Dynamic interaction between economic policy uncertainty and financial stress: A multi-scale correlation framework

Xiaolei Sun\textsuperscript{a,b,*}, Xiaoyang Yao\textsuperscript{a,b}, Jun Wang\textsuperscript{a,b}

\textsuperscript{a} Institute of Policy and Management, Chinese Academy of Sciences, No.15, Zhongguancun Beiyitiao, Haidian District, Beijing 100190, PR China
\textsuperscript{b} University of Chinese Academy of Sciences, No.19, Yuquan Road, Beijing 100049, PR China

\textbf{A B S T R A C T}

Quantifying the dynamic interaction between economic policy uncertainty and financial stress is in its infancy. To identify the inherent relationship between them, this paper proposes a multi-scale correlation framework. Empirical results show that interaction occurs significantly and distinctly on different scales. Correlation is significant and fluctuates drastically in short-term fluctuation with unidirectional spillover effect from financial stress to economic policy uncertainty. Bidirectional spillover effects exist in the medium pattern with periodic correlation of two-regime characteristic. It helps for decision making to establish a proper timing reference to design a more reasonable arbitrage portfolio and improve risk-hedging strategies.

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1. Introduction

Economic policy uncertainty and financial risk have been the most important issues in economics and finance recently. Emphasized in Hammoudah and Mcaleer (2015), financial risk management is difficult at the best of times, especially in times of economic policy uncertainty. In this regard, this paper complements previous studies, as it focuses on the relationship between financial stress (FS) and economic policy uncertainty (EPU).

As a typical financial risk status, financial stress (or financial instability) can affect economic activity through various channels (Lo Duca and Peltonen, 2011). Generally speaking, financial stress has been interpreted as the whole stress increasing with expected financial loss, with risk or uncertainty, the current state of instability similar to system risk (Illing and Ying, 2006). States of financial stress are important for optimal policy design and implementation, and a financial stress index would provide valuable information as a heightened index and could help to fine tune economic policy (Cevik et al., 2016).

Regarding macroeconomic policies, Baker et al. (2015) proposed the Economic Policy Uncertainty index, which combines economic policy uncertainty related to public views and economic policy making. Using the EPU index, a substantial amount

\* Corresponding author.
E-mail address: xisun@casipm.ac.cn (X. Sun).

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of information is available about the international EPU spillover among countries, the relationship between EPU and economic activities (Antonakakis et al., 2014; Gupta et al., 2016), and financial market, such as stock market (Arouri et al., 2016; Bekiros et al., 2016; Liu and Zhang, 2015). In recent studies, Karnizova and Li (2014) proved that the policy uncertainties indexed are statistically and economically significant in forecasting financial recessions. Reboredo and Uddin (2016) identified the impact of financial stress and policy uncertainty on the energy and metals markets. New research techniques in economics and finance have been used to address important issues that have emerged from the 2008–09 Global Financial Crisis originating in the USA, the sovereign debt crisis that emanated from Europe in 2010, and the resulting policy uncertainty in the USA and worldwide. However, very few researches focus on identifying and assessing the interaction between financial stress and macroeconomic policies.

Actually, the economic-financial system is complex of interacting agents with different term objectives. Highlighted in Huang et al. (2016), policy makers consider the market equilibriums in the long term; the seasonal cycle activates in a year’s time, and speculators deal in short time frames, perhaps intraday. All of these stakeholders or factors could be summarized into different time scales, and they could exert different influences on the entire market’s interactions. In brief, these multi-scale components and their impacts make the interaction complicated.

Generally, economic index in term of time series, are selected to reflect the entire market situation or some market components, but it is hard to get the special index to reflect the short-, medium- and long-runs. Considering all of the time-scale information is integrated as a whole in the original time series, some inherent correlation information may be hidden. How to dig the integrated and hidden information of the interaction between economic activities, attracts increasing attentions. Evidently, the results differ considerably not only due to the model specifics but also due to the analysis of different time scales where the most frequently analyzed scales range from weekly to monthly or quarterly (Vacha et al., 2013). In brief, decomposition to scales gives us an opportunity to study the inherent correlation on a scale-by-scale level or in different frequencies, which gives a broader picture than studying the aggregate time series only (Zhang et al., 2008; Sun et al. 2014; Yu et al., 2015).

Notably, the essence lies in the intricate components of the entire market from a variety of time horizon, which could exert different influences on the entire market’s interaction (Huang et al., 2016). This offers a novel multi-scale perspective to unveiling the interaction between economic activities in the short-, medium- and long-runs. Of particular interest and novelty is to examine the inherent interaction between EPU and financial stress in the USA, which is an important issue in both economy and finance. In this paper, an extension of the multi-scale correlation framework of Sun et al. (2014) is proposed to analyze the dynamic interaction between financial stress and economic policy uncertainty in the perspective of multi-scales.

2. Estimation methodology

In the proposed framework, the dynamic correlation can be divided into three separate scales: the long-term trend, medium pattern in low frequency and short-term fluctuation in high frequency. The following subsections give the detailed description of the three main steps: extracting the intrinsic mode functions (IMFs), constructing the multi-scale components and measuring the multi-scale correlations.

Step 1: IMFs extracted

As an efficient tool for identifying multi-scale properties, Empirical Mode Decomposition (EMD) and Ensemble EMD have been widely used to extract intrinsic modes from complex objects in reality (Li et al., 2012; Sun et al., 2014; Wu and Huang, 2009). Ensemble EMD model decomposes the original series $x(t)$, ($t=1, 2, ..., T$) into a series of IMFs and residue $r(t)$:

\[ x(t) = \sum_{i=1}^{N-1} IMF_i(t) + r(t) \]  

(1)

All IMFs satisfy the following two conditions: (1) The number of extrema and zero crossings must be equal or differ at most by one, and (2) the IMFs must be symmetric with respect to the local zero mean. Specifically, the IMFs and residue can be extracted through the following steps:

1. Let $r(t)=x(t)$.
2. Identify all local maxima (and minima) of $r(t)$.
3. Generate the upper and lower envelopes $e_{up}(t)$ and $e_{low}(t)$ of $r(t)$, with cubic spline interpolation.
4. Calculate the mean envelope $m(t)=\frac{|e_{up}(t)+e_{low}(t)|}{2}$, and define the difference $d(t)=r(t)−m(t)$.
5. Check the property of $d(t)$: If $d(t)$ satisfies the two conditions of IMF, consider it as an IMF and set $r(t)=m(t)$, or otherwise set $r(t)=d(t)$.
6. Repeat steps (2)–(5) until any of the following stop criteria is satisfied (Huang et al., 2003; Yu et al., 2015).

1 The values of the extracted IMF $d(t)$ or the residue $r(t)$ can be controlled smaller than the predetermined value of a substantial consequence, or the residue $r(t)$ becomes a monotonic function from which no more IMF can be extracted. Besides, the number of IMFs is limited to below $\log_2 T$, where $T$ is the length of data series. More details in Sun et al. (2014) and Yu et al. (2015).
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