5. VISITING THE ECONOMIC POLICY UNCERTAINTY SHOCKS - ECONOMIC GROWTH RELATIONSHIP: WAVELET-BASED GRANGER-CAUSALITY IN QUANTILES APPROACH

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Abstract

In this paper, the wavelet-based Granger-causality in quantiles method is employed to investigate the multi-scale causality between China's economic policy uncertainty shocks and economic growth. The results indicate that i) a single-directional causality from growth to economic policy uncertainty shocks in the shorter term and a strong bi-directional causality in the longer term between economic policy uncertainty shocks and economic growth using a conditional mean analysis, ii) the nonlinear causal relationship between economic policy uncertainty shocks and economic growth is time-varying in different quantiles and different timescales, and iii) a significant single-directional nonlinear causality from growth to economic policy uncertainty shocks for some τ- quantiles in D1-D4. The results of this paper show that economic policy uncertainty not only provides a new method to predict economic growth, but also warns us that the accumulation of economic policy uncertainty would increase economic crisis. Thus, it is vital for the policymakers to reduce economic policy uncertainty so as to keep the stability of economic growth. Overall, this paper offers a new methodological perspective, from different timescales and different quantiles, to deeply analyze the causality between macroeconomic variables.

Keywords: economic policy uncertainty shocks, economic growth, Granger causality, wavelet, different quantiles, different timescales

JEL Classification: C32; G11; E60

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1. Introduction

Since Baker *et al.* (2016) provided a quantitative indicator to measure policy uncertainty and constructed the economic policy uncertainty (hereafter EPU) index, it is an increasing amount of appealing researches on the EPU index. Some researches focus on its prediction application, using the EPU index to predict real returns of the US sustainable investments index (Antonakakis *et al.,* 2016) and considering whether the EPU index has the ability to predict the equity premium in the US (Gupta *et al*., 2014), or the future US precessions (Karnizova and Li, 2014).

In addition, using the EPU index can help the investors or policy makers to make a wiser decision in many fields. For instance, Liu and Zhang (2015) investigate the predictability of stock market with the EPU being used as an additional variable, and they have found that EPU could help to improve the existing prediction model. Ajmi *et al.* (2015) use Granger-causality method to test the correlation of the EPU and equity market uncertainty in the U.S. Balcilar *et al.* (2016) use a nonparametric causality test in quantiles to investigate the relationship between EPU and a total of sixteen U.S. dollar-based exchange rates, and the findings show that the potential correlation can help to make a better decision in exchange markets.

Though lots of researches have considered the importance of EPU, less literature is related to how EPU influences macro-economic field (see literature review part). So in this paper we investigate another interesting but not yet too much touched issue: Do the EPU shocks have any significance on economic growth?

2. Literature Review

Aisen and Veiga (2013) use a linear dynamic panel data models with system-GMM method and reach a point that political instability leads to a lower rate of productivity growth as well as GDP per capital. Baker *et al.* (2012) argues that with a high EPU, there is a consequence that fall of output and employment in the next 36 months. Dima *et al.* (2017) use a nonlinear ARCH model to investigate the uncertainty impact on economic activity. Salamaliki (2015) uses Granger causality to test the role of EPU in aggregate real economic activity. Fatima and Waheed (2014) consider the relationship between EPU and growth performance in a macroeconomic model and get the conclusion that EPU would decline investment and economic growth. Moreover, EPU would produce a further influence to them in the future. While, Sanjai *et al.* (2013) focus on how cross-country EPU makes sense to Indian investment and economy, which show a negative correlationship between cross-county EPU and stock market.

Besides, it is also highlighted as an important factor to some mac-economic activities, such as doing researches on US's unemployment from the perspective of EPU index (Caggiano *et al*., 2017), on interdependence between a country's stock market and global oil market (Kang *et al.*, 2015). There are also plenty of researches on how EPU affect micro-economic field, such as enterprise's investment decision (Wang *et al.*, 2014; Jens, 2017), asset prising (Brogaard, 2014), stock returns (Li *et al*., 2016), bank liquidity creation (Berger, 2017) and so on.

Compared with them, this paper is different in two ways. On one hand, we want to discuss the change of EPU not by the index itself but by the alternation of the index, for the reason that the change of EPU can be better to quantify the EPU shocks and be more suitable for the research purpose. On the other hand, we find it is rare to use the Granger-causality method to investigate the relationship between EPU shocks and economic growth. Hence, we want to use the Granger-causality method to examine the effects between EPU shocks and economic growth in China to complement the previous literatures. Besides, wavelet method is a good way to tackle the financial series from different timescales (Shahbaz *et al.*, 2015), and it is widely used in researches on Granger-causality test. Rua and Nunes (2009) use this method to examine the international comovement of stock market returns. Benhmad (2012) uses wavelet method modeling nonlinear granger causality between the oil price and US dollar. Alzahrani *et al.* (2014) use this method to investigate the linear and non-linear grange causality between oil futures and spot markets. Jiang *et al.* (2015) study the correlationship between money growth and inflation in china through wavelet analysis. Chu *et al.* (2016) use wavelet-based approach to test a non-linear Granger causality between stock returns and investor sentiment for Chinese stock market. Ko and Lee (2015) find that wavelet analysis can help to find the multi-scale relationship between policy uncertainty and stock prices over time in ascending frequency cycles.

We contribute to the literatures above in two ways. Firstly, some existing literatures only take day time or week time horizons of causality into consideration on the EPU (see Balcilar *et al.*, 2016), or only form single frequency or single quantile to investigate the relationship between variables (see Chu *et al.*, 2016). We, however, use a wavelet-based method to investigate different time horizons (Gencay and Signori, 2015) of causality between EPU shocks and economic growth. Not only the conventional mean Granger-causality test but also Granger-causality in quantiles, proposed by Troster (2016), are used, which is helpful to analyze the relationship between variables from different quantiles (Troster *et al.*, 2018). This is the main contribution of this paper, which is to provide a novel methodological perspective, from both different timescales and different quantiles to deeply analyze the causality of macroeconomic variables.

Secondly, as too many studies on the causality analysis of EPU in the developed markets (see Antonakakis *et al.*, 2016; Li *et al.*, 2015), few researches done on the emerging markets can be found. Hence we provide an additional insight on the causality analysis between the China's EPU shocks and economic growth. Meanwhile, this study shows some implication of the newly derived results for decision makers to increase the information efficiency for them, and fill the gap of literatures on the multi-scale causality between China's EPU shocks and economic growth. To our best knowledge, the contents have hardly been found in other studies before.

3. Methodology

3.1 The Wavelet Method

The wavelet method is used to decompose timeseries into different frequency data, and it can help to analyze the long-term and short-term relationship between two timeseries (see Alzahrani *et al.*, 2014; Chu *et al.*, 2016; Lee and Lee, 2016; Rua and Nunes, 2009). To describe the wavelet transform method briefly, we denote the raw time series *y(t)* with the following structure:

$$y(t) = \sum_k s_{J,k}\omega_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \ldots + \sum_k d_{1,k}\psi_{1,k}(t) \quad (1)$$

where: *J* is the decomposition level; *k* is the translation parameter; $\omega_{J,k}(t)$ and $\psi_{J,k}(t)$ are parent wavelet pairs, father wavelet and mother wavelet respectively.

Father wavelet is used to calculate the trend components, and mother wavelet is applied for all the deviations from trend. $s_{J,k}$ and $d_{J,k}$ represent the scaling and detail coefficients:

$$s_{J,k} = \int \omega_{J,k}(t)f(t)dt \tag{2}$$

$$d_{J,k} = \int \psi_{J,k}(t)f(t)dt \tag{3}$$

where: $s_{J,k}$ represents the smooth behavior of time series; $d_{J,k}$ represents the scale deviation from the smooth process. Detail and scaling coefficients with basis vector from the level J= 1…j are linked with a location t and scale $[2^{J-1}, 2^J]$.

We use a maximal overlap discrete wavelet transform algorithm, MODWT (Gencay and Signori, 2015), to decompose the raw data on quarterly information and investigate the EPU shocks - economic growth relationship.[4] Based on that, we can obtain the detailed coefficients of father wavelet and scaling coefficients of mother wavelet:

$$S_J(t) = \sum_k s_{J,k}\omega_{J,k}(t) \tag{4}$$

$$D_J(t) = \sum_k d_{J,k}\psi_{J,k}(t) \tag{5}$$

Considering all the coefficients, the raw data $y(t)$ can be described as follows.

$$y(t) = D_1(t) + \ldots + D_J(t) + S_J(t) \tag{6}$$

where: $D_J(t)$ is the recomposed data; $S_J(t)$ is the residue of the raw data.

3.2 The Granger-causality in Quantiles

As is shown by Granger (1969), given the past Y_t, if past Z_t can't predict future Y_t, series Z_t can't be Granger-cause of another series Y_t. Suppose there is an explanatory vector $I_t \equiv (I_t^Y, I_t^Z) \in \mathbb{R}^d, d = s + q$, where I_t^Z is the past information set of Z_t, $I_t^Z := (Z_{t-1}, \ldots, Z_{t-q})' \in \mathbb{R}^q$. The null hypothesis of Granger non-causality from Z_t to Y_t can be defined as follows:

$$H_0^{Z \nrightarrow Y}: F_Y(y|I_t^Y, I_t^Z) = F_Y(y|I_t^Y), \text{for all } y \in \mathbb{R} \tag{7}$$

where: $F_Y(\cdot\,|I_t^Y, I_t^Z)$ is the conditional distribution function of Y_t given (I_t^Y, I_t^Z). We make an assumption that the null hypothesis of equation (7) is a Granger non-causality in distribution. Lots of papers proposed tests for Granger non-causality in mean due to the complicated procession to estimate the conditional distribution. If

$$E(Y_t|I_t^Y, I_t^Z) = E(Y_t|I_t^Y), \text{a.s.} \tag{8}$$

Z_t can't be Granger cause Y_t in mean, where $E(Y_t|I_t^Y, I_t^Z)$ and $E(Y_t|I_t^Y)$ are the means of $F_Y(\cdot\,|I_t^Y, I_t^Z)$ and $F_Y(\cdot\,|I_t^Z)$, respectively. It is easy to extend Granger non-causality in mean of equation (8) to higher order moments (see, *e.g.,* Cheung and Ng, 1996). However, this may ignore the possibly dependence in the conditional tails of the distribution. Besides, if equation (7) is rejected, the null hypothesis of equation (7) does not show the level of the causality. So we test for Granger non-causality in conditional quantiles. Let $Q_\tau^{Y,Z}(\cdot\,|I_t^Y, I_t^Z)$ be the τ-quantile of $F_Y(\cdot\,|I_t^Y, I_t^Z)$, we can rewrite equation (7) as follows:

$$H_0^{QC:Z \nrightarrow Y}: Q_\tau^{Y,Z}(Y_t|I_t^Y, I_t^Z) = Q_\tau^Y(Y_t|I_t^Y), \text{a.s. for all } \tau \in \mathcal{T} \tag{9}$$

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[4] *We use an Empirical Mode Decomposition (EMD) method to replace wavelet to decompose the time series of economic policy uncertainty shocks and economic growth into different modes (i.e. different time scales) to do a robustness check. The causality results based on EMD are similar to the results based on the wavelet. Due to limited space, the results are not shown here.*

where: $\mathcal{T}$ is a compact set such that $\mathcal{T} \subset [0,1]$, and the conditional τ-quantiles of Y_t satisfy the following restrictions:

$$\Pr\{Y_t \leq Q_\tau^Y(Y_t|I_t^Y)|I_t^Y\} \coloneqq \tau, \text{a.s. for all } \tau \in \mathcal{T}$$

$$\Pr\{Y_t \leq Q_\tau^{Y,Z}(Y_t|I_t^Y, I_t^Z)|I_t^Y, I_t^Z\} \coloneqq \tau, \text{a.s. for all } \tau \in \mathcal{T} \quad (10)$$

Given an explanatory vector I_t^Y, then $\Pr\{Y_t \leq Q_\tau(Y_t|I_t)|I_t\} = E\{1[Y_t \leq Q_\tau(Y_t|I_t)]|I_t\}$, where $1[Y_t \leq y]$ is an indicator function while Y_t is less than or equal to *y*. Then, the null hypothesis of Granger non-causality in equation (9) is equivalent to:

$$E\{1[Y_t \leq Q_\tau^{Y,Z}(Y_t|I_t^Y, I_t^Z)]|I_t^Y, I_t^Y\} = E\{1[Y_t \leq Q_\tau^Y(Y_t|I_t^Y)]|I_t^Y\}, a.s. for\ all\ \tau \in \mathcal{T} \quad (11)$$

where: $\mathrm{E}\{1[Y_t \leq Q_\tau^Y(Y_t|I_t^Y)]|I_t^Y\}$ is the τ-quantile of $F_Y(\cdot\,|I_t^Y, I_t^Z)$. Following Troster (2016), we apply a parametric model to estimate the τ-th quantile of $F_Y(\cdot\,|I_t)$. We assume that $Q_\tau(\cdot\,|I_t)$ is defined by a parametric quantile model $m(\cdot, \theta(\tau))$ belonging to a family of functions $\mathcal{M} = \{m(\cdot, \theta(\tau))|\theta(\cdot): \tau \mapsto \theta(\tau) \in \Theta \subset \mathbb{R}^p, for\ \tau \in \mathcal{T} \subset [0,1]\}$. Under the null hypothesis in equation (11), the τ-conditional quantile, $Q_\tau^Y(\cdot\,|I_t^Y)$, is correctly specified by a parametric quantile model $m(I_t^Y, \theta_0(\tau))$. Then the null hypothesis in equation (11) can be rewritten as follows:

$$H_0^{Z \nrightarrow Y}: E\{1[Y_t \leq m(I_t^Y, \theta_0(\tau))]|I_t^Y, I_t^Z\} = \tau, \text{a.s. for all } \tau \in \mathcal{T} \quad (12)$$

versus

$$H_A^{Z \nrightarrow Y}: E\{1[Y_t \leq m(I_t^Y, \theta_0(\tau))]|I_t^Y, I_t^Z\} \neq \tau, \text{a.s. for some } \tau \in \mathcal{T} \quad (13)$$

where: $m(I_t^Y, \theta_0(\tau))$ clarifies the true conditional quantile $Q_\tau^Y(\cdot\,|I_t^Y)$, for all $\tau \in \mathcal{T}$. Then the equation (12) can be rewritten as $H_0^{Z \nrightarrow Y}: E\{[1(Y_t - m(I_t^Y, \theta_0(\tau)) \leq 0) - \tau]|I_t^Y, I_t^Z\} = 0, \text{for all } \tau \in \mathcal{T}$. Then, we can use a sequence of unconditional moment restrictions to characterize the null hypothesis equation (12):

$$E\{[1\big(Y_t - m\big(I_t^Y, \theta_0(\tau)\big) \leq 0\big) - \tau\big]\exp(i\boldsymbol{\omega}' I_t)\} = 0, \text{for all } \tau \in \mathcal{T} \quad (14)$$

where: $\exp(i\boldsymbol{\omega}' I_t) \coloneqq \exp[i(\omega_1(Y_{t-1}, Z_{t-1})' + \cdots + \omega_r(Y_{t-r}, Z_{t-r})')]$ is a weighting function, for all $\boldsymbol{\omega} \in \mathbb{R}^r$ with $r \leq d$, and $i = \sqrt{-1}$ is the imaginary root. The test statistic is a sample analog of $E\{[1(Y_t - m(I_t^Y, \theta_0(\tau)) \leq 0) - \tau]\exp(i\boldsymbol{\omega}' I_t)\}$:

$$v_T(\boldsymbol{\omega}, \tau) \coloneqq {}^1\!/_{\sqrt{T}} \sum_{t=1}^{T} [1(Y_t - m(I_t^Y, \theta_0(\tau)) \leq 0) - \tau] \exp(i\boldsymbol{\omega}' I_t) \quad (15)$$

where: θ_T is a $\sqrt{T}$-consistent estimator of $\theta_0(\tau)$, for all $\tau \in \mathcal{T}$.
Then, we apply the test statistic proposed by Troster (2016):

$$S_T \coloneqq \int_{\mathcal{T}} \int_{W} |v_T(\boldsymbol{\omega}, \tau)|^2 dF_{\boldsymbol{\omega}}(\boldsymbol{\omega}) dF_\tau(\tau) \quad (16)$$

where: $F_{\boldsymbol{\omega}}(\cdot)$ is the conditional distribution function of a d-variate standard normal random vector, $F_\tau(\cdot)$ follows a uniform discrete distribution over a grid of $\mathcal{T}$ in *n* equally spaced points, $\mathcal{T}_n = \{\tau_j\}_{j=1}^n$, and the vector of weights $\boldsymbol{\omega} \in \mathbb{R}^{\boldsymbol{d}}$ is drawn from a standard normal distribution. We can use its sample analog to estimate the test the statistic in equation (16). Let Ψ be a $T \times n$ matrix with elements $\psi_{i,j} = \Psi_{\tau_j}(Y_i - m(I_i^Y, \theta_T(\tau_j)))$, where $\Psi_{\tau_j}(\cdot)$ is the function $\Psi_{\tau_j}(\varepsilon) \coloneqq 1(\varepsilon \leq 0) - \tau_j$. Then, we use the test statistic as follows:

$$\mathrm{S_T} = {}^1\!/_{\mathrm{Tn}} \sum_{\mathrm{j=1}}^{\mathrm{n}} |\psi'_{\cdot \mathrm{j}} \mathrm{W} \psi_{\cdot \mathrm{j}}| \quad (17)$$

where: ***W*** is the $T \times T$ matrix with elememts $\boldsymbol{w}_{t,s} = \exp[-0.5(I_t - I_s)^2]$, and $\psi'_{\cdot j}$ denotes the *j*-th column of Ψ. whenever we observe large values of S_T in equation (17) we reject the null hypothesis of Granger non-causality in (12). We calculate critical values for S_T in equation (17) by using the subsampling procedure of Troster (2016). Given our series $\{X_t = (Y_t, Z_t)\}$ with sample size *T*, we get subsamples of size *b* followed by $B = T - b + 1$ (taken without replacement from the original data) of the form $\{X_i, \dots, X_{i+b-1}\}$. Next, we can calculate for each subsample using the test statistic S_T in equation (17), and then by averaging the subsample test statistics over the subsamples *B*, we obtain *p*-values.[5]

4. Data

We use the quarterly log change of index data over the period Q1st/1995 to Q2nd/2016. According to the neoclassical economic theory[6], this paper uses the quarterly log change of GDP[7] as a proxy for economic growth, and calculated as the equation (14):

$$economic\ \ growth_t = \ln(GDP_t) - \ln(GDP_{t-1}) \tag{14}$$

For the EPU shocks, we use the quarterly log change of EPU index[8] as a proxy, and calculated as the equation (15):

$$EPU\ \ shocks_t = \ln(EPU_t) - \ln(EPU_{t-1}) \tag{15}$$

The descriptive statistics of all these data is reported in Table1. We find that the standard deviation of EPU shocks is bigger than economic growth. The means of all indexes are near 0. Since the skewness of all the time series is negative, the time series of all index returns are shown negatively skewed, which means the peak lean more to the left. All of our time series are also shown to have leptokurtic shape due to positive kurtosis, a stylish behavior of stock returns. To obtain the general impression of the dataset, Figure1 reports the time-series plot of the quarterly log change of EPU index. We may notice that the EPU shocks highly fluctuated, and the standard deviation of EPU shocks is 37.6%. Figure 2 reports the time-series plot of quarterly log change of GDP index. We can notice that the economic growth is less fluctuated than EPU shocks, and the standard deviation of economic growth is 12.6%.

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[5] *Due to limited space, this paper excludes the detailed wavelet model defined by Gencay and Signor (2015) and the Granger-causality in quantiles method of Troster (2016). Please refer to their papers for further details on their approaches.*

[6] *For some details, please refer to Sanjai* et al. *(2013) and Zhang* et al. *(2017).*

[7] *The quarterly data of GDP are from the Wind official database, which is one of the most important and widely used databases for China macro-economic market.*

[8] *Available for download at: http://www.policyuncertainty.com/china_monthly.html. The index is available monthly (1995/1-2016/6), and we take averages of the monthly data to convert them into quarterly data. There are three components lying under the construction of the EPU index, which are coverage of economic uncertainty related with policies, federal tax's code provisions and disagreement among economic forecasters (see Baker* et al., *2016).*

Table 1

Summary Statistics

	EPU shocks	Economic growth
Mean	0.0076	0.03175
Std.Dev.	0.3760	0.1257
Variance	0.1414	0.0158
Skewness	-0.4478	-1.1308
Kurtosis	3.2764	2.6749
Minimum	-0.7235	-0.2585
Maximum	1.1374	0.1877

Note: EPU and GDP are the quarterly data from Q1st/1995 to Q2nd/2016.

Figure 1

Quarterly Log Change of EPU (in Log)

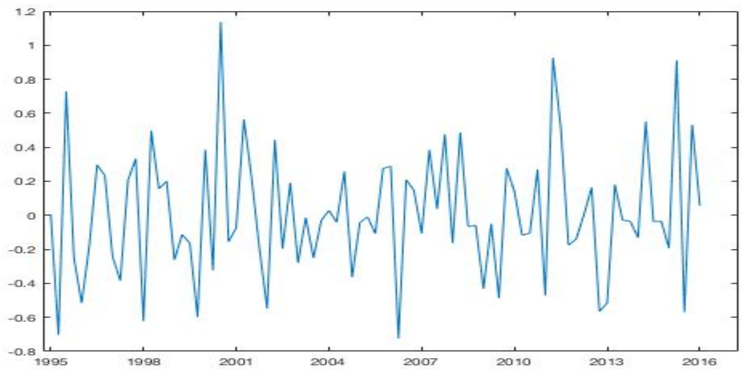
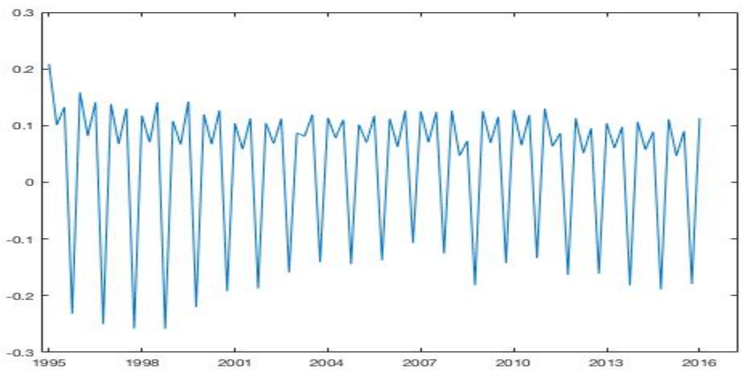


Figure 2

Quarterly Log Change of GDP (in Log)

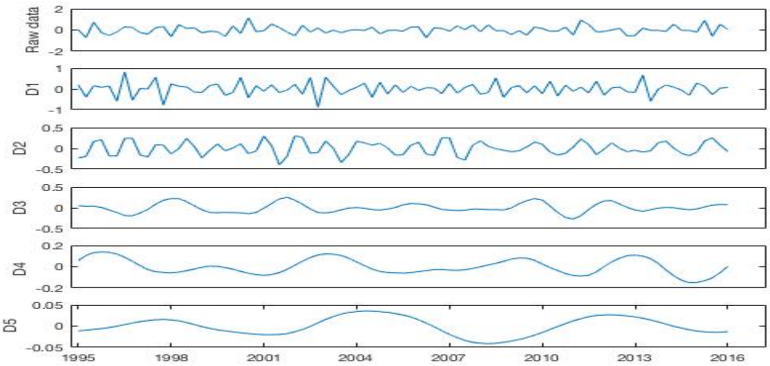


5. Empirical Results

To perform the wavelet method, we decompose the time series into both up to five time scales and the results are shown in Figure 3 and Figure 4. The five are denoted as D1, D2, D3, D4 and D5, representing the different time horizons with timescales of 2 to 4, 4 to 8, 8 to 16, 16 to 32 and 32 to 64 quarters, respectively.[9]

Figure 3

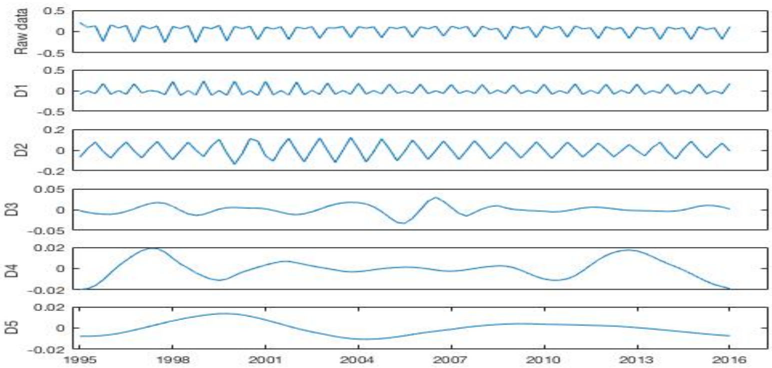
Wavelet-decomposed Series of EPU Shocks



Note: Figure 3 includes original series, and decomposed series D1-D5 of EPU shocks from up to bottom, respectively.

Figure 4

Wavelet-decomposed Series of Economic Growth



Note: Figure 4 includes original series, and decomposed series D1-D5 of economic growth from

[9] *See Crowley (2015) for more detailed interpretation of wavelet analysis and the reasons for the decomposed time-scales. Following Chu* et al. *(2016), we denote D1-D2 as the shorter term and D3-D5 as the longer term for simplified treatment. And there are some other treatments (see e.g. Alzahrani* et al.*, 2014; Benhmad, 2012; Jiang* et al.*, 2015). But they are all the same in essentials while differing in minor points.*

up to bottom, respectively.

We should check the stationary property of the financial variables, and Table 2 reports the results of unit root test. For the raw data and all the decomposed series, and the result shows all of our time series are stationary at 1% level.

Table 2

Unit Root Test

Time scale	EPU shocks ADF test (lag)	Economic growth ADF test (lag)
Raw data	-12.283***(0)	-15.153***(0)
D1	-19.409***(0)	-20.450***(0)
D2	-7.663***(0)	-8.705***(0)
D3	-14.659***(1)	-15.222***(1)
D4	-18.220***(1)	-16.581***(1)
D5	-19.479***(1)	-20.338***(1)

*Notes: The lag lengths of DF -GLS are chosen on Schwarz criterion. *** represents the significant level of null hypothesis rejected at 1%. D1-D5 represents the time horizons with timescales of 2 to 4, 4 to 8, 8 to 16, 16 to 32 and 32 to 64 quarters, respectively.*

Table 3 shows the *p*-value of the Granger causality in mean between EPU shocks and economic growth. The results indicate the single-directional causality from economic growth to EPU shocks in the shorter term, and the strong bi-directional causality in the longer term between them. We compare the wavelet-based Granger-causality method using a conditional mean analysis with results from methods without wavelet, and we can conclude that there is the single-directional causality from economic growth to EPU shocks overall, but the inner linkage between EPU shocks and economic growth in the shorter and longer term cannot be found. We note that, if based on raw data only, it may miss some potential information on the shorter and longer-term case. But the wavelet can help us to analyze different timescales of economic data to find the multi-scale EPU shocks - economic growth relationship. That is the advantage of this method comparing with others.

Table 3

Granger Causality in Mean: p-values

	Number of Lags				Number of Lags		
	1	2	3		1	2	3
Panel A: △EPU shocks to △Economic growth				*Panel B*: △Economic growth to △EPU shocks			
Raw data	0.0996	0.0290	0.5856	Raw data	0.0000***	0.0009***	0.0326**
D1	0.2906	0.0701	0.0370**	D1	0.0046***	0.0007***	0.0011***
D2	0.0810	0.0221**	0.0012***	D2	0.0000***	0.0061***	0.0861
D3	0.0059***	0.0247**	0.0923	D3	0.0156**	0.0256**	0.0279**
D4	0.0386**	0.0133**	0.0005***	D4	0.0166**	0.0031***	0.0021***
D5	0.0361**	0.0000***	0.0000***	D5	0.9760	0.0000***	0.0000***

*Notes: **, *** represents the significant level of null hypothesis rejected at 5% or 1%. D1-D5 represents the time horizons with timescales of 2 to 4, 4 to 8, 8 to 16, 16 to 32 and 32 to 64 quarters, respectively.*

Our results show that the economic growth has significance on EPU shocks all the time. Conversely, EPU shocks affect economic growth only in the long-term, exhibiting hysteresis, which confirms the long-term relationship result of Dima et al. (2017). So it is certain that EPU is a considerable influence factor of the economic growth. The uncertainty of economic policy will be increased followed by the economy development. That is the reason why the government highlights the importance of policy stability in government's work report every year. While hysteresis reflection in the long-term indicates that EPU is a new implement to predict economic growth. Taking EPU into consideration, the prediction of economic growth will be more complete.

Table 4 presents the *p*-values of the S_T test in subsamples. Considering the fact that the number of observations of EPU shocks and economic growth are a bit small, we just choose three different τ- quantiles (i.e. 0.1, 0.5 and 0.9) for our analysis. The τ- quantiles can be adjusted according to the different datasets. If all quantiles were considered only, there is a no clear bi-directional nonlinear causality between EPU shocks and economic growth. But if we take the regression in different quantiles and different timescales into account, we would find that the nonlinear relation between EPU shocks and economic growth is time-varying in different quantiles and different timescales, and a single-directional nonlinear causality from economic growth to EPU shocks of some τ- quantiles in D1-D4.

By comparing the wavelet-based Granger-causality method in quantiles with other methods without different quantiles and wavelet, the vavelet-based Granger-causality method shows its advantage: there is clear nonlinear causality between EPU shocks and economic growth; it is hard to get such a conclusion using other methods. In this way, it may miss some potential nonlinear causal relationship between them. Based on both wavelet and Granger-causality in quantiles method, we can deeply analyze the causality between EPU shocks and growth.

Moreover, the results imply that the nonlinear relationship between EPU shocks and economic growth may be varying in different economic period. In other words, EPU shocks affect economic growth in the long-term more distinctly than in the short-term. It indicates that as the uncertainty of economic policy increased in the long-term, the risk of economic crisis would increase. Thus, it is vital for the government to reduce EPU so as to keep the stability of economic growth. The multi-scale causality results of different τ-quantiles may help decision makers to master the comprehensive nonlinear relationship with more details when they come into contact the EPU shocks - economic growth relationship, and timely adjust the economic policy.

Table 4

Granger-causality in Quantiles of Troster (2016) Approach: Subsampling p-values

Panel A: △EPU shocks to △Economic growth					*Panel B*: △Economic growth to △EPU shocks				
	τ-quantiles	Number of Lags of I_Y^t				τ-quantiles	Number of Lags of I_Y^t		
Timescale		1	2	3	Timescale		1	2	3
Raw data	[0.10;0.90]	0.353	0.355	0.315	Raw data	[0.10;0.90]	0.138	0.118	0.129
	0.10	0.861	0.949	0.574		0.10	0.300	0.223	0.148
	0.50	0.092	0.169	0.129		0.50	0.307	0.240	0.185
	0.90	0.800	0.770	0.722		0.90	0.720	0.711	0.296
D1	[0.10;0.90]	0.615	0.525	0.462	D1	[0.10;0.90]	0.015**	0.016**	0.018**
	0.10	0.015**	0.118	0.148		0.10	0.015**	0.016**	0.018**
	0.50	0.400	0.372	0.611		0.50	0.107	0.203	0.166
	0.90	0.569	0.398	0.740		0.90	0.015**	0.017**	0.019**
D2	[0.10;0.90]	0.538	0.457	0.314	D2	[0.10;0.90]	0.015**	0.016**	0.018**
	0.10	0.107	0.067	0.055		0.10	0.015**	0.033**	0.037**

Panel A: △EPU shocks to △Economic growth					*Panel B*: △Economic growth to △EPU shocks				
	τ-quantiles	Number of Lags of I_Y^t				τ-quantiles	Number of Lags of I_Y^t		
Timescale		1	2	3	Timescale		1	2	3
	0.50	0.630	0.728	0.038**		0.50	0.015**	0.084	0.037**
	0.90	0.624	0.323	0.118		0.90	0.123	0.101	0.148
D3	[0.10;0.90]	0.012**	0.025**	0.942	D3	[0.10;0.90]	0.015**	0.016**	0.019**
	0.10	0.630	0.690	0.640		0.10	0.072	0.013**	0.091
	0.50	0.615	0.813	0.500		0.50	0.200	0.305	0.166
	0.90	0.615	0.474	0.592		0.90	0.039**	0.016**	0.018**
D4	[0.10;0.90]	0.650	0.546	0.350	D4	[0.10;0.90]	0.090	0.016**	0.129
	0.10	0.611	0.643	0.521		0.10	0.046**	0.016**	0.002***
	0.50	0.063	0.072	0.106		0.50	0.750	0.615	0.318
	0.90	0.122	0.307	0.138		0.90	0.243	0.116	0.129
D5	[0.10;0.90]	0.500	0.501	0.648	D5	[0.10;0.90]	0.030**	0.106	0.074
	0.10	0.476	0.661	0.759		0.10	0.559	0.271	0.777
	0.50	0.646	0.779	0.320		0.50	0.323	0.523	0.271
	0.90	0.205	0.126	0.151		0.90	0.104	0.207	0.119

*Notes: **, *** represents the significant level of null hypothesis rejected at 5% or 1%. D1-D5 represents the time horizons with timescales of 2 to 4, 4 to 8, 8 to 16, 16 to 32 and 32 to 64 quarters, respectively.*

Figure 1 shows that the EPU shocks show a noticeable obvious time-varying fluctuation. Hence, we use the GARCH (1, 1) model[10] to get filter residuals of different time-horizons in the volatility of EPU shocks and economic growth. This helps us to capture dynamic volatility spillover effects of them to do a robustness test, and the nonlinear results are shown in Table 5. We can obtain the similar results to those in Table 4, indicating that our findings could be reliable.

Table 5

Granger-causality in Quantiles Considering Time-varying Effect: Subsampling p-values

Panel A: △EPU shocks to △Economic growth					*Panel B*: △Economic growth to △EPU shocks				
	τ-quantiles	Number of Lags of I_Y^t				τ-quantiles	Number of Lags of I_Y^t		
Timescale		1	2	3	Timescale		1	2	3
Raw data	[0.10;0.90]	0.430	0.372	0.333	Raw data	[0.10;0.90]	0.446	0.322	0.314
	0.10	0.561	0.508	0.592		0.10	0.720	0.640	0.444
	0.50	0.092	0.118	0.111		0.50	0.230	0.280	0296
	0.90	0.840	0.680	0.944		0.90	0.640	0.407	0388
D1	[0.10;0.90]	0.261	0.186	0.240	D1	[0.10;0.90]	0.015**	0.016**	0.018**
	0.10	0.046**	0.508	0.092		0.10	0.015**	0.016**	0.018**
	0.50	0.415	0.813	0.911		0.50	0.360	0.303	0.172
	0.90	0.507	0.491	0.444		0.90	0.015**	0.017**	0.019**
D2	[0.10;0.90]	0.438	0.407	0.414	D2	[0.10;0.90]	0.015**	0.016**	0.018**
	0.10	0.207	0.183	0.325		0.10	0.015**	0.016**	0.018**

[10] *Jiang* et al. *(2017) show that the GARCH model can be enough to offer a good estimate of the volatility of financial variables, and it can capture the time-varying volatility of financial variables.*

Panel A: △EPU shocks to △Economic growth					*Panel B*: △Economic growth to △EPU shocks				
	τ-quantiles	Number of Lags of I_Y^t				τ-quantiles	Number of Lags of I_Y^t		
Timescale		1	2	3	Timescale		1	2	3
	0.50	0.490	0.668	0.510		0.50	0.504	0.421	0.641
	0.90	0.494	0.463	0.518		0.90	0.461	0.254	0.740
D3	[0.10;0.90]	0.520	0.552	0.537	D3	[0.10;0.90]	0.015**	0.016**	0.019**
	0.10	0.581	0.576	0.681		0.10	0.440	0.660	0.612
	0.50	0.301	0.472	0.721		0.50	0.255	0.134	0.163
	0.90	0.615	0.813	0.351		0.90	0.016**	0.006**	0.012**
D4	[0.10;0.90]	0.231	0.286	0.250	D4	[0.10;0.90]	0.015**	0.016**	0.018**
	0.10	0.671	0.713	0.632		0.10	0.006***	0.136	0.072
	0.50	0.493	0.712	0.532		0.50	0.435	0.425	0.523
	0.90	0.722	0.727	0.738		0.90	0.381	0.386	0.531
D5	[0.10;0.90]	0.840	0.881	0.901	D5	[0.10;0.90]	0.070	0.106	0.056
	0.10	0.646	0.490	0.334		0.10	0.091	0.161	0.038**
	0.50	0.246	0.372	0.292		0.50	0.331	0.443	0.556
	0.90	0.261	0.210	0.556		0.90	0.555	0.041	0.338

*Notes: **, *** represents the significant level of null hypothesis rejected at 5% or 1%. D1-D5 represents the time horizons with timescales of 2 to 4, 4 to 8, 8 to 16, 16 to 32 and 32 to 64 quarters, respectively.*

6. Conclusions

This paper wants to add a new methodological perspective on how to deeply analyze causal relationship between different key macroeconomic variables and to fill the investigation gap on the multi-scale Granger-causality in quantiles between China's EPU shocks and economic growth. Overall, we use a conditional mean analysis to find the single-directional causality from economic growth to EPU shocks in the shorter term and the bi-directional causality in the longer term. The subsample causality results indicate that the nonlinear relation between EPU shocks and economic growth may be varying in different subsamples and different timescales. The economic growth has significance on EPU shocks all the time. Conversely, EPU shocks affect economic growth only in the long-term, exhibiting hysteresis.

The results of this paper show that EPU not only provides a new method to predict economic growth but also warns us the accumulation of EPU would increase economic crisis. So it is virtual for the government to reduce EPU so as to keep the stability of economic growth. It helps decision makers to analyze the comprehensive linear and nonlinear EPU shocks - economic growth relationship, and timely adjust the economic policy to balance the economic development trend. Based on the results in this paper, we recommend that researches concern on reasons causing the different influences on the EPU shocks - economic growth relationship could be carried out in the future work. The wavelet-based Granger-causality in quantiles method offers a new methodological framework. Besides, it can also be used in many other areas such as for the stock, oil and gold markets, etc.

Considering the limitations of the paper, as for the future work, with respect to the relationship between EPU shocks and economic growth, there are at least two things can be further complemented. For one thing, we make use of the non-linear Granger causality test, moreover we may consider some other methods to get more decent results; For another, we can consider some other perspectives to shed light on the relationship, such as risk spillover, etc., to conduct a more comprehensive analysis.

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