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Exploring the Relationship between Economic Policy Uncertainty and Financial Stress Indices of the US: Evidence from Fourier Series Approximation Procedures

ABD’nin Ekonomi Politikası Belirsizliği ve Finansal Baskı Endeksleri Arasındaki İlişkinin Araştırılması: Fourier Serisi Yaklaşımı Yöntemlerinden Kanıtlar

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Abstract: We investigate the relationship between economic policy uncertainty (EPU) and St. Louis Fed’s financial stress (FS) indices for the US by using monthly data for the period 2013:1 – 2019:6 and employing linear (conventional) as well as nonlinear (exponential) unit root tests; nonlinear (exponential smooth transition autoregressive- ESTAR) cointegration test initially introduced by Kapetanios, Shin, and Snell (2006) (KSS) and residual-based Fourier cointegration test suggested by Yılancı (2019); conventional and Fourier Granger causality tests as well as asymmetric causality tests. Empirical findings from these procedures can be classified into three major categories: (i) The results from the KSS and residual-based Fourier cointegration analyses confirm each other that a long-run equilibrium exists between EPU and FS. (ii) Estimations from the Fourier Granger causality test that allows for structural breaks of unknown number and form unveiled that there is a one-way causality running from FS to EPU, a finding that contrasts with the one from the conventional procedure which shows a two-way causality. (iii) Finally, the findings from the asymmetric causality testing procedure verified that while two unidirectional causalities exist running from the negative and positive components of FS to the negative and positive components of EPU, respectively; we found no evidence for such asymmetric causality running from EPU to FS. These robust findings we believe shed a bright light on a major policy suggestion. The US policy makers should design policies and regulations aiming at lessening the stress on the financial markets in order to leash the uncertainty associated with economic policies.

Keywords: Economic Policy Uncertainty, Financial Stress, Fourier Series Approximation, Asymmetric Causality, ESTAR Cointegration Test

JEL Classification: C22, E44, E61, G10

Öz: Bu çalışmada, ABD’nin ekonomi politikası belirsizliği (EPU) ve St. Louis Fed’in finansal baskı (FS) endeksleri arasındaki ilişkiler, 2013:1-2019:6 dönemini kapsayan aylık veriler kullanılarak yürütülen doğrusal (geleneksel) ve doğrusal olmayan (üstel) birim kök testleri; Kapetanios, Shin ve Snell (2006) (KSS) tarafından literatüre kazandırılan doğrusal olmayan (üstel yumuşak geçişli otoregresif- ESTAR) eşbütünleşme testi ve Yılancı (2019) tarafindan geliştirilen kalıntı temelli Fourier eşbütünleşme testi; geleneksel Granger nedensellik, Fourier Granger nedensellik ve asimetrik nedensellik testleri aracılığıyla keşfedilmeye çalışılmaktadır. Ampirik analizlerden edinilen bulgular üç ayrı kümede özetlenebilir: (i) KSS ve kalıntı temelli Fourier eşbütünleşme testlerinden sağlanan bulgular birbirini destekler niteliktedir; yani, bu bulgular EPU ile FS arasında uzun dönemli bir denge ilişkisinin varlığını ortaya koymaktadır. (ii) EPU ile FS arasında iki yönlü nedensellik ilişkisinin varlığını gösteren geleneksel Granger nedensellik testinden farklı olarak, bilinmeyen formda ve sayıda yapısal kırılmaları dikkate alan Fourier Granger nedensellik testi, yalnızca FS’den EPU’ya doğru tek yönlü nedensellik ilişkisi olduğuna işaret etmektedir. (iii) Son olarak, asimetrik nedensellik testinden elde edilen sonuçlar, FS’nin negatif ve pozitif bileşeninden EPU’nun sırasıyla negatif ve pozitif bileşenine doğru tek yönlü nedensellik ilişkisinin varlığını kanıtlarken; EPU’dan FS’ye doğru benzer bir asimetrik nedensellik ilişkisinin varlığını desteklememektedir. Bu sonuçların ışığında, ABD’nin ekonomi politikalarının içerdiği belirsizliği dizginlemek amacıyla politika yapıcıların, finansal piyasalardaki baskıyı hafifletecek politika tedbirlerini uygulamaya koyabilecekleri söylenebilir.

Anahtar Kelimeler: Ekonomi Politikası Belirsizliği, Finansal Baskı, Fourier Serisi Yaklaşımı, Asimetrik Nedensellik, ESTAR Eşbütünleşme Testi.

JEL Sınıflandırması: C22, E44, E61, G10

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1. Introduction

The world has undergone major developments during the last couple of decades such as the Arab Spring which led to substantial political turmoil and local economic crises in Middle Eastern countries; 2008 global financial crisis that gave rise to a sovereign debt crisis in several European Union countries which led them to end up with a slump in economic activity, employment, and investment level as well as a deterioration in their fiscal positions in the years following the crisis; the war in Syria which triggered an ongoing refugee crisis; UK's Brexit decision that led the European nations to dispute their prospect regarding the monetary union and the future of their common monetary policies; and the rise of conservative or right-wing political parties that initiated major changes in international relations. Uncertainty associated with economic policies together with stress (or instability) implied by the financial markets are fueled by these events which have global consequences.

Baker et al. (2016) developed an index of economic policy uncertainty (EPU) based on newspaper coverage frequency. Several types of evidence—including human readings of 12000 newspaper articles—indicate that their index proxies for movements in policy-related economic uncertainty. Arouri et al. (2016) noted that EPU implies a non-zero probability of changes in the existing economic policies that determine the rules of the game for economic agents. EPU is transmitted to the financial markets and real economy via several linkages. Firstly, Gulen and Ion (2016) and Bernanke (1983) stress that EPU is one of the most significant issues altering or postponing the economic and financial decisions of the firms, investors, and consumers (or households) which in turn slows down economic activity. Secondly, EPU brings about a rise in the costs of production and financing thus deepens the fall in investments, which in turn lowers economic liveliness. Thirdly, Pastor and Veronesi (2012) showed that the decline in stock prices should be large if uncertainty about the government policy is large, and also if the policy change is preceded by a short or shallow economic downturn. Fourthly, EPU has an effect on volatility, correlation, and risk premia associated with the stock markets. This effect is intensified as the economy gets weaker (see, Pastor and Veronesi, 2013).

Measuring financial market risk represents the flip side of the coin. Policy makers, regulatory institutions, and financial investors need to know the risk associated with financial markets. Widely accepted financial indicators to assess the course of a national economy are generally based on the stock market prices due to the reason that market-based prices are farseeing indicators of future alterations in economic activity and financial situation. Interest rate spreads between the risk-free and risky financial instruments, for instance those between the long- and short-term Treasury bill yields, also referred to as the yield curve, are among the most famous indicators of future economic growth (see, McCracken, 2018; and Owyang and Shell, 2016). Financial market stress (FS, henceforth) has a wider and multidimensional definition compared to financial risk which may be seen in forms such as the default risk, liquidity risk, or inflation risk. The St. Louis Fed’s researchers computed a FS index in 2010 (see, Kliesen and Smith, 2010) that combines many risk indicators into a single index value by employing principal components analysis. They extracted the FS index as the first principal component of 18 different financial stress indicators. Recently, they improved the first version of the FS index to a second version by incorporating daily changes in interest rates and stock prices which replaced the levels of those variables in the principal components computation.

Financial instability affects economic activity through various channels (Lo Duca and Peltonen, 2011). First linkage is explained by Bernanke et al. (1999) by laying emphasis on the financial accelerator. In their model, endogenous developments in credit markets work to amplify and propagate shocks to the macroeconomy. Secondly, according to Bernanke and Lown (1991) a lending slowdown may be the case depending on the weakened balance sheets of the borrowers in the aftermath of the crisis, which in turn paves the way to even a deeper downturn in economic activity. Thirdly, as noted by IMF (2006), the strength of the connection between the financial and real sectors in a national economy is contingent on the development and structure of the financial system.

The relationship connecting FS and/or EPU with various real or financial variables is investigated by numerous studies by employing distinct empirical methodologies. For instance, Antonakakis et al. (2014), Gupta et al. (2016), and Balcılar et al. (2016a) examined the connection between EPU and real production. Karnizova and Li (2014), Liu and Zhang (2015), Arouri et al. (2016), Balcılar et al. (2016b), Bekiros et al. (2016), Dakhlaoui and Aloui (2016), and more recently Asgharian et al. (2018) analyzed the relationship between EPU and financial markets and/or volatility. In addition to these, there is also a voluminous literature on the association of EPU and/or FS with various commodity and energy markets or prices. More specifically, Nazlıoğlu et al. (2015) and Balcılar et al. (2017) investigated the relation between FS and oil prices; and EPU and oil markets, respectively. Balcılar et al. (2016c) explored the connection between EPU and gold prices. Reboredo and Uddin (2016) illustrated the relationship of both EPU and FS with energy and metal markets. The literature on the relationship between FS and EPU is thinner compared to the one depicted above (see, Hammoudeh and McAleer, 2015; Sun et al., 2017; Liow et al., 2018; and most recently, Tiwari et al., 2020).

This paper examines the relationship between FS and EPU for the US by using monthly data covering the period 2013:1 – 2019:6 and employing linear (conventional) as well as nonlinear (exponential) unit root tests; nonlinear (exponential smooth transition autoregressive- ESTAR) cointegration test initially introduced by Kapetanios, Shin, and Snell (2006) (KSS) and residual-based Fourier cointegration test suggested by Yılancı (2019); conventional and Fourier Granger causality tests as well as asymmetric causality tests. As far as the authors of this particular study are concerned there appears to be no previous study which investigates the relationship between FS and EPU by adopting Fourier series approximation procedures which allow for structural breaks of unknown number and form which generate nonlinearities. Another novelty associated with our empirical findings is that the existence of a causal linkage between the positive components of FS and those of EPU as well as that between the negative components of the variables is unveiled. This finding is crucial in the sense that it serves as a robustness check for both conventional- and Fourier-type Granger causality tests.

The organization of the study is as follows: Second section presents the model and data. Third section illustrates the econometric methodologies. Fourth section discusses the empirical findings and finally, fifth section concludes.

2. Data

We employed monthly FS and EPU series for the US covering the period 2013:1-2019:6. FS and EPU series are calculated by Kliesen and Smith (2010) and Baker et al. (2016), and released by “fred.stlouisfed.org” and “policyuncertainty.com” websites, respectively.

3. Econometric Methodology

A structural break changes the mean and/or time trend components of a time series at any point. Thanks to Perron’s (1989) groundbreaking paper we now know that structural breaks in a data series should be taken into consideration in both unit root testing procedures and cointegration analyses on the grounds that they lead to unreliable parameter estimates and thus misleading results when they are disregarded. Gregory and Hansen (1996) and Hatemi-J (2008) are other influential works that allow for breaks in the investigation of significant long-run cointegration relationships. However, they share the same flaw that the number of breaks is determined prior to the analysis by employing dummy variables. Moreover, another defect is that those dummies capture only sharp changes, not smooth ones. Tsong et al. (2015)

stresses that a Fourier component can approximate the structural breaks well, as suggested by Gallant (1981), Becker et al. (2006), and Enders and Lee (2012). By considering all of these contributions, we adopted a Fourier series approximation both in the cointegration and Granger causality testing procedures inasmuch as it considers structural breaks of unknown number and form, which gave us the opportunity to best describe the real-life data series as well as the association amongst them.

3.1. Residual-based Cointegration Analysis with a Fourier Series Approximation

Tsong et al. (2015) and Banerjee et al. (2017) are among the prominent studies that incorporate Fourier series components into cointegration equations. Similarly, Yılancı (2019) suggested a residual-based cointegration method with a Fourier series approximation as an alternative to the conventional Engle-Granger cointegration analysis which is initially suggested by Engle and Granger (1987). Yılancı's (2019) testing procedure begins with estimating Eq. (1).

$$y_t = d(t) + \beta' X_t + \varepsilon_t \tag{1}$$

where $t = 1, 2, \dots, T$. The dependent variable y_t is scalar, and $X_t = (x_{1t}, x_{2t}, \dots, x_{nt})'$ is a $(nx1)$ vector of independent variables. $d(t)$ is a deterministic function of t that can be approximated using the following Fourier expansion with a single-frequency component:

$$d(t) = \delta_0 + \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \varphi_1 \cos\left(\frac{2\pi kt}{T}\right) \tag{2}$$

where δ_0 is the traditional deterministic component that has a constant with or without a linear term; T implies the number of observations; and k stands for the optimal number of breaks, i.e. frequency, that minimizes the sum of squared residuals. t shows the time trend, and π equals to 3.1416. If the coefficients of the trigonometric components, i.e. γ_1 and φ_1, are proved to be zero or the F-statistic value for Eq. (1) points to the insignificance of the equation, Fourier approximation should be replaced by the conventional Engle-Granger approach. Substituting Eq. (2) into Eq. (1) yields Eq. (3).

$$y_t = \delta_0 + \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \varphi_1 \cos\left(\frac{2\pi kt}{T}\right) + \beta' X_t + \varepsilon_t \tag{3}$$

Having extracted the residuals of Eq. (3), we conducted Augmented Dickey-Fuller unit root test, which is represented by Eq. (4), to see whether that residual series is stationary. The null of no cointegration is rejected when the residual series turned out to be stationary.

$$\Delta\hat{\varepsilon}_t = \rho\hat{\varepsilon}_{t-1} + \sum_{i=1}^{p} \theta_i \Delta\hat{\varepsilon}_{t-i} + u_t \tag{4}$$

where $u_t \sim i.i.d.(0, \sigma^2)$. The test statistic τ_{FEG} is computed as follows:

$$\tau_{FEG} = \frac{\hat{\rho}}{se(\hat{\rho})} \tag{5}$$

where $\hat{\rho}$ and $se(\hat{\rho})$ represent the ordinary least squares estimator of ρ and the standard error of $\hat{\rho}$, respectively.

3.2. Granger Causality Tests

3.2.1. Conventional Granger Causality Test

Having seen that the variables under investigation are integrated of the same order, meaning that they both become stationary after first differencing, one can proceed with the Granger causality testing procedure by employing those stationary data series. Granger (1969) suggested the following simple causality model:

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t$$

$$Y_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \eta_t \qquad (6)$$

Eq. (6) hinges on the idea that each of the two stationary and zero mean time series, i.e. X_t and Y_t, is regressed on the lagged values of its own and those of the other. ε_t and η_t represent uncorrelated white-noise error terms.

3.2.2 Fourier Granger Causality Test

As noted by Enders and Jones (2016), when the structural break is sharp it is convenient to use a dummy variable to estimate the exact date and magnitude of the break. However, when the break is a smooth function of time, an alternative approach should be adopted. Following Gallant (1981), Enders and Jones (2016) employed a flexible Fourier series approximation, represented by Eq. (7). They substitute Eq. (7) into the conventional Granger causality framework, i.e. Eq. (6), which yields Eq. (8). Note that a similar practice is followed when substituting Eq. (2) into Eq. (1).

$$d(t) = a_0 + a_1 \sin\left(\frac{2\pi kt}{T}\right) + b_1 cos(\frac{2\pi kt}{T}) \qquad (7)$$

$$Y_t = \beta_0 + \beta_1 \sin\left(\frac{2\pi kt}{T}\right) + \beta_2 \cos\left(\frac{2\pi kt}{T}\right) + \sum_{i=1}^{p} \theta_i Y_{t-i} + \sum_{i=1}^{p} \delta_i X_{t-i} + \varepsilon_t$$

$$X_t = \gamma_0 + \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + \sum_{i=1}^{p} \tau_i Y_{t-i} + \sum_{i=1}^{p} \varphi_i X_{t-i} + u_t \qquad (8)$$

4. Empirical Findings and Inference

We employed Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test as linear procedures to determine the time series properties of FS and EPU[1]. According to the results shown in Table 1, the series are proved to be nonstationary at the level. They become stationary having taken the first difference, i.e. they are integrated of order one [$\sim I$ (1)].

[1] For more information concerning ADF, PP, and KPSS unit root tests see, Dickey and Fuller (1979), Phillips and Perron (1988), and Kwiatkowski et al. (1992), respectively.

Table 1. Conventional (linear) unit root test results

	ADF test		PP test		KPSS test	
	Constant	Constant and trend	Constant	Constant and trend	Constant	Constant and trend
$\boldsymbol{FS}$	-2.0919 [3]	-2.0127 [3]	-2.4398 [6]	-2.3735 [6]	0.2050 [6]**	0.1959 [6]
$\boldsymbol{EPU}$	-1.6927 [4]	-2.9735 [4]	-5.4067 [1]***	-6.4448 [6]***	0.7673 [4]	0.1538 [2]
$\boldsymbol{\Delta FS}$	-6.5749 [2]***	-6.5838 [2]***	-8.7087 [14]***	-8.8104 [15]***	0.1227 [13]**	0.0793 [14]**
$\boldsymbol{\Delta EPU}$	-8.3690 [3]***	-8.3582 [3]***	-23.1364 [3]***	-25.4014 [3]***	0.3223 [8]**	0.1321 [6]**

Note: Values in brackets represent the optimal lag length. Symbols *, **, and *** stand for statistical significance at 10%, 5%, and 1%, respectively.

We also employed a nonlinear unit root testing method suggested by Kapetanios, Shin, and Snell (2003) (KSS)[2]. KSS test tests the null of nonstationarity against the alternative of a nonlinear and globally stationary ESTAR process. The estimations indicate that the null hypothesis cannot be rejected for the two series at the level. KSS test results, illustrated in Table 2, are in line with those from the conventional procedures confirming that the findings are robust.

Table 2. KSS unit root test results

	KSS test	
	De-meaned	De-trended
$\boldsymbol{FS}$	-2.4267 [3]	-2.3708 [3]
$\boldsymbol{EPU}$	-1.6234 [4]	-2.7826 [4]
$\boldsymbol{\Delta FS}$	-7.3213 [0]***	-7.3388 [0]***
$\boldsymbol{\Delta EPU}$	-4.9199 [1]***	-4.7946 [1]***

Note: Values in brackets represent the optimal lag length. Symbols *, **, and *** stand for statistical significance at 10%, 5%, and 1%, respectively. Critical values at 1%, 5%, and 10% significance levels for the de-meaned and de-trended models are -3.48, -2.93, and -2.66, and -3.93, -3.40, and -3.13, respectively.

Since the findings from conventional and ESTAR-type unit root tests confirm that FS and EPU series are $I(1)$, we can continue with the estimation of the nonlinear KSS and residual-based Fourier cointegration models to investigate the empirical validity of a long-run equilibrium between FS and EPU[3]. KSS and residual-based Fourier cointegration test results are shown in Table 3 and Table 4, respectively. Both test results verified that there exists a long-run relationship for Model I, where the independent and dependent variables are FS and EPU, respectively. Besides, such a long-run equilibrium is not the case for Model II, where these two variables are interchanged. We demonstrated that the parameter estimates from both KSS and residual-based Fourier cointegration tests are robust, since these two cointegration techniques generated parallel outcomes.

[2] For more information concerning the ESTAR unit root test see, Kapetanios et al. (2003)
[3] For more information concerning the ESTAR cointegration test, see Kapetanios et al. (2006).

Table 3. KSS cointegration test results

	Test statistic	Critical value		
		1%	5%	10%
Model I: $\boldsymbol{EPU_t = \delta_0 + \delta_1 FS_t + \omega_t}$	-5.5284 [0]***	-3.84	-3.28	-2.98
Model II: $\boldsymbol{FS_t = a_0 + a_1 EPU_t + u_t}$	-2.6398 [0]	-3.84	-3.28	-2.98

Note: Values in brackets represent the optimal lag length. Symbols *, **, and *** stand for statistical significance at 10%, 5%, and 1%, respectively.

Table 4. Residual-based Fourier cointegration test results

	Frequency (k)	SSR	Test statistic	F statistic
Model I: $\boldsymbol{EPU_t = \delta_0 + \delta_1 FS_t + \delta_2 \sin\left(\frac{2\pi kt}{T}\right) + \delta_3 \cos\left(\frac{2\pi kt}{T}\right) + \omega_t}$	1	4.094403	-7.593584 [0]***	17.24214***
Model II: $\boldsymbol{FS_t = a_0 + a_1 EPU_t + a_2 \sin\left(\frac{2\pi kt}{T}\right) + a_3 \cos\left(\frac{2\pi kt}{T}\right) + u_t}$	1	4.578060	-3.919229 [0]	26.27553***

Note: Values in brackets represent the optimal lag length. Symbols *, **, and *** stand for statistical significance at 10%, 5%, and 1%, respectively. Critical values for $T = 78$, $k = 1$, and $n = 1$ are -4.906, -4.302, and -3.988 at 1%, 5%, and 10% significance levels, respectively.

To sum up, we showed that estimation results for Model I provide evidence in favor of a cointegration between FS and EPU. For this reason, we estimated both the long-run and error correction models by the Fully Modified Ordinary Least Squares (FMOLS) estimator and displayed the findings in Table 5 and Table 6, respectively. According to the findings reported in Table 6, we see that the coefficient of the error correction term is negative and statistically significant, i.e. -0.7609, indicating that there exists a tendency for a long-run equilibrium to be restored between FS and EPU. Error correction term is a short-run component, but it brings the long-run information into the cointegration equation as it is obtained from the long-run model in the form of lagged residuals. Depending on the estimates from the long-run model depicted in Table 5, one can conclude that a 1% rise in FS brings about a 0.40% increase in EPU. Though the economic theory generally deals with the long-run correlations, we also proved that FS affects EPU positively also in the short run.

Table 5. Long-run equation estimation results

Dependent variable: EPU	Model I
Independent variables	Coefficients
c	5.0168 (108.2873)
FS	0.4059*** (4.319619)
$\sin(2\pi kt/T)$	-0.2130*** (-5.914540)
$\cos(2\pi kt/T)$	0.1735*** (3.728635)
R^2	0.42

Note: Values in parentheses represent t-statisitcs. Symbols *, **, and *** stand for statistical significance at 10%, 5%, and 1%, respectively.

Table 6. Cointegration (short-run) equation estimation results

Dependent variable ΔEPU	Model I
Independent variables	Coefficients
c	-0.0019 (-0.0869)
ΔFS	0.3110*** (2.7286)
ECT	-0.7609*** (-7.8455)
R^2	0.4768

Note: Values in parentheses represent t-statisitcs. Symbols *, **, and *** stand for statistical significance at 10%, 5%, and 1%, respectively.

Having established that there is a cointegration relationship between FS and EPU, we can now proceed with Granger causality testing procedures depending on the principle that at least one (either a unidirectional or a bidirectional) causality relationship exists between two variables when they turn out to be cointegrated. We employed both conventional and Fourier Granger causality tests and reported the findings in Table 7[4].

[4] Findings from the procedures followed to determine the optimal lag length in conventional Granger causality analysis are presented in the Appendix.

Table 7. Conventional and Fourier-type Granger causality test results

Procedures		Null	Wald statistic	Probability	Optimal lag length	Optimal frequency number (k)
Conventional (linear)	Granger (1969) causality	$EPU \neq> FS$	8.6324	0.0710	4	0
		$FS \neq> EPU$	9.1019	0.0586	4	0
Nonlinear (Enders and Jones, 2016)	Fourier Granger causality (single frequency)	$EPU \neq> FS$	7.105	0.529	8	3
		$FS \neq> EPU$	16.437	0.059	8	3
	Fourier Granger causality (cumulative frequency)	$EPU \neq> FS$	4.060	0.847	8	3
		$FS \neq> EPU$	15.599	0.078	8	3

Note: Probability values for Fourier Granger causality tests are determined by 10000 bootstrap replications. $A \neq> B$ represents the null of "A does not Granger cause B". First differenced, i.e. stationary series are used.

The findings document that the conventional and Fourier Granger causality tests provided conflicting results. More precisely, Table 7 uncovers that the findings from the conventional causality test point to a bidirectional causality, whereas the Fourier-type causality test results suggest only a unidirectional causality running from FS to EPU. This outcome is consistent with our expectations as the latter test has a more advanced specification which enables modelling genuine causality under structural breaks. The findings from the Fourier causality technique parallel those from the Fourier-type residual-based cointegration method, uncovering that the parameter estimates from these two different but statistically and mathematically coherent methodologies are robust.

An asymmetric causality test initially introduced by Hatemi-J (2012) is also applied for robustness check purposes[5]. The findings, shown in Table 8, are compatible with those from the Fourier causality tests. To put it more clearly, we found evidence for the existence of a causal linkage between the positive components of FS and those of EPU, running from the first to the latter and not vice versa. In addition, the findings suggested also that a causal relationship is also the case between the negative components of FS and those of EPU, running from the first to the latter and not vice versa.

[5] For more information concerning the asymmetric causality test, see Hatemi-J (2012).

Table 8. Asymmetric causality test results

Procedures		Null	Test statistic	Critical Value			
				p	1%	5%	10%
Asymmetric causality test	$EPU \neq> FS$	$EPU^{+} \neq> FS^{+}$	2.021	1	7.467	3.994	2.732
		$EPU^{-} \neq> FS^{-}$	0.130	1	7.120	3.875	2.750
	$FS \neq> EPU$	$FS^{+} \neq> EPU^{+}$	3.596*	1	9.237	4.425	2.891
		$FS^{-} \neq> EPU^{-}$	12.885***	1	8.264	4.157	2.822

Note: p which is determined by the Hatemi-J Criterion (HJC) shows the optimal lag length of the VAR model. Symbols *, **, and *** stand for statistical significance at 10%, 5%, and 1%, respectively.

5. Conclusion

Today's world can well be characterized by the words "uncertainty" and "instability" on the grounds that substantial global developments which have macroeconomic, financial, political, or social consequences ceaselessly deepen the financial risks and economic policy uncertainties that concern both the real and financial sectors of open national economies. For this reason, the relation between these two key concepts, financial instability and economic policy uncertainty, emerges as an important research question for the finance and macroeconomics scholars and as a problematic for the policy makers and investors. This study sheds light on this issue from the perspective of the largest economy in the world, the US.

More specifically, we investigate the relationship between the financial stress (or instability) (FS) and economic policy uncertainty (EPU) indices of the US by using monthly data for the period 2013:1-2019:6 and conducting linear (conventional) as well as nonlinear (exponential) unit root tests; nonlinear (exponential smooth transition autoregressive-ESTAR) cointegration test (KSS) and residual-based Fourier cointegration test; conventional and Fourier Granger causality tests as well as asymmetric causality tests. The bunch of testing procedures adopted in this study serves as a robustness and plausibility check for the parameter estimates, since this practice gives us the chance to compare the findings from different unit root, cointegration and causality methodologies.

According to the findings from both nonlinear (KSS) and residual-based Fourier cointegration methods, there exists a long-run equilibrium between FS and EPU, where the first has a positive impact on the latter. Furthermore, Fourier and asymmetric causality testing procedures provided consistent findings and they also support the findings from the cointegration tests, an outcome evidencing that our parameter estimates are robust. These findings we believe shed a bright light on a major policy suggestion. The US policy makers should implement policies and regulations aiming at mitigating the stress on the financial markets so as to leash the uncertainty associated with economic policies, since the first is proved to have a substantial impact on the latter, according to our estimation results.

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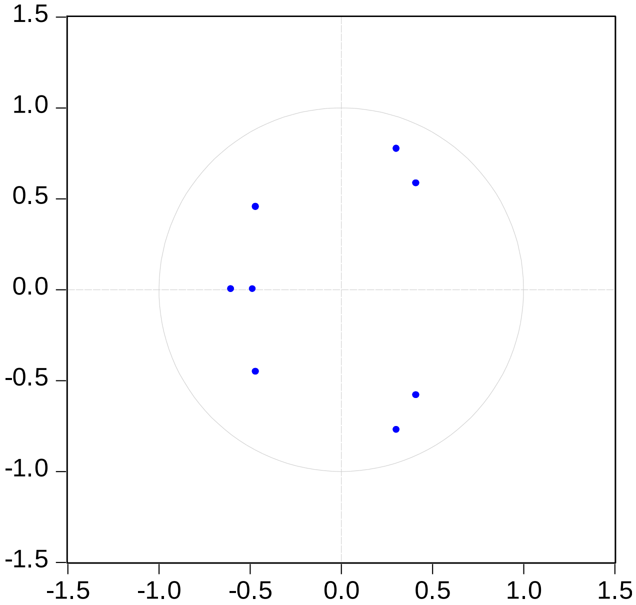
APPENDIX

A1. Determination of the lag length for conventional Granger causality test

Lag	Log Likelihood	Likelihood Ratio test statistic	Final Prediction Error	Akaike information criterion	Schwarz information criterion	Hannan-Quinn information criterion
0	3.113802	NA	0.003321	-0.031823	0.032420	-0.006305
1	11.61590	16.27544	0.002920	-0.160454	0.032274*	-0.083900
2	15.45813	7.135577	0.002935	-0.155947	0.165267	-0.028357
3	22.71407	13.06068	0.002676	-0.248973	0.200726	-0.070347
4	29.36615	**11.59362***	**0.002485***	**-0.324747***	0.253437	**-0.095085***
5	29.96134	1.003328	0.002745	-0.227467	0.479203	0.053231
6	31.98023	3.287900	0.002915	-0.170864	0.664292	0.160870
7	32.73417	1.184767	0.003214	-0.078119	0.885522	0.304651

Note: Symbol * indicates statistical significance at 5%. Optimal lag length is determined as 4, since majority of the tests point to 4 as the optimal lag length.

A2. Display of Inverse Roots of AR Characteristic Polynomial



A3. Autocorrelation LM test results

Lags	LM-Statistic	Probability
1	5.970474	0.2014
2	4.735396	0.3155
3	2.398746	0.6629
4	1.540264	0.8195
5	0.700228	0.9513
6	3.745674	0.4415
7	0.806795	0.9375
8	4.437384	0.3500
9	0.565385	0.9668
10	1.632155	0.8030
11	2.170884	0.7044
12	2.869757	0.5799

A4. VAR residual heteroscedasticity test results

Joint test:		
Chi-squared	Degrees of freedom	Probability
44.95110	48	0.5985

Individual components:					
Dependent	R-squared	F (16,56)	Probability	Chi-squared (16)	Probability
res1*res1	0.218973	0.981282	0.4889	15.98506	0.4540
res2*res2	0.316946	1.624049	0.0925	23.13709	0.1101
res2*res1	0.105496	0.412785	0.9733	7.701236	0.9573

Note: res1 and res2 represent residual terms.