How does stock market co-move with domestic economic policy uncertainty? New evidence from symmetric thermal optimal path method

Ying-Hui Shao\textsuperscript{a}, Yan-Hong Yang\textsuperscript{b,∗}

\textsuperscript{a}School of Statistics and Information, Shanghai University of International Business and Economics, Shanghai 201620, China
\textsuperscript{b}Faculty of Education, East China Normal University, Shanghai 200062, China

Abstract
We revisit the dynamic relationship between stock market and domestic economic policy uncertainty (EPU) with the symmetric thermal optimal path (TOPS) method. We observe totally different interaction pattern in emerging and developed markets. Economic policy uncertainty can drive stock market in China, while stock market plays a leading role in the UK and the US. Meanwhile, the lead-lag relationship of the three countries react significantly when extreme events happen. Our findings have important implications for investors and policy makers.

Keywords: Economic policy uncertainty, Stock market, Lead-lag relationship, Symmetric thermal optimal path

JEL classification: C14, G13, G14

1. Introduction

The interaction between economic policy uncertainty (EPU) and stock market has received wide attention in recent years, such as the causal relationship (Li et al., 2016), the spillover effect (He et al., 2020), the impact of economic policy uncertainty on stock prices (Das and Kumar, 2018; Liang et al., 2020), predictive power of policy uncertainty on stock market (Bekiros et al., 2016; Liu et al., 2017), and so on. A plethora of literature reveals the negative effect of economic policy uncertainty on stock market (Kang and Ratti, 2013; Yang and Jiang, 2016; Christou et al., 2017; Guo et al., 2018; Arouri et al., 2016) using both linear and market switching models, report that an increase in the US economic policy uncertainty causes a decrease in the US stock returns. Li et al. (2015) confirm that policy uncertainty shocks impact negatively on the US stock-bond correlations. He et al. (2020) also provide evidence for the negative affect of EPU on stock returns. Li and Peng (2017) show that the absolute US economic policy uncertainty changes have a negative influence on the co-movements of Chinese and US stock markets. Chen et al. (2017) reveal that EPU predicts negatively stock market return at various horizons.

On the flip side, policy-makers might react to the stock market movements and adjust policy accordingly (Li et al., 2016). Hence stock market can also have an impact on policy uncertainty (Antonakakis et al., 2013; Li et al., 2016). Antonakakis et al. (2013) observe that increase in stock market conditional volatility raises policy uncertainty. Li et al. (2016) report weak bidirectional causal relationships between stock returns and EPU in China and India via a bootstrap rolling causality test. Dakhlaoui and Aloui (2016) analyze volatility spillovers and time-varying correlation between the US economic policy uncertainty and the BRIC equity markets. Their work indicate a bidirectional causality relationships between the US EPU index returns and the four BRIC stock market returns. Yang and Jiang (2016) show that stock market influences policy uncertainty negatively in China, which peaks after four months. Li et al. (2020) use continuous and discrete wavelet tools to examine the correlation and causality between the US EPU and stock markets in China and India. The result show there is unidirectional or bidirectional causality in the medium and long term.

The linkage between police uncertainty and stock market is changeable and dynamic. Antonakakis et al. (2013) suggest that the time-varying correlation between stock returns and policy uncertainty is sensitive to the influential
events like financial crisis. Ko and Lee (2015) examine the relationship between economic policy uncertainty and stock price of 11 economies with wavelet analysis and conclude that the relationship is negative and time-varying. Applying quantile regression, You et al. (2017) indicate that effects of economic policy uncertainty on Chinese stock returns is related to market conditions. Xiong et al. (2018) find that the correlation policy uncertainty and stock returns in China drops dramatically during financial crisis and Chinese stock market crash. Some researchers point out that the connectedness between stock market and policy uncertainty is country dependent. Das and Kumar (2018) unveil emerging markets are less vulnerable to both domestic and international EPU than developed markets. Using predictive regression model, Phan et al. (2018) report that EPU has stronger influence on some countries market than others.

To give a more detailed analysis, we revisit the time-varying lead-lag structure between stock market and local economic policy uncertainty via the nonlinear and nonparametric symmetric thermal optimal path (TOPS) method. Further, to examine the difference between developed and developing countries, we compare interaction pattern of China, the UK and the US respectively. The thermal optimal path (TOP) method (Sornette and Zhou, 2005) and TOPS method (Meng et al., 2017) do not require the stationarity of signals. The TOP/TOPS method are effective to capture dynamic non-linear structural changes and has been fruitfully applied into lead-lag dependencies investigation (Zhou and Sornette, 2006; Shao et al., 2019; Yang and Shao, 2020; Yang et al., 2020). As an improve version of the TOP method, the TOPS method enables a more accurate investigation. Our paper contributes to the literature by providing empirical evidence of the dynamic co-movement between stock market and domestic policy uncertainty. Our findings may provide important implications for financial stability and risk management.

The reminder of this paper is organized as follows. Section 2 depicts data and summary statistics. Section 3 describes the methodology. Section 4 presents the dynamic lead-lag relationship between EPU and stock market index, and section 5 summarizes the paper.

### Table 1: Summary statistics of EPU and stock market index returns.

|                | CNEPU | UK EPU | USEPU | SSEC | FTSE100 | S&P500 |
|----------------|-------|--------|-------|------|---------|--------|
| Mean           | 0.4635| 0.5214 | 0.4948| 0.5065| 0.5509  | 0.5393 |
| Maximum        | 1.0000| 1.0000 | 1.0000| 1.0000| 1.0000  | 1.0000 |
| Minimum        | 0.0000| 0.0000 | 0.0000| 0.0000| 0.0000  | 0.0000 |
| Std. Dev       | 0.1086| 0.0653 | 0.0787| 0.0894| 0.0389  | 0.0554 |
| Skewness       | 0.0992| -0.0207| 0.0359| -0.6409| -0.3705 | -0.5536|
| Kurtosis       | 4.2635| 5.8831 | 5.0753| 7.6649| 12.4175 | 15.9152|
| JB p-value     | 0.0010| 0.0010 | 0.0010| 0.0010| 0.0010  | 0.0010 |
| ADF p-value    | 0.0010| 0.0010 | 0.0010| 0.0010| 0.0010  | 0.0010 |

Notes:

- JB is the Jarque-Berra test of normality, which is distributed as $\chi^2(2)$, and the $JB_{p-value}$ is the associated $p$-value.
- ADF is the Augmented Dickey-Fuller test of unit root, the $ADF_{p-value}$ is the associated $p$-value.

### 2. Data description

We consider the economies of China, the UK and the US on which the daily EPU data were available. The data cover a period from 2000 to 2020. The policy uncertainty series for the UK and the US come from Baker et al. (2016), which is a commonly used proxy of real economic policy uncertainty. The Chinese policy uncertainty index is developed by Huang and Luk (2020) on the basis of work of Baker et al. (2016). We utilize daily closing prices of Shanghai Stock Exchange Composite index (SSEC) for China, Financial Times Stock Exchange 100 index (FTSE 100) for the UK, and Standard and Poor’s 500 Index (S&P 500) for the US.

We take logarithmic returns for the analysis. Figure 1 and Table 1 illustrates the data. China EPU has the largest standard deviation while S&P 500 has the lowest. The distribution of all returns is skewed and has thick tails, which suggest that the dataset is not normally distributed. The Jarque–Bera test yields similar conclusions for all variables. The $p$-value of ADF test does not transcend 0.05, indicating that the dataset is stationary.
Figure 1: EPU, stock market index returns and lead-lag path ($x(t)$). The first two columns correspond to EPU and stock market returns. The lower three columns report the average optimal thermal path ($\langle x(t) \rangle$) implemented at $T = 2$, which correspond to three pairs of “CNEPU vs. SSEC”, “UKEPU vs. FTSE100” and “USEPU vs. S&P500” respectively.
As illustrated Figure 1, China’s stock market has gone up and down sharply in 2008, 2015 and 2019. The UK has witnessed wild swings in 2008 and 2020. The same phenomena are observed in the US stock market. Moreover, UK’s EPU shows similar changes as US’ EPU.

3. Methodology

The TOPS method was introduced to effectively identify the structural changes of lead-lag relationships between two time series (Meng et al., 2017). The details of this method are depicted in the following context.

Consider there are two standardized time series $X(t_1) : t_1 = 0, \cdots, n-1$ and $Y(t_2) : t_2 = 0, \cdots, n-1$, in which $X(t_1)$ and $Y(t_2)$ are the logarithmic returns of EPU and the stock index, respectively. First, we form a distance matrix $E_{XY}$ that allows us to compare the disparities between all the values of $X(t_1)$ with $Y(t_2)$ along the two time axes $t_1$ and $t_2$. The elements of the distance matrix $E_{XY}$ are defined as

$$
\epsilon(t_1, t_2) = |X(t_1) - Y(t_2)|. \tag{1}
$$

The $n \times n$ distance matrix $E_{XY}$ further defines the mapping $t_1 \rightarrow t_2 = \phi(t_1)$ expressed as

$$
\phi(t_1) = \min_{t_2} \epsilon(t_1, t_2), \tag{2}
$$

where Eq. (2) is a local minimization. To eliminate the unreasonable large jumps or contradicting causality, Sornette and Zhou replace the local minimization Eq. (2) by the following global minimization

$$
\min_{\{\phi(t_1), t_2 = 0,1, \cdots, n-1\}} E := \sum_{t_1=0}^{n-1} |X(t_1) - Y(\phi(t_1))|, \tag{3}
$$

with a continuity constraint

$$
0 \leq \phi(t_1 + 1) - \phi(t_1) \leq 1. \tag{4}
$$

The continuous time limit of condition Eq. (4) is to ensure continuity of the one-to-one mapping $t_1 \rightarrow t_2 = \phi(t_1)$.

To solve the global optimization problem Eq. (3) more efficiently, one can transform the original coordinates $(t_1, t_2)$ to $(t, x)$ as follows (Sornette and Zhou, 2005)

$$
\begin{align*}
    t &= t_2 + t_1, \\
    x &= t_2 - t_1. 
\end{align*} \tag{5}
$$

Then, Meng et al. (2017) determine the optimal thermal path $\langle x(t) \rangle$ of the TOPS method by

$$
\langle x(t) \rangle = \sum_x \frac{G(t,x)\overrightarrow{G}(t) + \overrightarrow{G}(t,x)/\overrightarrow{G}(t)}{2}, \tag{6}
$$

where $\overrightarrow{G}(t,x)$ is the local weight factor for the searching direction from past to future and

$$
\overrightarrow{G}(t) = \sum_x \overrightarrow{G}(t,x). \tag{7}
$$

Here, $\overrightarrow{G}(t,x)/\overrightarrow{G}(t)$ is the probability for a path to be at position $x$ at time $t$. To keep the direction of time required by ‘causality’, a feasible path arriving at $(t_1 + 1, t_2 + 1)$ can stem from $(t_1 + 1, t_2)$ vertically, $(t_1, t_2 + 1)$ horizontally, or $(t_1, t_2)$ diagonally. Thus, the local weights at $(t, x)$ can be calculated in a recursive way as the following equation

$$
\overrightarrow{G}(t+1,x) = \overrightarrow{G}(t,x) + \overrightarrow{G}(t,x+1) + \overrightarrow{G}(t-1,x) e^{-\epsilon(t+1,x)/T}, \tag{8}
$$

where $T$ is a parameter controlling the effect of noise. Correspondingly, $\overrightarrow{G}(t,x)$ represents that the recursive weight
process is along the time-reversed direction.

Finally, one can unveil the dependence structure between the EPU and the stock index by the value of $\langle x(t) \rangle$. If $\langle x(t) \rangle > 0$, it represents EPU leads the stock index, otherwise EPU lags the stock index when $\langle x(t) \rangle < 0$. In particular, neither the EPU nor the stock index is dominant when $\langle x(t) \rangle = 0$.

4. Results

Following Meng et al. (2017), we examine the dynamic coherence between EPU and stock market index based on the TOPS method with $T = 2$. We illustrate result in Figure 1, Figure 2 and Table 2.

Figure 2: Histograms and probability density curves of $\langle x(t) \rangle$. From left to right, each column corresponds to $\langle x(t) \rangle$ of “CNEPU vs. SSEC”, “UKEPU vs. FTSE100” and “USEPU vs. S&P500”.

As is shown in Figure 1 Chinese EPU is dominating the stock market, which means stock market in China is significantly influenced by policy uncertainty. Our findings is consistent with previous studies of Guo et al. (2013). Their results unveil that Chinese stock is a “policy market”. Throughout the global financial crisis the Chinese $\langle x(t) \rangle$ has been increasing steadily. Obviously $\langle x(t) \rangle$ peaks during the financial crisis in late 2008. Since 2009 it shows a clear downward trend, although there are periods of slight fluctuations. Then $\langle x(t) \rangle$ fluctuates around 30 until the Chinese stock market crash in 2015. During trade disputes between China and the US since 2018, there is a general uptrend in $\langle x(t) \rangle$ with volatile movement. As China is highly export-dependent, it is not surprising that economic activity in China is affected by the US trade protection (Tsai, 2017). Since the initial outbreak of COVID-19 in December 2019 $\langle x(t) \rangle$ drops very sharply.

The lead-lag path $\langle x(t) \rangle$ of China have 100.00% positive values, which implies that EPU returns leads stock market index returns in China during the whole sample period. The mean value of Chinese $\langle x(t) \rangle$ is 37.31, and its median is 35.16, which also support the view that EPU leads stock market. As illustrated in Figure 2 the average lead-lag paths for China is mostly in the range of 26 to 40, indicating that the stock index leads EPU between 26 and 40 days.

Overall, the UK stock market index leads the UK EPU. From 2007, the UK $\langle x(t) \rangle$ decreased and then increased. Before 2008 the path is mostly negative, which means that stock market leads EPU. Since the second half of 2008,
positive $\langle x(t) \rangle$ is observed. The path increases continually and reaches its peak at 47.36 on July 16th, 2008, which corresponds to the violent fluctuations in EPU. During this period, the lead-lag relationship reverses and EPU index leads stock market index. The statement followed a falling period for $\langle x(t) \rangle$ until late 2009. Since then to 2020 there exists a slightly negative lead-lag structure in UK with occasional, which implies that stock market takes the lead. After the COVID-19 outbreak in December of 2019, $\langle x(t) \rangle$ drops sharply to its minimum of -57.48 on July 27th, 2020.

As is illustrated in Figure 2, the probability density curve of the UK lead-lag path is almost symmetrical around 0. Table 2 documents the mean and median of UK $\langle x(t) \rangle$ namely -2.21 and -1.27, respectively. Negative $\langle x(t) \rangle$ has a higher percentage of the whole paths (69.15%), which also suggests changes in UK stock market preceded that in EPU.

The US stock market and EPU have almost the same lead-lag structure as that of UK. This result is not unexpected, since EPU and stock market index of the two countries bears strong resemblance. Similar to that of UK, the US lead-lag relationship has large fluctuations during 2008 financial crisis and 2020 COVID-19 pandemic. The $\langle x(t) \rangle$ reached its maximum and minimum values on August 5th, 2020 (16.39) and August 4th, 2008 (-83.61), respectively. Between the two periods, the US lead-lag path reveals that stock market index leads policy uncertainty slightly.

Table 2: Summary of the $\langle x(t) \rangle$ between EPU and stock market index.

| $\langle x(t) \rangle$ | Length | Mean | Median | Max | Min | Positive Values% | Negative Values% |
|-----------------------|--------|------|--------|-----|-----|-----------------|-----------------|
| CNEPU-SSEC            | 3393   | 37.31| 35.16  | 68.87| 7.93| 100.00          | 0.00            |
| UK-EPU-FTSE100        | 3517   | -2.21| -1.27  | 47.36| -57.48| 30.85           | 69.15           |
| USEPU-S&P500          | 3515   | -5.38| -3.35  | 40.88| -67.17| 16.39           | 83.61           |

As Table 2 reports, the mean and median of the US $\langle x(t) \rangle$ is -5.38 and -3.35 respectively. The negative paths account for 83.61% of the whole paths, which also support the view that the US stock market leads EPU slightly. The results suggests that the US stock market index plays a leading role in general, whilst EPU takes the lead occasionally.

Dynamic correlation between economic policy uncertainty and stock market returns is vulnerable to international shocks like the 2008 financial crisis, which is in line with work of Antonakakis et al. (2013) and Xiong et al. (2018).

5. Conclusion

We explore the time-varying co-movements between local economic policy uncertainty and stock market returns using the TOPS method. The results show that the lead-lag relationship between economic policy uncertainty and stock market on a developed county is different from that on a developing county, which is in line with work of Das and Kumar (2018). In China the stock market holds an overwhelming position during whole period. The stock market in the UK is leading EPU slightly during the whole period. We observe almost the same lead-lag relationship in the US. However, the lead-lag relationship is volatile and sensitive to extreme events like financial crisis, stock market crash and COVID-19 pandemic.

We complement the literature on relationship between EPU and stock market returns.

Acknowledgements

This work was supported by the Peak Discipline Construction Project of Education at East China Normal University, the National Natural Science Foundation of China (11805119, 12005064), and the Postdoctoral Science Foundation of China (2020M681240).

References

Antonakakis, N., Chatziantoniou, I., Filis, G., 2013. Dynamic co-movements of stock market returns, implied and policy uncertainty. Economics Letters 120 (1), 87–92.

Arouri, M., Estay, C., Rault, C., Roubaud, D., 2016. Economic policy uncertainty and stock markets: Long-run evidence from the US. Finance Research Letters 18, 136–141.
