Online Appendix

to

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

AHDI NOOMEN AJMI
Salman bin Abdulaziz University

GOODNESS C. AYE
University of Pretoria

MEHMET BalcilAR
Eastern Mediterranean University

GHASSEN EL MONTASSER
Ecole supérieure de commerce de Tunis

RANGAN GUPTA *
University of Pretoria

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The Online Appendix outlines the basics of the linear, nonlinear and time-varying Granger causality tests used to obtain the results reported in the main text of the paper.

A1. The classical linear Granger causality testing

* Rangan Gupta (Corresponding Author): Department of Economics, University of Pretoria, 0002, Pretoria, South Africa; email: rangan.gupta@up.ac.za. Ahdi Noomen Ajmi: College of Science and Humanities in Slayel, Salman bin Abdulaziz University, Kingdom of Saudi Arabia; email: ajmi.ahdi.noomen@gmail.com. Goodness C. Aye: Department of Economics, University of Pretoria, 0002, Pretoria, South Africa; email: goodness.aye@gmail.com. Mehmet Balcilar: Department of Economics, Eastern Mediterranean University, Famagusta, Turkish Republic of Northern Cyprus, via Mersin 10, Turkey; email: mehmet@mmbalcilar.net. Ghassen El montasser: Ecole supérieure de commerce de Tunis, Ecole supérieure de l'économie numérique; email: ghassen.el-montasser@laposte.net. We thank the anonymous referees and the Co-Editor, Professor, Jorge M. Streb for many helpful comments and suggestions. Any remaining errors are however, solely ours.
Granger (1969) defines causality between two stationary series in terms of predictability. Suppose \( x_t \) and \( y_t \) of length \( n \) are \( EMU \) and \( EPU \), respectively. Testing for causal relations between the two series involves estimating a \( p \)-order linear vector autoregressive model, \( VAR(p) \), as follows:

\[
\begin{bmatrix}
    y_t \\
    x_t
\end{bmatrix} = \begin{bmatrix}
    \alpha_1 \\
    \alpha_2
\end{bmatrix} + \begin{bmatrix}
    \phi_{1,1,l} & \phi_{1,2,l} \\
    \phi_{2,1,l} & \phi_{2,2,l}
\end{bmatrix} \begin{bmatrix}
    y_{t-1} \\
    x_{t-1}
\end{bmatrix} + \begin{bmatrix}
    \phi_{1,l,p} & \phi_{1,2,p} \\
    \phi_{2,1,p} & \phi_{2,2,p}
\end{bmatrix} \begin{bmatrix}
    y_{t-p} \\
    x_{t-p}
\end{bmatrix} + \begin{bmatrix}
    \epsilon_{1t} \\
    \epsilon_{2t}
\end{bmatrix},
\]

where \( \epsilon_t = (\epsilon_{1t}, \epsilon_{2t}) \) is a white noise process with zero mean and covariance matrix \( \Sigma \) and \( p \) is the lag order of the process. In the empirical section, the Schwarz Information Criteria (SIC) is used to select the optimal lag order \( p \). \( \alpha_1 \) and \( \alpha_2 \) are constants and \( \phi's \) are parameters. In this setting, the null hypothesis that \( EMU \) does not Granger cause \( EPU \) can be tested by imposing zero restrictions \( \phi_{1,2,i} = 0 \) for \( i = 1, 2, \ldots p \). In other words, \( EMU \) does not contain predictive content, or is not causal, for \( EPU \) if we do not reject the joint zero restrictions under the null hypothesis:

\[
H_0^{EPU} : \phi_{1,2,1} = \phi_{1,2,2} = \ldots = \phi_{1,2,p} = 0,
\]

Analogously, the null hypothesis that \( EPU \) does not Granger cause \( EMU \) implies that we can impose zero restrictions \( \phi_{2,1,i} = 0 \) for \( i = 1, 2, \ldots p \). In this case, \( EPU \) does not contain predictive content, or is not causal, for \( EMU \) if we do not reject the joint zero restrictions under the null hypothesis:

\[
H_0^{EMU} : \phi_{2,1,1} = \phi_{2,1,2} = \ldots = \phi_{2,1,p} = 0,
\]

In either case, the rejection of non-Granger causality means that the movement in one series can be predicted by the other series. If only the hypothesis in either Eq. (2) or Eq. (3) is rejected, then there is a unidirectional causality. In the case that both hypotheses in Eq. (2) and Eq. (3) are rejected, the evidence points to bidirectional causality, which in this context implies a feedback system where \( EMU \) and \( EPU \) react to each other. It is also possible that neither of the two hypotheses are rejected implying that neither of the two variables has predictive content for the other.
A2. Heteroscedasticity-consistent covariance matrix estimator

The HCCME is given by:

\[
\hat{\Omega} = \text{diag}(\hat{\epsilon}_i^2 / (1-h_i)^2),
\]

where \( \hat{\epsilon}_i \) are the estimated residuals from a VAR(p) model and \( h_i \) is the \( i^{th} \) diagonal hat matrix. The HC3 estimator appears to have better performance in small samples. A more extensive study of small sample behavior was carried out by Long and Ervin (2000) which arrive at the conclusion that the HC3 estimator provides the best performance in small samples as it gives less weight to influential observations.

A3. Wild bootstrap procedure

The wild bootstrap procedure is set up as follows:

1. Estimate the VAR(p) model and obtain the Wald statistic for non-causality as described by Hafner and Herwatz (2009).
2. Estimate the restricted VAR(p) model and obtain the estimated parameter values and the restricted residuals \( \hat{\epsilon}_i \).
3. Form a bootstrap sample of \( t \) observations, \( \epsilon_t^* = \hat{\epsilon}_i \eta_t \), where \( \eta_t \) are a sequence of random variables with zero mean and unit variance being also independent of the variables occurring in VAR model. The pseudo disturbances \( \eta_t \) are generated using the Rademacher distribution

\[
\eta_t = \begin{cases} 
-1 & \text{with probability } \pi = 0.5 \\
+1 & \text{with probability } 1 - \pi 
\end{cases}
\]
4. Estimate the VAR($p$) model for each artificial series and compute the Wald statistic in order to obtain the empirical distribution under the null hypothesis.

5. Repeat previous steps 1000 times to form a bootstrapping distribution. The p-value ($p_b$) of the test can be obtained as the proportion of the number of times the Wald test is smaller than the bootstrapped-Wald test.

6. Reject the null if $p_b$ is smaller than the chosen significance level.

A4. **Hiemstra and Jones (1994) nonlinear causality test**

Hiemstra and Jones (1994) proposed a nonparametric statistical method for detecting nonlinear causal relationships based on the correlation integral. To define nonlinear Granger causality, assume that there are two strictly and weakly dependent time series \( \{X_t\} \) and \( \{Y_t\} \), \( t=1,2,3,...T \). Let \( m \)-length lead vector of \( X_t \) be designated by \( X_t^m \), and the \( L_x \)-length and \( L_y \)-length vectors of \( X_t \) and \( Y_t \), respectively, by \( X_{t-L_x}^{L_x} \) and \( Y_{t-L_y}^{L_y} \). For given values of \( m \), \( L_x \) and \( L_y \geq 1 \) and for all \( e > 0 \), \( \{Y_t\} \) does not strictly Granger \( \{X_t\} \) if:

\[
P\left( \left\| X_t^m - X_t^m \right\| < e \right. \left. \left\| X_{t-L_x}^{L_x} - X_{t-L_x}^{L_x} \right\| < e \right) \left. \left\| Y_{t-L_y}^{L_y} - Y_{t-L_y}^{L_y} \right\| < e \right) \right.

\[
= P\left( \left\| X_t^m - X_t^m \right\| < e \right. \left. \left\| X_{t-L_x}^{L_x} - X_{t-L_x}^{L_x} \right\| < e \right) \right.
\]

where \( P(\cdot) \) denotes probability and \( \|\| \) denotes the maximum norm. Eq. (5) states that the conditional probability that two arbitrary \( m \)-length lead vectors of \( \{X_t\} \) are within distance \( e \), given that the corresponding lagged \( L_x \)-length lag vectors of \( \{X_t\} \) are \( e \)-close, is the same as when one also conditions on the \( L_y \)-length lag vectors \( \{Y_t\} \) of being \( e \)-close.

A test based on Eq. (5) can be implemented by expressing the conditional probabilities in terms of the corresponding ratios of joint probabilities:

\[
1 \text{ Strict Granger causality relates to the past of one time series influencing the present and future of another time series (Hiemstra and Jones 1994).}
\[
\frac{C(m + Lx, Ly, e)}{C2(Lx, Ly, e)} = \frac{C3(m + Lx, e)}{C4(Lx, e)},
\]

where \( C1, C2, C3 \) and \( C4 \) are the correlation integral estimator of the joint probabilities which are discussed in detail by Hiemstra and Jones (1994). With an additional index \( n \), Hiemstra and Jones (1994) show that, under the assumption that \( \{X_t\} \) and \( \{Y_t\} \) are strictly stationary, weakly dependent, if \( \{Y_t\} \) does not strictly Granger cause \( \{X_t\} \) then,

\[
\sqrt{n} \left( \frac{C1(m + Lx, Ly, e, n)}{C2(Lx, Ly, e, n)} - \left( \frac{C3(m + Lx, e, n)}{C4(Lx, e, n)} \right) \right)^a \sim N(0, \sigma^2(m, Lx, Ly, e)).
\]

where \( n = T + 1 - m - \max(Lx, Ly) \). See the appendix of Hiemstra and Jones (1994) for both definition and an estimator of \( \sigma^2(m, Lx, Ly, e) \). One-sided (right-tailed) critical values are used, based on this asymptotic result, rejecting when the observed value of the test statistic in Eq. (7) is too large.

To test for nonlinear Granger causality between \( \{X_t\} \) and \( \{Y_t\} \), the test in Eq. (7) is applied to the estimated residual series from the bivariate VAR model. The null hypothesis is that \( Y_t \) does not nonlinearly strictly Granger cause \( X_t \), and Eq. (7) holds for all \( m, Lx, Ly \geq 1 \) and \( e > 0 \). By removing linear predictive power from a linear VAR model, any remaining incremental predictive power of one residual series for another can be considered as nonlinear predictive power (Baek and Brock 1992).

**A5. Diks and Panchenko (2006) nonlinear causality test**

Diks and Panchenko (2005, 2006) argue that their test reduces the risk of over rejection of the null hypothesis of noncausality, observed in the Hiemstra and Jones (1994) widely used test. In this line, Diks and Panchenko (2006)
introduced a new nonparametric test for Granger non-causality which avoids this by replacing the global test statistic by an average of local conditional dependence measures. On the basis of these arguments, we employ both Hiemstra and Jones (1994) and Diks and Panchenko (2006) nonlinear Granger causality tests in this study.

Suppose that \( X_t^{iX} = (X_{t-\ell_X+1}, \ldots, X_t) \) and \( Y_t^{iY} = (Y_{t-\ell_Y+1}, \ldots, Y_t) \) are the delay vectors - where \( \ell_X, \ell_Y \geq 1 \).

The null hypothesis of \( X_t^{iX} \) contain any additional information about \( Y_{t+1} \) is specified as:

\[
H_0 = Y_{t+1} | (X_t^{iX}, Y_t^{iY}) - Y_{t+1} | Y_t^{iY}, \tag{A8}
\]

The null hypothesis becomes a statement about the invariant distribution of the \((\ell_X + \ell_Y + 1)\)-dimensional vector \( W_t = (X_t^{iX}, Y_t^{iY}, Z_t) \), where \( Z_t = Y_{t+1} \). If we ignore the time index and we assume that \( \ell_X = \ell_Y = 1 \), the distribution of \( Z \) - given that \((X, Y) = (x, y)\) - is the same as that of \( Z \) - given \( Y = y \). In other words, \( X \) and \( Z \) are independent conditionally on \( Y = y \) for each fixed value of \( y \), so the joint probability density function \( f_{X,Y,Z}(x,y,z) \) and its marginals must satisfy the following relationship:

\[
\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \cdot \frac{f_{X,Z}(y,z)}{f_Y(y)} \tag{A9}
\]

Diks and Panchenko (2006) show that the restated null hypothesis implies:

\[
q = E[f_{X,Y,Z}(X,Y,Z)f_Y(Y) - f_{X,Y}(X,Y)f_{Y,Z}(Y,Z)] = 0, \tag{A10}
\]
where \( f_{W}(W_i) \) is a local density estimator of a \( d_W \)-variate random vector \( W \) at \( W_i \), defined by \( f_{W}(W_i) = (2\varepsilon_n)^{-d_W} (n - 1)^{-1} \sum_{j \neq i} I_{W_j} \), where \( I_{W_j} = I(\|W_i - W_j\| < \varepsilon_n) \), \( I(\cdot) \) the indicator function and \( \varepsilon_n \) the bandwidth, which depends on the sample size \( n \).

The test statistic, which is a scaled sample version of \( q \) in Eq. (10), is simplified as:

\[
T_n(\varepsilon_n) = \frac{n-1}{n(n-2)} \sum_i \left( \hat{f}_{X,Y,Z}(X_i,Z_i,Y_i)f_Y(Y_i) - \hat{f}_{X,Y,Z}(X_i,Y_i)f_{Y,Z}(Y_i,Z_i) \right)
\]

(A11)

where \( T_n \) consist of a weighted average of local contributions \( \hat{f}_{X,Y,Z}(X_i,Z_i,Y_i)f_Y(Y_i) - \hat{f}_{X,Y,Z}(X_i,Y_i)f_{Y,Z}(Y_i,Z_i) \), which tend to zero in probability under the null hypothesis.

Diks and Panchenko (2006) prove that if \( \varepsilon_n = Cn^{-\beta} (C > 0, 0 < \beta < \frac{1}{3}) \) for one lag that the test statistic in Eq. (11) satisfies the following:

\[
\sqrt{n} \frac{T_n(\varepsilon_n) - q}{S_n} \overset{D}{\to} N(0,1)
\]

(A12)

where \( \overset{D}{\to} \) denotes convergence in distribution and \( S_n \) is an estimator of the asymptotic variance of \( T_n(\cdot) \).

Kyrtsou and Labys (2006) introduced the bivariate noisy Mackey-Glass (hereafter “M-G”) model defined as follows

\[ X_t = \alpha_{11} \frac{X_{t-\tau_1}}{1 + X_{t-\tau_1}} - \gamma_{11} X_{t-1} + \alpha_{12} \frac{Y_{t-\tau_2}}{1 + Y_{t-\tau_2}} - \gamma_{12} Y_{t-1} + \epsilon_t, \quad \epsilon_t \to N(0,1), \quad (A13) \]

\[ Y_t = \alpha_{21} \frac{X_{t-\tau_1}}{1 + X_{t-\tau_1}} - \gamma_{21} X_{t-1} + \alpha_{22} \frac{Y_{t-\tau_2}}{1 + Y_{t-\tau_2}} - \gamma_{22} Y_{t-1} + \vartheta_t, \quad \vartheta_t \to N(0,1), \]

where \( t = \tau, \ldots, N \), \( \tau = \max(\tau_1, \tau_2) \) and \( X_0, \ldots, X_{t-1}, \ Y_0, \ldots, Y_{t-1} \) are given. The \( \alpha_{ij} \) and \( \gamma_{ij} \) are parameters to be estimated, \( \tau_i \) are integer delays, and \( c_i \) are constants which can be chosen via prior selection. In this respect, the best delays, \( \tau_1 \) and \( \tau_2 \), are selected on the basis of likelihood ratio tests and the Schwarz criterion. Different values for \( \tau \) and \( c \) can change dramatically the dynamic behaviour of the process. As pointed by Kyrtsou and Labys (2007) the multivariate transformation of the model does not modify its dynamic properties in a univariate context.

Kyrtsou and Labys (2006) are the first to highlight Granger causality testing in this nonlinear setting by finding nonlinear positive feedback in the relationships between commodity prices and US inflation. Later, this nonlinear Granger causality testing was well explained in Hristu-Varsakelis and Kyrtsou (2008) and Hristu-Varsakelis and Kyrtsou (2010).

The model in Eq. (13) is more appropriate than a simple VAR in case where dependency structures of time series are more complicated and cannot be taken into account by vector autoregressions. The M-G-based causality test is similar to the linear Granger causality test, except that the models fitted to the series are M-G processes. This test is performed by estimating the M-G model parameters under no constraint with ordinary least squares. To examine whether \( Y \) causes \( X \), another M-G model is estimated under the constraint \( \alpha_{12} = 0 \) that reflects our null hypothesis. Such a constraint arises from the fact that when \( Y \) has a significant nonlinear effect on the current value of \( X \) in the model M-G, \( \alpha_{12} \) must be significantly different from zero. Let \( \hat{\omega}_t \) and \( \hat{\nu}_t \) be the residuals obtained respectively by the unconstrained and constrained best-fit M-G models. Thus, the corresponding
sums of residuals squares can be defined as $S_u = \sum_{t=1}^{T} \hat{\omega}_t^2$ and $S_c = \sum_{t=1}^{T} \hat{\omega}_t^2$. Recall that $n_u = 4$ is the number of free parameters in the M-G model and on the other side $n_c = 1$ is the number of parameters required to be zero when estimating the restricted model. Obviously, the test statistic follows a Fisher distribution as

$$S_F = \frac{(S_c - S_u)/n_c}{S_u / (T - n_u - 1)} \rightarrow F(n_c, T - n_u - 1). \quad (A14)$$

where $S_F$ is the test statistic.

What we have just presented is called the Kyrtos-Labys "symmetric" version of the causality between X and Y. The "asymmetric" version of Kyrtos-Labys test can be implemented by conditioning for positive or negative values of the causing series. Note that, since both series contain only positive values, we use demeaned data for this part of the analysis. To keep the matters tractable, suppose that we test, in Eq. (13), whether nonnegative returns in the series X cause the series Y. In this case, an observation $(X_t, Y_t)$ is included in the regression model only if $X_{t-\tau_1} > 0$. The same restricted set of observations is used to compute the model corresponding to the null hypothesis, i.e., $\alpha_{21} = 0$. The procedure is then repeated with the order of the series reversed. That is, one can test whether positive returns in Y cause X and again with the subset of nonnegative returns. Note that conditioning in terms of causing series sign is not the only way to carry out an asymmetric causality. The sign conditioning is frequently chosen because it offers many advantages in practical relevance. Moreover, the nonpositivity, or respectively nonnegativity is not the only possible conditioning way as one can consider other events such as start/end of the week, price movement thresholds.

**A7. Sato, Morettin, Arantes and Amaro (2007) time-varying causality analysis**

The VAR used in Granger causality testing is an adequate approach only in cases when the processes to be modeled are stationary, i.e., the property of the models (expectation, variance, auto/cross-correlations) are invariant in time. These restrictions are not valid in many cases, since the system dynamics in real datasets exhibit changes depending
on external factors (e.g., crisis, governmental interventions, and multinational agreements). In this line, Sato et al. (2007) have introduced a time-varying vector autoregressive modelling, by considering the model parameters as functions of time.

The time-varying vector autoregressive model (Sato et al., 2007) for a multivariate time series \( x_{t,T} = (x_{1t,T}, x_{2t,T}, \ldots, x_{st,T})' \), where \( s \) is the dimension and \( T \) is the number of observations, is given by

\[
x_{t,T} = u(t/T) + \sum_{l=1}^{p} A_l(t/T) x_{t-l,T} + \varepsilon_{t,T},
\]

where \( \varepsilon_{t,T} \) is an error vector of independent random variables with zero mean and covariance matrix \( \Sigma(t/T) \), \( u(t/T) \) is the vector of intercepts and \( A_l(t/T) \) are the autoregressive coefficients matrices with \( l = 1, 2, \ldots, p \).

The time-varying vector autoregressive model is an extension of the conventional VAR model. In this model, each VAR coefficient is described as a function of time. Here, we proposed to decompose these functions by using the B-splines decomposition (Eilers and Marx 1996) because it’s less restrictive than the wavelets.

By using the B-splines time-function decomposition approach, the multivariate time-varying autoregressive model can be represented as:

\[
x_t = \sum_{k=0}^{\infty} \mu_k \psi_k(t) + \sum_{l=1}^{p} \sum_{k=0}^{\infty} A^{(l)}_k(t) \psi_k(t) x_{t-l-1} + \varepsilon_t,
\]

where \( \psi_k(t) \) are B-splines functions (obs: \( \psi_0(t) = 1 \), constant for all \( t \), \( u_k \) are vectors and \( A^{(l)}_k \) \( (l = 1, 2, \ldots, p; k = 0,1,2,\ldots) \) are matrices containing the B-splines expansion coefficients.

The basic idea of the estimation of the time-varying VAR is to represent the decomposition of the intercept and autoregressive time-functions as an approximation using finite linear combination of B-splines functions. In other words, each intercept and autoregressive function is described as a linear combination of \( M \) B-splines functions. By using this expansion, the model is approximated by a linear model with finite parameters, given by

\[
x_t = \sum_{k=0}^{M} \mu_k \psi_k(t) + \sum_{l=1}^{p} \sum_{k=0}^{M} A^{(l)}_k(t) \psi_k(t) x_{t-l-1} + \varepsilon_t,
\]
and the parameters of this model (which are the B-splines expansion coefficients) can then be estimated by using the least squares method in a linear multiple regression, similarly to the estimation of the conventional VAR models. Then, the time-varying Granger causality test can be carried out by testing whether there is at least one autoregressive time-function from $y_t$ to $y_t$ which is different from zero at least in one time point\(^2\).

**A8. Sub-sample bootstrap rolling window causality approach**

Generally, standard causality test statistics for joint parameter restriction and standard asymptotic properties include the Wald, Likelihood ratio ($LR$) and Lagrange multiplier ($LM$) statistics. With non-stationary data, as is typical in macroeconomic studies, these tests may not have standard asymptotic distributions (Toda and Phillips 1993, 1994). To address the problems of non-stationary underlying data, Toda and Yamamoto (1995) proposed a modified Wald test by estimating an augmented VAR model with I(1) variables to obtain standard asymptotic distribution for the Wald test. However, Mantalos and Shukur (1998) and Shukur and Mantalos (2000, 2004) have shown that the modified Wald test does not have correct size in small and medium size samples using Monte Carlo simulations. Hence, it is suggested that an improvement (in terms of power and size) can be achieved by using residual based bootstrap ($RB$) method critical values.

Further, the excellent performance of the $RB$ method over the standard asymptotic tests, regardless of integration order or whether the series are cointegrated or not, has been confirmed in a number of Monte Carlo simulation studies (Shukur and Mantalos 2000; Hacker and Hatemi-J 2006; Balcilar et al. 2010). In light of this we also use the bootstrap $RB$ based modified-$LR$ statistics proposed by Balcilar et al. (2010) to examine the causality between $EPU$ and $EMU$ in the US. The starting point of the bootstrap $RB$ based modified-$LR$ Granger causality is Eq. (1) and the corresponding hypotheses in Eqs. (2) and (3).

Although the presence of structural changes can be detected beforehand and the estimations can be modified to address this issue using several approaches, such as including dummy variables and sample splitting, such an approach introduces pre-test bias. To overcome the parameter non-constancy and avoid pre-test bias, the rolling window sub-sample Granger causality tests, based on the modified bootstrap test is implemented.\(^3\)

The rolling window estimators, also known as fixed-window estimators, are based on a changing subsample.

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\(^2\) Further technical details about the estimation of the time-varying VAR and hypothesis testing can be found in Sato et al. (2007).

\(^3\) The technical details of the bootstrap test are explained in the appendix of Balcilar et al. (2010).
of fixed length that moves sequentially from the beginning to the end of sample by adding one observation at the end of the sample while dropping one at the start. Specifically, given a fixed-size rolling window including \( l \) observations, the full-sample is converted to a sequence of \( T-l \) subsamples, that is, \( r-l+1, r-l, \ldots, T \), for \( r = l, l+1, \ldots, T \). The RB based modified-LR causality is then applied to each subsample, instead of estimating a single causality test for full sample. Possible changes in the causal links between EPU and EMU for US are intuitively identified by calculating the bootstrap p-values of observed LR-statistic rolling through \( T-l \) sub-samples. More importantly, the magnitude of the effect of EPU on EMU as well as that of EMU on EPU is also assessed in this study. The effect of EMU on EPU is defined as the mean of all the bootstrap estimates, that is, \( N_b^{-1} \sum_{k=1}^{p} \hat{\phi}_{12,k}^* \), where \( N_b \) equals the number of bootstrap repetitions. Analogously, the effect of EPU on EMU is calculated as the mean of all the bootstrap estimates, that is \( N_b^{-1} \sum_{k=1}^{p} \hat{\phi}_{21,k}^* \). The estimates \( \hat{\phi}_{12,k}^* \) and \( \hat{\phi}_{21,k}^* \) are the bootstrap least squares estimates from the VAR in Eq. (1) estimated with the lag order of \( p \) determined by the SIC. The 90-percent confidence intervals are also calculated, where the lower and upper limits equal the 5\(^{th}\) and 95\(^{th}\) quantiles of each of \( \hat{\phi}_{12,k}^* \) and \( \hat{\phi}_{21,k}^* \), respectively.
Figure A1. Kernel density of p-value for testing economic policy uncertainty does not Granger cause stock market volatility

Figure A2. Kernel density of p-value for testing stock market volatility does not Granger cause economic policy uncertainty
References


