP	-4.99***	-3.654***	
EMU	ADF	-6.838***	-6.836***	I(0)
	PP	-150.881***	-150.889***	
	NP	-4.44***	-4.482***	

Notes: *** indicates significance at the 1% level.

III. Empirical procedures and results

Following the above preliminaries the study now proceeds with the investigation of the causal connection between equity market uncertainty (*EMU*) and economic policy uncertainty (*EPU*) in the US. The null hypothesis is Granger non-causality between the two series. Granger non-causality occurs when the information set on the first variable (e.g., *EMU*) does not improve the prediction of the second variable (e.g., *EPU*) over and above the predictive capacity of the information in the second variable. The two null hypotheses at stake are (a) that *EPU* does not Granger cause *EMU* and (b) that *EMU* does not Granger cause *EPU.* We use both linear and non-linear models for testing causality. This is because the linear test is only sensitive to causality in the conditional mean and may not be sufficient to detect nonlinear effects on the conditional distribution (Baek and Brock 1992). Hiemstra and Jones (1994) also noted that traditional linear Granger causality test have low power in detecting certain kinds of nonlinear relations. Higher order structure, such as conditional heretoskedasticity, is also often ignored (Diks and Panchenko 2005, 2006). In view of this, nonparametric approaches are appealing because they place direct emphasis on prediction without imposing a certain functional form.

First we use the classical linear Granger causality testing. Next, we also account for heteroscedasticity due to volatility clustering in our data as is evident in Figure 1. To take account of possible conditional heteroscedasticity of unknown form (Cheung and Ng 1996), we employ a popular heteroscedasticity-consistent covariance matrix estimator (HCCME) developed by MacKinnon and White

(1985), known in the literature as the HC3 estimator, for robustifying the classical linear Granger causality test. An alternative way to improve the performance of the classical Granger causality test in the presence of heteroscedasticity is to use a fixed design wild bootstrap procedure as in Hafner and Herwartz (2009). The wild bootstrap has been shown to yield reliable finite sample inference even when applied to data that are homoscedastic (Gonçalves and Kilian 2004). Therefore, we use the wild bootstrap method in addition to the HCCME. The technical details of the various linear models are provided in online appendices 1 to 3.

The results from the linear Granger causality are presented in Table 2. The uppermost panel reports the results from the classical Granger test, the middle panel reports the tests with the heteroscedasticity-robust variance covariance matrix and the lower panel reports the results from the wild-bootstrap procedure. The optimal lag length based on the Schwarz Information Criteria (SIC) test is eight (8) for the variables in their log-levels forming a VAR. In all the three versions of the linear tests, the null hypotheses are rejected at 1 percent, thus providing evidence in favour of bidirectional causality over the full sample. This implies the existence of a feedback system where *EMU* and *EPU* react to each other. In other words, movements in the *EPU* index can be significantly predicted by movements in the *EMU* index and vice versa.

Table 2. Results from linear causality tests

Classical Granger Causality test	
Hypothesis	p-value
EPU ≠> EMU	2.2473×10^{-08a}
EMU ≠> EPU	0.000[a]
Granger causality tests with the heteroscedasticity-robust variance covariance matrix	
Hypothesis	p-value
EPU ≠> EMU	5.194×10^{-05a}
EPU ≠> EMU	0.000[a]
Granger causality tests with the wild-bootstrap procedure	
Hypothesis	p-value
EPU ≠> EMU	0.003[a]
EPU ≠> EMU	0.000[a]

Notes: This table reports the p-values of the Granger causality tests.[a] indicates the rejection of the null hypothesis of absence of causality at the 1% level.

In the standard Granger causality testing, the full-sample is used for estimation. The assumption is that parameters of the VAR model used in testing are constant over time. However, when the underlying full-sample time series have structural changes, this assumption is probably violated. The results from the full sample causality would become invalid (Balcilar and Ozdemir 2013). Therefore, we test for parameter stability of the VAR results reported in Table 2 using four different tests. We use the *Sup-F*, *Ave-F* and *Exp-F* tests developed by Andrews (1993) and Andrews and Ploberger (1994) to investigate the stability of the short-run parameters.

However, it is noted that when the underlying variables in levels are cointegrated, the VAR model in first differences is misspecified unless it allows for error-correction. Therefore, we use the *Lc* tests of Nyblom (1989) and Hansen (1992) to investigate the long-run parameters stability. If the series are I(1), the Nyblom-Hansen Lc test also serves as a test of cointegration (Balcilar et al. 2010). To avoid the use of asymptotic distributions, the p-values are obtained from a bootstrap approximation to the null distribution of the test statistics, constructed by means of Monte Carlo simulation using 2000 samples generated from a VAR model with constant parameters. The Sup-F, Ave-F and Exp-F tests needs to be trimmed at the ends of the sample. Following Andrews (1993) we trim 15 percent from both ends and calculate these tests for the fraction of the sample in [0.15, 0.85].

The results from the parameter stability tests are reported in Table 3. The first three rows of Table 3 report tests statistics for short-run parameter stability, starting with the *EMU* equation in the first two columns and followed by the *EPU* equation and the overall VAR system in turn. In row 1 the *Sup-F* statistic reports the test of parameter constancy against a one-time sharp shift in parameters. This is followed in rows 2 and 3 by two test statistics *Ave-F* and *Exp-F*, which assumes that parameters follow a martingale process, and test against the possibility that the parameters might evolve gradually.[3] The final test reported in Table 3 is the L_c test for the stability of the parameters for the *EPU* and *EMU* equations.

[3] The Ave-F and Exp-F are both optimal tests as shown by Andrews and Ploberger (1994).

Starting with the L_c tests, the final row of Table 3 indicates significant evidence of parameter instability in both the *EMU* and *EPU* equations. Turning now to the first three rows of Table 3 where the sequential *Sup-F*, *Ave-F*, and *Exp-F* tests are reported, we find evidence of parameter instability in both equations and for the VAR as a whole. The evidence in Table 3 suggests both one-time shifts as well as a gradual evolution of the parameters in the *EMU-EPU* VAR. Parameter instability of the kind identified here would undermine traditional Granger causality tests of the connection between equity uncertainty and policy uncertainty. Hence, one would expect that the Granger causality tests to be sensitive to sample period changes in this case.

Table 3. Parameter stability tests

	EMU Equation		EPU Equation		VAR (8) System	
	Statistics	Bootstrap p-value[a]	Statistics	Bootstrap p-value[a]	Statistics	Bootstrap p-value[a]
Sup-F	243.38	<0.01	417.76	<0.01	644.43	<0.01
Ave-F	104.60	<0.01	275.73	<0.01	381.96	<0.01
Exp-F	114.22	<0.01	203.04	<0.01	316.40	<0.01
Lc	12.45	<0.01	34.71	<0.01		

Notes: *, **, and *** denote significance at 10, 5 and 1 percent, respectively. [a]p-values are calculated using 2000 bootstrap repetitions.

Accordingly we proceed to investigate the association between *EMU* and *EPU* with nonlinear, time varying VAR and bootstrap rolling window Granger causality tests. Various nonparametric tests have been proposed in the literature. The most prominent one is perhaps the one developed by Hiemstra and Jones (1994), which is a modified version of Baek and Brock (1992). An alternative nonlinear model is that proposed by Diks and Panchenko (2005, 2006) who show that the relationship tested by Hiemstra and Jones (1994) is not generally compatible with Granger causality leading to the over rejection of the null hypothesis. Hence, we use both the Hiemstra-Jones (1994) and Diks-Panchenko (2006) nonlinear causality tests. In addition, we also employ the Kyrtsou and Labys (2006) symmetric and asymmetric nonlinear approach. We also use Sato et al. (2007) time varying causality as well as Balcilar et al. (2010) sub-sample bootstrap rolling window causality to account for time variation in the relationship between the series. The technical details of the various nonlinear models are provided in online appendices 4 to 8.

Table 4 reports the results from Hiemstra and Jones (1994) nonlinear Granger causality test based on the residual from the bivariate VAR. Following Hiemstra and Jones (1994), we set the value for the lead length of $m=1$, the common lag lengths $(Lx=Ly)$ of 1 to 8 and a common scale parameter of $e=1.5\sigma$, where $\sigma=1$ denotes the standard deviation of the standardized time series test statistic. The standardized test statistic, denoted by TVAL, is asymptotically distributed N(0,1) under the null hypothesis of nonlinear Granger noncausality. The results in Table 4 indicate that the null hypothesis that *EPU* does not Granger cause *EMU* is rejected at 1 and 5 percent significance level, respectively for the 4^{th} and 5^{th} lags only. Analogously, the null hypothesis that *EMU* does not Granger cause *EPU* is rejected at 1 percent for lags 6, 7 and 8. Overall, the Hiemstra and Jones (1994) test provides evidence in favour of bidirectional nonlinear causality between *EMU* and *EPU* though this occurred at uncommon lags. The evidence is also stronger for causality from *EMU* to *EPU* than the reverse.

Table 4. Hiemstra and Jones (1994) nonlinear causality test

	H_0: *EPU* ≠> *EMU*			H_0: *EMU* ≠> *EPU*	
Lags	CS	TVAL	Lags	CS	TVAL
1	-0.1882	-18.8810	1	-0.5186	-52.0237
2	-0.1271	-12.7553	2	-0.5265	-52.8226
3	-0.0517	-5.1948	3	-0.5921	-59.4024
4	-0.0199	1.9967[b]	4	-0.8317	-83.4289
5	0.2898	29.0757[a]	5	-1.4940	-149.8658
6	-160.6963	-16119.3726	6	463.0408	46447.4101[a]
7	-0.6315	-63.3553	7	1.3329	133.7093[a]
8	-0.5153	-59.6967	8	0.6342	63.6236[a]

Notes: CS and TVAL are respectively the difference between the two conditional probabilities, and the standardized test statistic. "Lags" denote the number of lags in the residual series used in the test. [a] and [b] indicate the rejection of the null hypothesis of absence of causality at the 1% and 5% levels, respectively.

Turning now to the results from the Diks and Panchenko (2006) nonlinear Granger causality test. The p-values of the test statistics are reported in Table 5. The results suggest evidence of bidirectional nonlinear causality between *EMU* and *EPU* for all the common lag lengths used in conducting the test. However, looking at the levels of significance, it is observed that *EMU* has stronger predictive power for *EPU* than does *EPU* for *EMU*. The evidence suggests that the *EMU* can be more helpful in predicting movements in the *EPU* index.

Table 5. Diks and Panchenko nonlinear causality test

$Lx = Ly$	H_0: *EPU* ≠> *EMU*	H_0: *EMU* ≠> *EPU*
1	0.0000[a]	0.0000[a]
2	0.0002[a]	0.0000[a]
3	0.0051[a]	0.0000[a]
4	0.0783[b]	0.0000[a]
5	0.0991[b]	0.0000[a]
6	0.0010[a]	0.0000[a]
7	0.0025[a]	0.0000[a]
8	0.0067[a]	0.0000[a]

Notes: This Table reports the p-values of the Diks-Panchenko causality tests. [a] and [b] indicate the rejection of the null hypothesis of absence of causality at the 1% and 10% levels.

The next nonlinear Granger causality we consider is that developed by Kyrtsou and Labys (2006). Our parameter prior selection is presented in Table 6. Our optimal integer delay variables for the causality from the EPU index to the EMU index (τ_1), and for the causality from *EMU* index to *EPU* index (τ_2) as selected by SIC are set to 7 and 10, respectively. We also set the power of the lagged values of the *EPU* index (c_1) and the *EMU* index (c_2), respectively to 2 and 1.

Table 6. Parameter-prior selection in the M-G model

τ_1	τ_2	c_1	c_2
7	10	2	1

Notes: This table reports the results for the parameter-prior selection. τ_1 and τ_2 are the optimal integer delay variables for the causality from policy index to equity index, and for the causality from equity index to policy index, respectively. c_1 and c_2 are the power of the lagged values of policy index and equity index, respectively.

The results for both symmetric and asymmetric causality are presented in Table 7. From Table 7, we observe strong evidence of bidirectional causality between the *EPU* index and the *EMU* index. Whether the direction of changes in the studied series has a significant effect on their causal relationships can be examined by using the asymmetric version of the Kyrtsou–Labys test. In order to do so, we demeaned both series since they contain only positive values. We find no evidence that positive values of the *EPU* index cause the *EMU* index. Negative values of the former series significantly cause the latter only at 10% level. Moreover, we observe that only positive values of the *EMU* index cause the *EPU* index at the 1% level of significance.

Table 7. Kyrtsou-Labys nonlinear causality test

Relation $(A \to B)$	F-statistic	Probability
$EPU \to EMU$	8.2228	0.0041
$EMU \to EPU$	2988.2	0.0000
$EPU^{+} \to EMU$	1.9490	0.1627
$EMU \to EPU^{+}$	30.6654	0.0000
$EPU^{-} \to EMU$	3.1822	0.0745
$EMU \to EPU^{-}$	584.0920	0.0000
$EMU^{+} \to EPU$	41.8094	0.0000
$EPU \to EMU^{+}$	3.4596	0.0629
$EMU^{-} \to EPU$	0.0246	0.8753
$EPU \to EMU^{-}$	0.0035	0.9526

Notes: we consider the null hypothesis that A does not cause B.

We also conduct time-varying Granger causality tests developed by Sato et al. (2007). We implemented a dynamic Granger causality test (i.e., we test whether the Granger causality between two time series is time-invariant or not), as well as time-varying Granger causality test (i.e., we test if one variable does not cause the other versus one variable causes the other at least at one point in time). The results from the dynamic Granger causality are presented in the upper panel of Table 8. Interestingly, the null hypotheses that the causality from *EPU* to *EMU* and the causality from *EMU* to *EPU* are constant over time are both rejected. Turning now to the time-varying version of the Sato et al. (2007) test as reported in the lower panel of Table 8, we reject the null hypothesis of no causality in favour of the existence of strong time varying bidirectional causality between *EPU* and *EMU*.

These findings support the results from the parameter stability test.

Table 8. Sato et al. (2007) time-varying test

Dynamic Granger causality test	
Hypothesis	P-value
EPU ≠> EMU	0.0000[a]
EMU ≠> EPU	0.0000[a]
Time-varying Granger causality test	
Hypothesis	P-value
EPU ≠> EMU	0.0000[a]
EMU ≠> EPU	0.0000[a]

Notes: The dynamic Granger causality test allows to test whether the Granger causality between two time series is time-invariant or not (i.e., H0: The causality from X to Y is constant over time vs. H1: The causality from X to Y is not constant over time). – The time-varying Granger causality test examines the following hypotheses: H0: X does not cause Y vs. H1: X causes Y at least at one point in time. – Values in table are p-values. [a] indicates the rejection of the null hypothesis of absence of causality at the 1% level.

The analysis so far points to the fact the causality between *EPU* and *EMU* cannot be constant. It therefore becomes important to see at which specific periods there is causality from one to the other, as well as to determine the magnitude and direction of impact. We now turn to the rolling sub-sample causality testing using the residual based modified-LR causality tests with the null hypothesis that that *EPU* does not Granger cause *EMU* and vice versa. The bootstrap p-values of LR-statistics are estimated from the VAR models in equation (A1) using the rolling sub-sample data (see Online Appendix, where the different causality tests are outlined). We set the maximum lags to 8 for a window of 60 and use SIC to choose lags for each window separately. After trimming 60-days observations from the beginning of the full sample, these rolling estimates move from 1985:03:02 to 2013:06:14. We present both the intensity and kernel density plots of the p-values for each sub-sample. Besides, the magnitude of the total effect of *EPU* on *EMU* and that of *EMU* on *EPU* are also calculated and presented.

Figure 2 shows the intensity plot of the bootstrap p-value of the *LR*-statistics for testing the hypothesis that *EPU* does not Granger cause *EMU* while Figure 3 shows the same plot for the hypothesis that *EMU* does not Granger cause *EPU*. These figures are based on counting the p-values falling in a grid of 1 year length in the horizontal axis and 0.1 on the vertical axis. From Figure 2, the p-values of testing that *EPU* does not Granger cause *EMU* have concentrations scattered everywhere. There are only three periods when the intensity is below 0.10. These are around 1993, 2004 and 2006. This shows that *EPU* has predictive power for *EMU* only for these few periods. On the other hand, Figure 3 indicates that the p-values of testing that *EMU* does not Granger cause *EPU* concentrate heavily below 0.10, almost uniformly from 1985 to 2013. There are minor exceptions around 1998, 2003 and 2005. These results point to a stronger evidence of causality from *EMU* to *EPU* over most of the periods. We also present the density plots in Figures A1 and A2 in the Online Appendix. They show where the predictive power is concentrating from a nonparametric estimation. Based on the density plots, we find no evidence that *EPU* can help predict *EMU*, and very strong evidence that *EMU* has predictive power for *EPU*.

The strong causality from *EMU* to *EPU* can be linked to a number of important events that have strong financial and market connection. These include the 1987 stock market crash, the 1997 Asian crisis, the 1997–2000 dot-com bubble, the 2001 9/11 terrorist destruction of the World Trade Center's Twin Towers, the stock market crash of 2000–2002, the stock-market scandals of early 2002 (WorldCom, Enron etc), Lehman Brother's collapse in 2008 due to the continuing subprime mortgage crisis, 2007-2009 global financial crisis and the 2011 debt ceiling debate. These findings suggest that stock market uncertainty increases economic policy uncertainty in the US. The few cases where *EPU* holds predictive power for *EMU* may be associated with a number of events as well. The unanticipated election outcome that saw Bill Clinton as the winner in late 1992 might explain the 1993 effect. The 2004 period effect may reflect the expiration of accelerated capital depreciation allowances. The Federal Reserve somewhat surprising move from a cycle of increasing interest rates, to a cycle of flat rates between June 2004 to August 2007 may also have influenced investors decisions and hence the equity market uncertainty.

Further, we consider the magnitude of the total effect of *EPU* on *EMU* and that of *EMU* on *EPU.* The bootstrap estimates of the sum of the rolling coefficients that *EPU* (*EMU*) does not have significant effect on *EMU* (*EPU*) is 0.0257 (0.0510) with the lower and upper 90% confidence bounds of -0.0121 and 0.0647 (0.0411 and 0.0612). These results show that *EMU* has a larger, positive and significant impact on *EPU* at the 10 percent level. On the other hand, *EPU* has a smaller and insignificant impact on *EMU*.[4]

[4] We also apply the Hafner and Herwartz (2006) causality in variance test, finding that the volatility in equity uncertainty more strongly affects economic uncertainty. Specifically, in terms of volatility: *EMU* $^{1}>$ *EPU*: LM-stat: 486.9296 (p-value=0.000000); *EPU* $^{1}>$ *EMU*: LM-stat: 10.36887 (p-value=0.005603).

Figure 2. Intensity plot of p-value for testing economic policy uncertainty does not Granger cause stock market volatility

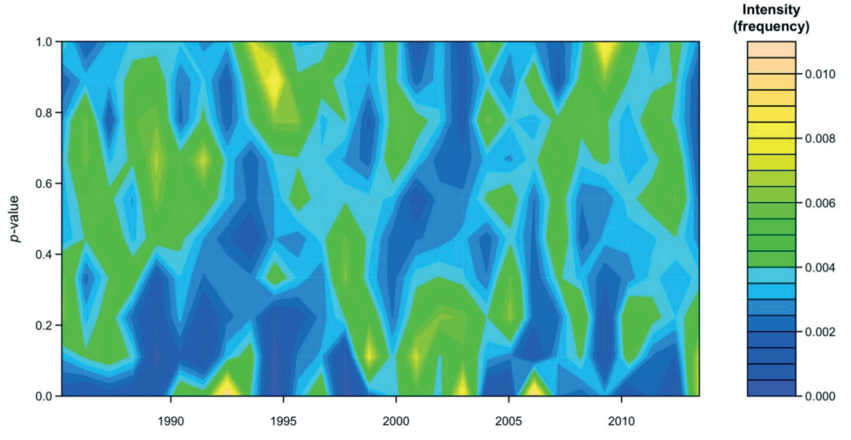
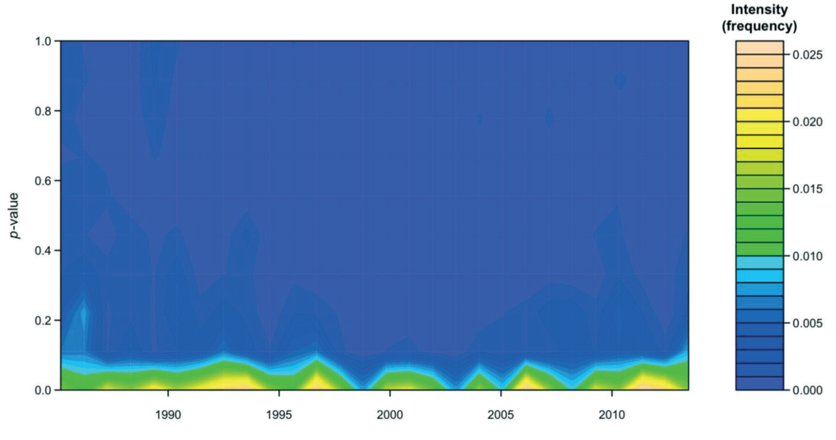


Figure 3. Intensity plot of p-value for testing stock market volatility does not Granger cause economic policy uncertainty



IV. Conclusion

Using new US economic policy uncertainty (*EPU*) and equity market uncertainty (*EMU*) indexes from Baker et al. (2013a), we investigate the causality between the two series with daily data from 1985 to 2013. Empirical results based on the full-sample classical linear causality, heteroscedasticity-consistent covariance matrix estimator, and wild bootstrap versions of the linear test indicate a bi-directional causality between the two series. We conduct parameter stability tests on the full sample standard Granger tests and find that the short run relationship between *EPU* and *EMU* for the US is unstable over the sample period. Therefore, we also examine causality using various nonlinear Granger causality tests. While the Hiemstra and Jones (1994) nonlinear tests suggest evidence of bidirectional causality at higher but uncommon lags, the Diks and Panchenko (2006) nonlinear test suggest evidence of bidirectional causality at all common lags. Using the Kyrtsou–Labys (2006) nonlinear symmetric and asymmetric tests, we observe evidence of bidirectional causality with the symmetric tests while the asymmetric tests indicates that only positive values of *EMU* index cause *EPU* index with strong evidence while only negative values of the *EPU* significantly cause the *EMU* but only at 10% level.

Using the Sato et al. (2007) time-varying Granger causality tests, we show that the causality between *EPU* and *EMU* is not constant over time but rather time-varying. Therefore, we extend our analysis by fully taking structural breaks into account using the bootstrap rolling window approach proposed by Balcilar et al. (2010). The bootstrap rolling window approach allows the causal relationship between series to be time-varying, instead of assuming that a permanent causal relationship holds over the whole period. Using the intensity plots of the bootstrap p-values from the rolling testing approach, we observe that *EPU* has predictive power for *EMU* only for the 1993, 2004 and, 2006 sub-periods while *EMU* has predictive power for *EPU* almost at all sub-periods except for the 1998, 2003 and 2005 sub-periods. Finally, our bootstrap residual-based total effects test based on sum of coefficients suggest a positive and strong significant effect of *EMU* on *EPU*, but smaller and insignificant predictive power from *EPU* to *EMU*.

Our findings provide vital implications for policy makers and investors. First, the uncertainties surrounding the US equity market in recent years may be largely attributed to factors other than economic policy uncertainty (e.g., declined expectations for economic growth), at least based on the time varying tests which take into full account structural changes and regime switches. This is not to say that economic policy uncertainty does not matter for equity market uncertainty. However, the weak causal effect of *EPU* on *EMU* in this study shows that there are other fundamental factors that account for much of the movement in the US stock market. The idea here was to look at two measures of uncertainty based on a similar set of information obtained from newspapers rather than a realized measure of uncertainty for the equity market, given by the squared returns of a specific stock market index for the US, for instance. Also, the objective here was purely trying to analyze what is the dominant source of uncertainty, since identifying which type of uncertainty is the leading variable would imply that we can ignore the other form of uncertainty from an econometric framework that involves, say, other financial and macroeconomic variables in a structural vector autoregressive framework, since the information will already be contained in the leading uncertainty variable. Secondly, the strong in-sample predictive power of *EMU* for *EPU* indicates that both soaring and crashing stock market performance may increase uncertainty about economic policies. Therefore, reducing stock market uncertainties for enhanced economic policy, investor confidence and overall economic growth is important. Future research might test if stock market uncertainty and economic policy uncertainty have out-of-sample forecasting ability for each other, and other macroeconomic and financial variables.

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