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Multiscale relationship between economic policy uncertainty and sectoral returns: Implications for portfolio management

Abstract: This study examines the multiscale links between economic policy uncertainty (EPU) and sectoral stock returns in China, India, the UK, and the US. We find that the impact of domestic EPU on sectoral returns persists at low frequencies and over the full sample period, especially in the financial sectors of China, the UK, and the US. The combined impact of domestic and US EPU endures the longest in the UK and China over a 16–32 month horizon. We also observe a high Sharpe ratio (low Value-at-Risk; VaR) in the presence of considerable US EPU that flips across sectors. During rising US EPU, the portfolio optimization exercise suggests weighting Chinese and Indian sectors higher. Finally, the VaR exercise produces identical portfolio diversification benefits in the equally weighted global and China stocks portfolios.

JEL classifications: C22; G11; G12

Keywords: Wavelet coherence; economic policy uncertainty; sectoral returns; value at risk; Sharpe ratio

1. Introduction.

Economic policy uncertainty (henceforth, EPU; Baker et al., 2016) is said to affect equity market returns (Pastor and Veronesi, 2012) because it is a significant driver of capital flows across numerous nations (Choi and Furceri, 2019). The influence of EPU on financial markets is investigated utilizing a variety of scenarios and approaches (Christou et al., 2017; Yang et al., 2019; Luo and Zhang, 2019, Zhang et al., 2019). Among them, studies examine the impact on stock market returns (Balcilar et al., 2019; Phan et al., 2018), as well as firm-level effects (Balcilar et al., 2019; Phan et al., 2018; Kang et al., 2017). Chiang (2019) finds evidence of predictability from EPU for risk and stock returns in the G7. Guo et al. (2018) reveal an asymmetric relationship between stock returns and EPU in both developed and BRIC markets. According to Lin and Bai (2021), economic policy uncertainty not only affects major economic indicators, like oil prices, but also appears sensitive to any subsequent changes. According to recent work by Wu et al. (2021), economic policy uncertainty not only affects conventional assets but also affects newly emerging assets like cryptocurrencies. Xiong et al. (2018) report a time-varying association with EPU in the Shanghai and Shenzhen stock markets, while Arouri et al. (2016) find a stronger relationship between EPU and returns in the US market during periods of excessive volatility. Das and Kumar (2018) show that the impact of EPU on stock returns varies over time scales using a wavelet approach (see, also, Bahmani-Oskooee and Saha, 2019). However, according to Emmanuel et al. (2021), cross-country linkages among economic policy uncertainty of the biggest economies is nominal.

Existing empirical research mainly focuses on market-level analysis, leaving an opportunity to investigate the influence of EPU at a more disaggregated level. Indeed, we argue that that more emphasis should be paid to sectoral stock market analyses. This need arises because equity market contagion is caused by crisis and policy uncertainty, dependent on economic fundamentals (Bekaert et al., 2014). Karnizova and Li (2014) support this hypothesis by finding that EPU has predictive value for succeeding US recessions, primarily in the long run. In turn, these links, between a crisis, which can proxy for the economic situation, and EPU volatility (Benati, 2013) are predicted to influence stock market investing strategies. For example, stock market investors may find it beneficial to use a sector rotation strategy rather than repeatedly increasing the same investments, regardless of market conditions.

The principle of sector rotation states that different economic sectors can under- or over-perform the market at different business cycle times. As a result, an investor tries to pick suitable industries and move according to the current economic situation. The financial press frequently provides investors with advice on sector specific investing. For example, a CNN Money article discusses the impact of an economic slowdown on sectoral returns following a delay in Federal Reserve Bank interest rate hikes. According to this study, pharmaceuticals, financials, consumer staples, and utilities are recommended as having the best performance during economic downturns.[1] Moreover, when an economy starts a growth period, conventional market wisdom holds that cyclical sectors provide the best relative performance. Stovall (1996) discusses when sectors are projected to provide investors with the best returns during various economic phases in his investing guide "Segment Investing."

With a sector rotation strategy, investors have a different perspective on market behavior than market efficiency advocates. According to market efficiency, a strategy based on repeating economic situations should not create systematic profits. Regardless, asset prices can be affected by swings in macroeconomic conditions, resulting in short-term cyclic returns. According to Fama

[1] http://money.cnn.com/2006/08/08/markets/fed_pause_stocks.moneymag/index.htm

and French (1989), stocks and bonds have term premiums that vary with the status of the economy. Similarly, pricing variables, such as size, value, and momentum, are linked to economic states (Chordia and Shivakumar, 2002; Avramov and Chordia, 2006). Following this, several researchers examine the lead/lag relationship across economic states. For instance, Hou (2007) reports a lead/lag impact in sector reaction to economic news. Furthermore, Hong et al. (2007) and Eleswarapu and Tiwari (1996) show that sectors, such as retail, metals, services, and oil, exhibit a relationship whereby the economic level leads the market by up to two months. Menzly and Ozbas (2004) show that sector profits correlate with its production/consumption supply chain position, while a constant lag relationship exists among returns to upstream and downstream sectors. Stovall (1996) also observes this upstream and downstream relationship, noting that essential materials are the first sector to rise out of a downturn, followed by manufacturing. Stovall (1996) argues that sectors identified with end-user consumption, for example, customer durables, are the last sector to recover from a downturn.

Despite this, the topic of whether sector rotation outperforms the market is largely unsolved, with studies yielding mixed results. Compared to the S&P 500, Chong and Phillips (2015) discover that a portfolio of sector ETFs formed as a response of sectors to economic conditions perform better. According to further studies, there is a lead/lag link between sectors, resulting in differential sector performance throughout economic scenarios (Stangl et al., 2008; Conover et al., 2008). However, more data is needed before sector rotation can be deemed a systematic link. As a result, we examine whether an investor may outperform the market with an equally weighted portfolio by rotating sectors among economic states characterized by EPU.

Our research adds to the existing body of knowledge in three ways. We first investigate the link between EPU and sectoral stock market returns across periods using the wavelet coherence technique. This strategy enables the multiscale and magnitude of the relationship between variables to be discovered over various investment horizons. This also alludes to the investor heterogeneity hypothesis, which distinguishes between the frequency domain behaviors of short- and long-term investors. In other words, we expect disparities in the speed and size of reaction to EPU surrounding specific events to develop across sectors. For example, during the financial crisis, we would expect to see a higher impact on the banking sector.[2] Second, we look at cross-country differences between China and India, two fast-growing Asian markets, and the United Kingdom and the United States as two established developed markets.[3]

There are several reasons we select these four countries. First, both India and China are members of the BRIC group, and their economic relations with the UK have grown significantly in the previous ten years. According to the Office for National Statistics, China became the UK's fourth largest source of imports and sixth largest export market in 2020. Second, the UK market has proven to be a vital hub for Chinese firms, particularly firms with nuclear power capabilities. Third, the Department for International Trade recognizes the nature of a substantial Indian–British economic link. In July 2021, the agency ranked India as the UK's second-largest source of foreign direct investment after the United States. These economic ties and competition between the four economies can impact the political decisions they make. Therefore, this might be reflected in the success of these countries' stock markets. Fourth, and perhaps most crucially, we deviate from the existing literature and investigate the economic consequences of our findings by designing a set of optimal portfolios spanning time scales and examining their performance in terms of multiscale

[2] Closing price indexes of sectors also have to be determined by firms' performance in these sectors. These firms, however, can be impacted the EPU differently. For example, Kang et al. (2014) documented that EPU does not influence the investment decisions of the most prominent firms in the US.

[3] Using a sample of 9 countries, including China, India, the UK, and the US, Wu et al. (2016) found that not all stock markets fall when negative EPUs increase.

Sharpe ratio and Value-at-Risk (VaR). This latter analysis is also graphically undertaken to determine how much and when this developed-emerging portfolio risk metric lowers in response to changes in EPU. Our research adds to the small but growing body of knowledge about the EPU-sectoral stock market relationship. Among these, Rehman et al. (2021) recently investigate the causation in mean and variance between US sectoral stock market returns and the EPU and find various connections across return quantiles and market sectors. Si et al. (2021) use a temporal frequency connectedness approach to find that the EPU has the most significant impact on Chinese energy, finance, IT, telecommunication services, and utility sectors. Their research also uncovers substantial evidence of a medium and long-term link between volatility and EPU.

This study differs from the two previously stated studies in three respects. First, we compare emerging and developed economies to assess the outcomes on a global scale rather than a national one. International investors who want to diversify their portfolios globally can benefit from this. Second, neither of the previous studies consider the consequences of their findings. This is an apparent constraint to their work, which also prohibits interested investors from implementing a sensible investing strategy and aiming to reduce portfolio risk. Finally, we analyze the individual (joint) influence of the domestic (local and global) EPU on sectoral market returns in each sample nation using several wavelet coherence techniques.

Two significant findings emerge from this paper. First, compared to linear regression, wavelet techniques (partial and multiple wavelet coherence) indicate a more extensive range of dynamics between EPU and sector stock returns. While a linear regression shows no relationship between China and the United Kingdom, we find substantial evidence that policy uncertainty impacts sector returns in all four markets studied (including India and the US). Furthermore, the findings show disparities across time horizons and in the aftermath of significant economic crises.

These findings remain when accounting for local and global EPU. Second, the findings show that the wavelet technique has economic benefits for investors as a sector rotation strategy, with both Sharpe ratio and VaR enhancements over a buy-and-hold portfolio. From a US investor's perspective, applying the wavelet results to implement a portfolio rotation strategy across sectors results in a lower VaR. This conclusion is consistent with, for example, the findings of Conover et al. (2008) for sector rotation. Specifically, the findings show that it is better for a US investor to overweight investments in Indian and Chinese stock markets during significant US policy uncertainty. Furthermore, at times of low uncertainty, portfolio rotation is more beneficial (with a higher Sharpe ratio).

The remainder of this work is arranged as follows. The following section describes the methodology, Section 3 defines the dataset and study sample, and Section 4 discusses the key empirical findings. The extra analysis is detailed in Section 5, and in Section 6, we look at the economic consequences of our findings before summarizing them and presenting their policy implications in Section 7.

2. Empirical Methodology.

This paper employs wavelet coherence analysis to examine the linkage between the variables of interest. Wavelets separate our data across different time scales, which can then be examined. Wavelets can be considered small waves that grow and decay quickly. In practice, this complements the simple assumption of Fourier transform of variations over an infinite length of sines and cosines. The basis of the wavelet transform is the mother wavelet with its translation and dilation parameters. The first parameter controls for time position (T), while the second accounts for scaling (S). The result of considering the two parameters can then decompose the time series on a time-scale basis. According to Percival and Walden (2000), the mother wavelet $\Psi(t)$ must fulfill two main conditions. It must have a zero mean, such as $\int_{-\infty}^{+\infty} \Psi(t)dt = 0$, and its square integers to one with $\int_{-\infty}^{+\infty} \Psi^2(t)dt = 1$, meaning that the mother wavelet performs on a limited time horizon and then decays. The wavelet transform also relies on the admissibility condition of $\int \frac{\left|\hat{\Psi}(t)\right|^2}{|t|} \Psi(t) < \infty$, with $\hat{\Psi}$ being the Fourier transform of Ψ. This paper employs the most common form of wavelet, namely Morlet, which is mathematically considered a complex sine wavelet combined with a Gaussian form.[4] The Morlet mother wavelet can then be defined as follows:

$$\Psi(t) = \pi^{-0.25}(e^{iwot} - e^{-\frac{wo^2}{2}})e^{\frac{-t^2}{2}} \tag{1}$$

Applying wavelet transform on two time series, $x(t)$ and $y(t)$, along with the corresponding wavelet transforms, $W_x\ (T, S)$ and $W_y(T, S)$, should produce the cross-wavelet spectrum:

$$W_{xy}\ (T, S) = W_x\ (T, S)\, W_y^*\ (T, S) \tag{2}$$

From the above equation, one can derive the wavelet-squared coherency as:

$$R^2(y, x) = \frac{\left|S\left(s^{-1}W_y\,(T, S)\right)\right|^2}{S\left(s^{-1}\left|W_x\,(T, S)\right|^2\right) S\left(s^{-1}\left|W_y\,(T, S)\right|^2\right)} \tag{3}$$

where $S(\cdot)$ represents smoothing in both the time and scale properties. The resulting squared correlation coefficient from the equation ranges from 0 to denote weak correlation to 1 for high

[4] Further details on Morlet wavelet and its related equations can be found in Percival and Walden (2000) and Grinsted et al. (2004)

correlation. The estimation is based on dividing the covariance over the product of two wavelet variances, which is a standard correlation calculation between two variables. Wavelet coherence adds to a standard estimate by analyzing the correlation coefficient over many time horizons. When plotting the wavelet coherence throughout the sample period, it can be seen where the two time series converge. On the same wavelet coherence graph, variations in such a relationship might be highlighted using different colors. These changes are likely to correspond to specific events, such as the global financial crisis and other country-specific occurrences. The time scales from the wavelet analysis can be compared with their counterparts from a baseline analysis. Therefore, we run a simple linear regression as follows:

$$R_t = \alpha + \beta_1 \Delta EPU_t + \beta_2 R_{t-1} + \varepsilon_t \qquad (4)$$

Where the dependent variable is the monthly return series R_t for the selected country *c* and sector *i* on the month *t*. ΔEPU denotes for the changes in the EPU for each country. R_{t-1} is the lagged monthly return and accounts for potential serial autocorrelation.

3. Data.

This paper employs a sectoral monthly price index for China, India, the UK, and the USA, and all data is obtained from DataStream. Ten sectors for each country are selected according to the DataStream classification: oil and gas, basic materials, industrial, consumer goods, consumer services, financial, health care, basic utilities, technology, and telecommunication sectors. We also employ the constructed EPU monthly indexes from Baker et al. (2016).[5] Monthly prices are

[5] More details on the EPU indexes can be found in (http://www.policyuncertainty.com/).

converted to returns, such as $R_{i,t} = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \times 100$. Additionally, we generate the change in EPU (i.e., ΔEPU) over two subsequent months.

The sample period is from December 1994 to April 2019 for China, January 2003 to February 2019 for India, January 1998 to February 2019 for the UK, and January 1985 to July 2019 for the USA. However, China's health care, basic utilities, technology, and telecommunication sectors started in February 2004. The four nations in the sample are all large economies; therefore, comparing them is crucial for determining the differences in EPU's impact on their markets. The study aims to determine if EPU has a varied impact on different industries in different nations and if the results are consistent across countries, indicating if EPU's effects on returns vary over different investment horizons.

Table 1 provides descriptive statistics for all variables in the sample. The table shows that, except for the oil and gas and industrial sectors, all sectors in India reject normality. While only the EPU in China appears to be non-normally distributed. However, China's standard deviation indicates the highest volatility compared to its counterpart in other countries. At the country level, the basic materials sectors in both China and India and the technology sectors in the United Kingdom and the United States are the most volatile. For all of the series, the augmented Dickey–Fuller (ADF) statistic test confirms the rejection of the unit root hypothesis.

4. Empirical Results.

Table 2 presents the baseline regression results in equation (4). As seen, EPU has a significant impact on returns in almost all industries in India and the United States, but not in China or the United Kingdom. Except for health care, EPU has a continuously negative and statistically significant effect on sector stock returns in India. The results also show that EPU has a negative predictive effect on sectoral stock returns in the United States. Except for health care, telecommunications, and technology, EPU has a negative predictive coefficient for all sector returns in China. The same conclusion may be drawn for the UK's oil and gas, consumer services, and telecommunications industries; however, the relationship in China and the UK is minor. Overall, while EPU has a primarily negative impact on sector stock returns, its statistical significance is mixed. However, we argue that because these results overlook investment horizons beyond the first day, they do not provide a complete picture of the sector EPU-return relationship. As a result, we use the wavelet technique to report the results for each country over various time scales. The results are graphically represented in two dimensions, with multiple colors (shades) employed in the same graph. The horizontal axis represents the period, while the frequency is shown by the vertical axis, characterized as high or low depending on the graph's location. The top (bottom) area shows the relationship between the two variables at high (low) frequencies. Areas on the graph with red colors (dark shade) are significant at the 5% level. A significant relationship at the end (beginning) of the sample period is reflected by such a region on the surface's right (left) side. The 5% significant relationship is estimated using 2000 random iterations in a Monte Carlo simulation.[6]

[6] Our wavelet coherency estimation is performed using the *biwavelet* package in the R program. Using a different number of random iterations produces very similar results with the same degree of relations.

Figure 1 shows the charts for sectoral stock returns in China using EPU as a predictor. We observe clear persistence in the relationship at low frequencies during the sample period for both the industrial and financial sectors. However, this tends to shift to higher frequencies after the global financial crisis. Following the global crisis, a strong relationship may be seen in the consumer services sector, while the same occurred in the oil industry before 2002; neither finding occurs regularly. Before 2013, China's consumer goods, finance, healthcare, and telecommunications sectors appear to be impacted by EPU, which coincide with the lowest GDP since 1999. Conversely, the impact on the technology sector appears strongest in the aftermath of the global financial crisis, with investment horizons ranging from four to 16 months and long horizons of [32–64] months. After 2013, policy uncertainty drives basic utilities returns over the intermediate investment horizon [16–32], with a positive relationship. Before 2002, the favorable relationship continued to show in the basic materials and finance industries throughout the same investment horizon. During this year, the Chinese economy was stimulated, with annual GDP and GDP per capita hitting higher levels than in prior years.[7]

[Insert Figure 1 about here]

Figure 2 provides similar data for India. During and after the global financial crisis of 2008, the effect of EPU on all sectoral returns is minor and lasts for only a few months [4–8]. At the low-frequency level, notably the [32–64] months, this influence tends to last longer in the industrial sector until 2013. Similarly, policy uncertainty continues to influence India's consumer goods and basic utility sectors during the following [8–16] months, leading up to 2013. A new Indian Prime Minister was elected in 2014, and the amount of EPU generated in the Indian economy as a result of the appointment can justify the break in the results. The influence of EPU on all industries after

[7] For more details, refer to https://countryeconomy.com/gdp/china?year=2002.

2005 at a short time-scale [4–8] months is another apparent conclusion in the graph. This finding could be attributed to an increase in EPU from late 2005 to the end of June 2007.[8] The healthcare industry is an exception, where a substantial negative association is observed across extended periods. This relationship exists throughout the sample period and is stronger following the financial crisis.

[Insert Figure 2 about here]

We see several things when we focus on the findings in the United Kingdom (shown in Figure 3). First, in the oil, industrial, consumer services, financial, and healthcare sectors, the relationship is statistically significant at the lowest frequency over the full data period. From the beginning of the sample period through 2006, at the intermediate scale [8–16] months, basic materials, consumer goods, and financial returns appear linked to EPU. At horizons longer than 32 months, the same is true for the technology sector. Second, Figure 3 shows how the 2016 Brexit referendum affected stock market returns. More specifically, we can observe the influence on the industrial, consumer services, financial, and telecommunications sectors over time.

[Insert Figure 3 about here]

In the case of the United States, Figure 4 shows that the impact of EPU on sector returns is only present at intermediate and high frequencies. However, this influence endures beyond the 1998 crisis on very low frequencies in the oil sector. After the dotcom bubble burst, it also lasts in the financial and industrial sectors. In the aftermath of the 2008 financial crisis, all sectors are affected, except telecommunications, starting from the second investment horizon. On the horizon between 32 and 64 months, the global crisis appears to have a more concentrated influence on the healthcare sector. This illustrates that, depending on investment horizons, the impact of the

[8] For confirmation, refer to Baker et al. (2016).

financial crisis varies across sectors and over time. Furthermore, Figure 4 demonstrates that the EPU effect is entrenched in the financial, consumer goods, and basic utilities returns during the sample period of more than 128 months. However, the relationship for the other sectors is significantly different, as noted for the [8–16] time scale. At that magnitude, some continuity in the relationship returns to the consumer services industry.

[Insert Figure 4 about here]

In short, among the four counties in our sample, the effect of EPU varies across sectors and frequencies on returns. Most of the effect persists over the low frequencies, lasting over the full sample period in some sectors. These results complement Guo et al. (2018), who note variations in the return-EPU relationship across the return quantiles. We also detect some time-breaks in the correlation between the EPU and return that coincide with specific events in our sample period, notably the global financial crisis.

5. Additional Analysis

5.1. Partial wavelet coherence (PWC): Controlling for the US EPU

The above section examines the effect of EPU on sector returns. However, country EPU could mix both market-specific and global effects. Therefore, this section applies the PWC to examine the effect of domestic EPU (DEPU) on sectoral return after controlling for US EPU (IEPU) to proxy for global policy uncertainty.[9] Analogous to the multiple wavelet coherence, the resulting squared

[9] We also performed the quantile regression analysis as a comparative analysis in four stages. In the first stage, the sectoral returns in the US are regressed on the US EPU and the DEPU and one lag of the return series. For the other remaining three stages, the domestic sectoral returns in the UK, China, and India are regressed on the US EPU and the DEPU. The new results became quantitatively and qualitatively similar to those reported here. Specifically, the impact of the US EPU tends to be statistically stronger than the DEPU, which is found to be more evident during the bullish market conditions (i.e., upper quantiles). Furthermore, performing the Wald test revealed some statistical differences in the impact of US EPU across sectors. This result was truer for the analysis conducted in the UK and China. The complete findings from the analysis are omitted to save the space but made available upon request.

correlation from PWC ranges from 0 (i.e., weak correlation) to 1 (i.e., strong correlation), and it can be considered in localized time and frequency as follows:

$$RP^2(y,x,z) = \frac{\left| R(y,x) - R(y,z).R(y,x)^* \right|^2}{\left[1 - R(y,z)\right]^2 \left[1 - R(z,x)\right]^2}; \tag{5}$$

Where:

$$R(y,x) = \frac{S\left[W(y,x)\right]}{\sqrt{S[W(y)].S[W(x)]}};$$

$$R(y,z) = \frac{S\left[W(y,z)\right]}{\sqrt{S[W(y)].S[W(z)]}};$$

$$R(z,x) = \frac{S\left[W(z,x)\right]}{\sqrt{S[W(z)].S[W(x)]}};$$

Figures 5, 6, and 7 show the results of the PWC exercise for China, the UK, and India, respectively. The effects of the DEPU on greater time-scale returns in the industrial, healthcare, and telecommunications sectors are partially reduced in Figure 5 (China). Surprisingly, after adjusting for the IEPU, the consumer goods and financial sectors are less affected, especially noticeable before the 2008 financial crisis. Nonetheless, significant effects appear in the consumer services, financial, and basic utilities sectors 32 to 64 months after the start of the US debt ceiling crisis in 2011.

When examining the UK sectoral returns in Figure 6, the time-scale relation persists for the industrial, financial, consumer services, and telecommunication sectors from 2016 until the end of the 16–32 month period. The impact of the 2008 financial crisis is still felt in all sectors; however, there is less evidence in the basic materials and health care sectors. The image shows an interesting feature connected to the EPU's strong negative influence on the technology industry before and during the dotcom bubble. Figure 7 shows that the Indian technology sector returns are closely associated with IEPU at the time-scale of 32–64 months, following the global crisis. In other industries, this effect is basically absent. Significant relationships between the consumer goods and health care industries exist at short time frames, from 4 to 8 years after 2010.[10] Excluding oil and gas, banking, basic utilities, and telecommunications, the impact on sectoral returns appears significant from the beginning of the sample period until 2005. However, relationships exist in these sectors at the smallest investment horizon throughout the same period.

[Insert Figure 5 about here]

[Insert Figure 6 about here]

[Insert Figure 7 about here]

In sum, the results from PWC uncover the combined effects of the DEPU and the IEPU on the sectoral returns in China, India, and the UK. The PWC analysis confirms that China and US policy uncertainty indexes appear to interact less at higher frequencies. This result partially confirms the recent finding of Li et al. (2020), who note stronger integration between the IEPU and the long-term stock market return in China and India around the significant financial events. However, our findings for India somewhat contradict theirs; our results show that the impact of IEPU differs across sectors in the same country.

5.2. Multiple wavelet coherence (MWC)

The MWC is similar to multiple correlation analysis and specifically aims to examine the impact of multiple independent variables on a given dependent variable, such as:[11]

$$RM^2(y,x,z) = \frac{R^2(y,x) + R^2(y,z) - 2\,\mathrm{Re}[R(y,x).R(y,z)^{*}.R(z,x)^{*}]}{1 - R^2(z,x)} \qquad (6)$$

[10] In 2011, the World Bank announced that the Indian economy had become the third-largest economy.
[11] Further details on the approach can be found in Ng and Chan (2012) on page 1850.

Applying the MWC then allows examining the collective impact of the DEPU in each market along with the IEPU.

Figures 8–10 show the results of this exercise. Figure 8 shows the results for UK sectors, confirming previous findings of a minimal association between EPU and sector returns. The combined impact of EPU and IEPU, in contrast, appears to be more significant. These findings imply that when foreign EPU exists, the co-movement between EPU and sector returns increases. Co-movement is visible across sectors between 4 and 16 months in most situations. During the financial crisis (2008–09), the industrial, consumer services, financial, and technology sectors were most affected by both the UK EPU and the global EPU, whereas the consumer goods and basic utilities sectors were most affected by the European crisis period (2012–2014) under the 4–8 month horizon. Over the entire sample period at the longest time scale, the combined impact of uncertainty appears in all sectors except basic utilities, basic materials, technology, and telecommunications. Concerning the co-movement of Indian sector returns with local and global EPU, basic materials, industrials, and utilities show co-movement over short investment periods. In contrast, over lengthy run periods ranging from 16 to 64 months, the basic materials, industrial, financial, and healthcare sectors demonstrate co-movement with local and global EPU. In short- and long-run timeframes, returns in the consumer goods and consumer services sectors are sensitive to local and global EPU. The findings reveal that basic materials, consumer goods, consumer services, financial, and technology sectors are the most affected by co-movement between Chinese sector returns and local and global EPU. During the 4–16 month period, the global financial crisis (2008–09) has had the greatest impact on the basic materials and consumer services sectors. Additionally, over [16–32] months, the effects of both types of policy uncertainty tend to persist on some sectoral returns in the industrial, consumer services, financial, telecommunications, and basic utilities sectors.

[Insert Figure 8 about here]

[Insert Figure 9 about here]

[Insert Figure 10 about here]

In sum, MWC analysis confirms the relationship of the EPU-sector return at the long horizons of more than 32 months in the UK, India, and China markets. However, the persistence in this relationship is more evident on the higher scales in China and the UK. The MWC exercise emphasizes the importance of considering both sources of uncertainty (i.e., local and global) when diversifying the investments between sectors in the same country.

6. Portfolio Implications

6.1. Multiscale portfolio optimization[12]

This section examines the economic implications of our findings, and we begin by decomposing sector returns using the maximum overlap discrete wavelet transform (MODWT). This approach allows for an appropriate decomposition of the series and aims to disentangle the individual effects of several predictors at different horizons (Gallegati and Ramsey, 2014).

The MODWT relies on a function $f(t) \in L^2(R)$ that can be represented by wavelet analysis. It has a sequence of projections arising from mother and father wavelets ϕ and ψ through scaling and translation. Specifically:

$$\phi_{j,k}(t) = \frac{1}{2^{j/2}} \phi\left(\frac{t-2^j k}{2^j}\right) \tag{7}$$

[12] The analysis considers the risk-free rate investment in the US to evaluate the optimal portfolio performance from the US investor's point of view.

and

$$\psi_{j,k}(t) = \frac{1}{2^{j/2}} \psi \left(\frac{t-2^j k}{2^j} \right) \tag{8}$$

Where j and k index the scale and translation, respectively. 2^j is a measure of the scale or the width of functions $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$, where the larger index j, the larger the scale 2^j, showing that function gets shorter and more spread out. The translation factor $2^j k$ is then matched to 2^j, and as the functions $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$ get wider, the corresponding translation steps tend to be larger.

Next, the decomposition incorporates the mother and father wavelets in a linear combination over high-pass and low-pass filters, respectively. Using the mother filter, the return series R_n for the number of observations n can show up over different horizons to generate the approximation series. That part captures the events that are long in time and appear less in each frequency. However, the other decomposition output generates the details components D_j that are short in time and redundant in frequency. The decomposition process is described as follows:

$$V_{i,t} = \phi A_n + \sum_{j=1}^{n} \Psi D_j \tag{9}$$

Following Percival and Walden (2000), we employ the asymmetric Daubechies filter with the length of 8 (L8) as it can work with the volatile time series data. The decomposition is executed over six time scales, which is found to preserve the variance of the return series. More specifically, time-scale 1 belongs to the range [2–4] months, scale 2 displays the range [4–8] months, scale 3 is for [8–16] months, scale 4 for [16–32] months, scale 5 for [32–64] months, and scale 6 for [64–128] months. Galagedera and Maharaj (2008) also select the same number of scales.

The second analysis step involves using the resulting decomposed return series to construct the optimal and benchmark sectoral portfolios. We also decompose the IEPU on time scales using the same decomposition described above. The details of the policy uncertainty are then classified into increasing and decreasing uncertainty states to reflect the positive and negative changes (i.e., 1, 0 dummies) in IEPU. Afterward, the decomposed sectoral returns on each time scale are categorized into two groups based on the variations on the IEPU. We then evaluate the performance of the two portfolios. The first is an equally weighted portfolio comprising 40 sectors from China, India, the UK, and the US, and representing a benchmark. Constructing the second competing portfolio aims at examining the ability of sectors rotation on time scales to maximize the Sharpe ratio and minimize the VaR. The calculation of the VaR for the competing portfolio employs the optimal weights from maximization of the Sharpe ratio exercise. The Sharpe ratio is estimated as follows[13]:

$$S_p = \frac{(ER_p - R_f)}{\sigma_p} \tag{10}$$

Where ER_p is the portfolio's expected return, R_f corresponds to the end of 2019 10-year treasury rate in the US (1.92%), and σ_p is the portfolio standard deviation. We calculate the VaR, which shows the maximum loss of a portfolio consisting of several assets (n) at a previously determined confidence level over a specific period. For the (1-α) confidence level, the VaR estimates can be given by:

$$VaR = I_0 \phi^{-1}(1-\alpha)\sigma_P \tag{11}$$

Where I_0 is the $1 portfolio value. $\phi(.)$ denotes the standard normal-based cumulative distribution function and σ_P is the risk of the optimal or benchmark portfolio, while α denotes the risk threshold of 1%, selected for consistency with Basel risk requirements.

[13] More details on obtaining the optimal weights of the sectors in the portfolios are omitted to save space. These can be provided upon request.

Table 3.a shows the performance of the constructed multiscale portfolios over the full sample period in panel (a) and during increasing and decreasing IEPU states in panels (b) and (c), respectively. The results in the table include the competing portfolio return and risks along with the top three sectors with the highest assigned weights. Several interesting findings can be observed in panel (a) of the table. First, constructing the optimal portfolio on the first time scale over the full sample tends to overweight the consumer goods sector in China. It also becomes the second-best sector for inclusion in the portfolio at the second horizon. Second, in the second and third scales, the industrial sector in the United Kingdom and China are the most favored. Third, the consumer goods sectors in India and China are tied more closely to the [16–32] month horizon. Fourth, on a lengthy time scale of [64–128] months, the competitive portfolio's return and Sharpe ratio are likely to be the highest. The VaR tends to be the lowest on the same scale compared to the preceding time scales. Fifth, for all time scales except scale 4, when the Indian and Chinese sectors are overweighted in the portfolio, executing the trade with the benchmark portfolio appears to result in lower Sharpe ratios and lower VaR. At this point, putting too much emphasis on these two countries has negative consequences.

Panel (b) shows similar results to those seen during the entire sample period. At investment horizons of more than a month, the Sharpe ratio (VaR) tends to increase (drop). This finding is in line with Fernandez (2005) and Mensi et al. (2017), who find that the VaR of portfolios decreases as investment horizons increase. Other results show that the Indian and Chinese industries are given the highest weights across all horizons. On a scale of [32–64] months, China's consumer goods and financial sectors rank first, confirming the findings of the PWC exercise. For the first time across the scales, this also creates a positive Sharpe ratio. This also highlights the need to look at the Chinese consumer and financial sectors over a longer time horizon when the IEPU rises. In panel (c), we see that the profitability of competing portfolios increases at all scales compared to those observed during the growing IEPU stage. The only instance with a negative Sharpe ratio is when the time scale is [32–64] months. This looks to conflict with the panel results (a). Furthermore, the portfolio's VaR (profitability) achieves its minimal (highest) level at the longest horizon. However, when investing in benchmark portfolios, the low IEPU state always results in a lower VaR than competitive portfolios. This supports the widely held belief in the finance literature that high risk is associated with high market uncertainty. In other words, a US investor should invest in other competing economies.

[Insert Table 3.a about here]

Table 3.b shows sector rotation in the United States due to policy uncertainty. Panel (a) demonstrates that the consumer services, health care, and industrial sectors are assigned less weight. Over the entire sample period, there appears to be less investment in the telecommunications, basic utilities, and consumer goods sectors. According to the same panel, the risk-return performance of the portfolio is best at the longest investment horizon. This evidence is similar to the benchmark portfolio, with the latter having a greater Sharpe ratio. Panels (b) and (c) support the findings in panel (a), with the competitive portfolio outperforming over extended periods and having a larger Shape ratio. Additionally, resembling the results in Table 3.a, rotating between sectors seems to minimize the risk of the optimal portfolio during the increasing IEPU state, at least at the short and intermediate horizons.

[Insert Table 3.b about here]

Tables 3.a and 3.b show the importance of portfolio rotation strategy over time in the US market and India, the United Kingdom, and China. At the time-scale [32–64] months, a higher allocation in consumer goods, basic materials, and financial sectors can reduce the optimal portfolio risk. This is especially true when the US market is dealing with a high level of policy uncertainty. A US investor should be overweight in the Indian and Chinese industries. Furthermore, when the uncertainty is low, the rotating portfolio technique is more profitable than when the uncertainty is high.

6.2. Wavelet VaR: Graphical analysis and equally weighted portfolios

Some research emphasizes the usefulness of wavelet analysis in risk management (Fernandez, 2005; Rua and Nunes, 2012; Mensi et al., 2017; Meng and Hunag, 2019). These studies generally show that if newly added equity is negatively related to existing equity, the VaR of a portfolio tends to drop over time. We revisit the portfolio VaR in light of recent research and to support the findings in Section 6.1. To begin, we use equation (11) to represent the VaR of a multi-country (k) portfolio. When global policy uncertainty is higher, the research examines whether adding stocks from the United Kingdom, China, and India reduces the VaR of a benchmark portfolio comprising only US stocks. The variance of the constructed portfolio is given by:

$$\sigma_p^2 = \sum_{i=1}^{k} \omega_i^2 \sigma_i^2 + \sum_{i}^{k} \sum_{i \neq j}^{k} \omega_i \omega_j \operatorname{cov}(r_i, r_j) \tag{12}$$

Where ω_i , and r_i are the weights and the sectoral return of sector i , while σ_i^2 denotes its variance. Also, $\operatorname{cov}(r_i, r_j)$ is the covariance between the set of stocks in the portfolio.

Because it is based on evenly weighted portfolios, this approach varies from Section 6.1. More importantly, we follow Meng and Huang (2019) and Mensi et al. (2017), among others, in estimating the VaR at a given time scale while assuming no co-movement (i.e., $\operatorname{cov}(r_i, r_j)=0$) between the collection of assets under discussion. In the second stage, assuming that co-movement varies over horizons, we ease this constraint. Hence, we calculate the ratio of VaR without restriction (VaR_c) to VaR with restriction (VaR_u) to investigate the influence of co-movement at a specific scale. The goal is to test the null hypothesis that time-scale co-movement affects the VaR estimation.

Figures 11–14 present the results of wavelet VaR when including all sectoral stocks of each market in a portfolio.[14] That is, we measure the VaR of a portfolio comprising of sector returns under the presence of EPU. The results in Figure 11 highlight that the sector stocks in a portfolio are affected by the UK EPU during [1–2] month period; however, the results appear quite significant when considering the impact of global EPU on UK sector returns. Sector diversification benefits are quite low, attributable to the high magnitude of correlation during the investment period of 1–2 months across the entire sampling period.

Figure 12 shows the outcome of the wavelet VaR for US sector returns, implying that including all US companies in a portfolio provides optimal diversification advantages. The inclusion of EPU appears to diversify US sector stocks, implying that these sectors respond well in a portfolio when US EPU increases. Figure 13 shows that on portfolios of Indian sector equities, the outcomes for country-based and global EPU appear identical. We can see that the correlation appears to be relatively high over the investment term of 16–64 months, implying that as EPU develops, there are few diversification options, as seen in Figure 13 panel (a). In the case of Chinese portfolios, the global EPU has a stronger impact than the Chinese EPU. As a result, the portfolios perform well in the face of country-specific EPU, but the diversification benefits reduce as global EPU increases.

[14] We are not taking EPU as equity rather trying to figure out the effect of EPU on stock returns in a portfolio. EPU is measured as a standardized index, and the wavelet technique measures short, and long-run returns coherence. Therefore, including EPU with a group of assets in a portfolio can highlight co-movement between EPU and a collection of portfolio stocks. This can help explain the diversification abilities of assets together against country-based and global EPU.

It is worth noting that investing in a global portfolio of equities from four different countries produces mixed results. Under the effect of global EPU, the diversification potential of a global portfolio (Figure 15) resembles that of a Chinese portfolio (Figure 14, panel b). The diversification potential is larger on an [8–32] month period from 2017 to the end of the study period. A specific observation can be related to Donald Trump's election as president of the United States[15] during this time, which increased economic and political tensions have between the US and China. Surprisingly, this precise finding on a scale up to 32 months mimics that seen in Table 3 panel (b). During the growing IEPU condition, the prior observation in the table represents the lowest VaR at a time scale of [16–32] months. The new VaR exercise shows that it is preferable to adopt a global portfolio diversification approach across the four countries with the most investment horizon. Finally, Figures 11–14 demonstrate the diversification possibilities of a US-based portfolio that includes the United Kingdom, India, and China.

[Insert Figure 11 about here]

[Insert Figure 12 about here]

[Insert Figure 13 about here]

[Insert Figure 14 about here]

7. Conclusion And Policy Implications

This study highlights the importance of time and frequency co-movements between EPU and sector stock returns. We present a thorough picture of the link between EPU and returns across

[15] This observation can also be linked to the recent finding of Goodell et al. (2020) that uncertainty associated with the election drives the EPU in the days preceding the US presidential election. Efficient portfolio diversification is then required to minimize the risk resulting from that uncertainty.

time scales using wavelet coherence analysis. The results in China, India, the United Kingdom, and the United States indicate considerable heterogeneity in the linkages between EPU and stock returns across sectors and time scales. Most of the effect endures in some sectors throughout low frequencies and for the whole sample period. The findings align with Guo et al. (2018), who find that the return-EPU relationship varies among return quantiles. The findings here also support Gábor-Tóth and Georgarakos (2019), who report evidence of lower stock market involvement when uncertainty is high. Increased market volatility coincides with uncertainty at a greater frequency, potentially encouraging investors to defer their trading to at a lower frequency. The disparities in performance across sectors also corroborate the catering theory concept, according to which investors react differently to information arriving in the market and invest in different asset groupings as a result (Barberis and Shleifer, 2003). These findings also support the idea of sector rotation, in which investors switch across industries based on the degree of EPU.

There are also time-breaks in the relationship between the EPU and returns around specific events, like the global financial crisis. By analyzing the effect of EPU on stock markets spanning time scales during and around specific events, our findings may be helpful for policymakers and foreign investors operating at varying investment horizons across countries. Furthermore, in a PWC experiment, controlling for US policy uncertainty reduces the effect of local EPU at lower time scales in some industries in the three other nations. The long-term returns of the Chinese consumer goods industry and the financial sector show resilience to the effect of IEPU. Nonetheless, the MWC analysis somewhat confirms the cross-wavelet coherence exercise results. On the higher scales, the combined impact of both EPU and IEPU is discovered. The new research verifies the EPU-sector return link in the UK, India, and China sectoral markets across long periods of more than 32 months. On the upper tiers, China and the United Kingdom appear to be the most committed to this connection. As a result, the significance of diversifying investments across industries in each country is reinforced. Our research also considers the financial ramifications for international investors. In particular, a portfolio optimization experiment shows that it is not a good idea to invest in an evenly weighted international sector portfolio over time. In other words, adopting a portfolio rotation strategy between sectors is less risky, especially given the current state of US policy uncertainty. When investment is overweighted in China's consumer goods, basic materials, and financial sectors, lower VaR is obtained in that period over a long horizon of [32–64] months. This study supports the findings of Conover et al. (2008) regarding sector rotation and monetary conditions, among other things.

Generally, the findings show that it is better for a US investor to overweight investing in India and China during high US policy uncertainty regardless of the investment horizon. Furthermore, the sector rotating strategy is more profitable when uncertainty is low than when uncertainty is high. The Sharpe ratio is used to assess profitability, and a wavelet coherence VaR exercise suggests diversification potential in the UK, India, and China in the face of local policy uncertainty. However, when developing both global and Chinese stock portfolios, the impact of global policy uncertainty delivers similar diversity. Overall, this study emphasizes the importance of carefully diversifying international stock market portfolios in the face of policy unpredictability.

Table 1. Descriptive Statistics

Country		Variable	Mean	S.D.	J.B test	ADF (p-value)	Country		Variable	Mean	S.D.	J.B	ADF (p-value)
	ΔEPU		0.004	0.479	0.004	0.000		ΔEPU		0.005	0.094	11.66***	0.000
	Sector							**Sector**					
	Oil and Gas		0.003	0.116	131.49***	0.000		**Oil and Gas**		0.005	0.038	130.43***	0.000
	Basic materials		0.004	0.123	23.48***	0.000		**Basic materials**		0.005	0.038	130.43***	0.000
	Industrial		0.004	0.117	42.07***	0.000		**Industrial**		0.006	0.028	44.01***	0.000
	Consumer Goods		0.008	0.113	233.6***	0.000		**Consumer Goods**		0.005	0.019	65.44***	0.000
China	**Consumer Services**	R	0.003	0.123	67.85***	0.000	**India**	**Consumer Services**	R	0.002	0.021	36.92***	0.000
	Financial		0.006	0.099	28.41***	0.000		**Financial**		0.003	0.019	27.75***	0.000
	Health care		0.005	0.024	23.47***	0.000		**Health care**		0.004	0.003	33.46***	0.000
	Basic utilities		0.000	0.020	42.18***	0.000		**Basic utilities**		0.003	0.005	33.66***	0.000
	Technology		−0.001	0.015	6737.61***	0.000		**Technology**		0.004	0.004	22.88***	0.000
	Telecommunication		0.001	0.019	45.50***	0.000		**Telecommunication**		0.003	0.005	10.08***	0.000
	ΔEPU		0.001	0.324	30.93***	0.000		ΔEPU		0.001	0.055	67.05***	0.000
	Sector							**Sector**					
	Oil and Gas		0.002	0.066	1.24	0.000		**Oil and Gas**		0.006	0.056	32.94***	0.000
	Basic materials		0.003	0.092	111.96***	0.000		**Basic materials**		0.007	0.064	622.01***	0.000
	Industrial		0.003	0.064	0.31	0.000		**Industrial**		0.008	0.055	360.69***	0.000
	Consumer Goods		0.004	0.061	18.70***	0.000		**Consumer Goods**		0.005	0.051	326.26***	0.000
	Consumer Services		0.001	0.055	76.86***	0.000		**Consumer Services**		0.008	0.052	324.52***	0.000
UK	**Financial**	R	−0.001	0.070	297.10***	0.000	**USA**	**Financial**	R	0.007	0.059	296.72***	0.000
	Health care		0.002	0.048	24.424***	0.000		**Health care**		0.010	0.044	112.06***	0.000
	Basic utilities		0.001	0.048	47.278***	0.000		**Basic utilities**		0.004	0.042	62.35***	0.000
	Technology		0.003	0.100	50.752***	0.000		**Technology**		0.009	0.073	100.66***	0.000
	Telecommunication		−0.001	0.070	15.606***	0.000		**Telecommunication**		0.004	0.053	75.17***	0.000

Notes: *, **, and *** are the statistical significance at the 10, 5, and 1 percent significance levels, respectively. The lag selection in the ADF test is based on the AIC information criteria. R denotes the sectoral return.

Table 2. Linear predictive regressions

Country	Sector	α	β_1	Adj. R^2	Country	Sector	α	β_1	Adj. R^2
China	**Oil and Gas**	0.003	−0.006	−0.002	India	**Oil and Gas**	0.004***	−0.073***	0.101
	Basic materials	0.003	−0.010	0.008		**Basic materials**	0.002***	−0.050***	0.231
	Industrial	0.007	−0.005	0.023		**Industrial**	0.004**	−0.069***	0.251
	Consumer Goods	0.007	−0.005	0.002		**Consumer Goods**	0.003***	−0.037***	0.183
	Consumer Services	0.003	−0.016	−0.003		**Consumer Services**	0.001	−0.039**	0.122
	Financial	0.005	−0.008	0.018		**Financial**	0.002	−0.042***	0.156
	Health care	−0.003	0.070	−0.002		**Health care**	−0.006*	0.053**	0.028
	Basic utilities	−0.002	−0.095	0.000		**Basic utilities**	0.000	−0.012***	0.053
	Technology	−0.001	0.113	0.010		**Technology**	0.000	−0.006***	0.033
	Telecommunication	0.002	0.082	−0.003		**Telecommunication**	0.000	−0.008**	0.020
UK	**Oil and Gas**	0.002	0.008	0.006	USA	**Oil and Gas**	0.006**	−0.111**	0.009
	Basic materials	0.003	−0.003	0.008		**Basic materials**	0.007**	−0.185***	0.022
	Industrial	0.003	−0.007	0.012		**Industrial**	0.008***	−0.149***	0.017
	Consumer Goods	0.004	−0.002	−0.008		**Consumer Goods**	0.005**	−0.180***	0.036
	Consumer Services	0.001	0.001	0.007		**Consumer Services**	0.008***	−0.188***	0.036
	Financial	−0.001	−0.003	0.022		**Financial**	0.007**	−0.177***	0.023
	Health care	−0.001	−0.004	0.007		**Health care**	0.010***	−0.091**	0.010
	Basic utilities	0.003	−0.029	−0.006		**Basic utilities**	0.004**	−0.034	−0.003
	Technology	0.002	−0.012	0.044		**Technology**	0.010***	−0.172***	0.013
	Telecommunication	−0.001	0.114	0.010		**Telecommunication**	0.004	−0.103**	0.010

Notes: This table shows the main estimated parameters from the equation $R_{c,i,t} = \alpha + \beta_1 \Delta EPU_t + \beta_2 R_{t-1} + \varepsilon_t$ with White's (1987) standard errors. *, **, and *** denote statistical significance at the 10%, %5, and %1 significance level, respectively.

Table 3.a Multiscale portfolio optimization: all countries

	[2–4] months	[4–8] months	[8–16] months	[16–32] months	[32–64] months	[64–128] months
Panel a: Full sample						
	Top three weights					
Sector-country	CONGD-CH	IND-UK	IND-CH	CONGD-IND	FIN-CH	CONSV-US
	TEL-US	CONGD-US	HC-UK	HC-IND	IND-CH	IND-UK
	FIN-IND	OIL-CH	OIL-CH	CONGD-CH	UTI-US	OIL-CH
Portfolio return	0.0002	0.0004	0.0022	0.0013	0.0048	0.0570
Portfolio risk	0.1033	0.0641	0.1287	0.0239	0.0797	0.0430
Portfolio Sharpe ratio	−0.1834	−0.2371	−0.1320	−0.7489	−0.1807	0.8791
Portfolio VaR (at 1%)	0.2401	0.1487	0.2973	0.0543	0.1807	0.0425
	Benchmark Portfolio					
Sharpe ratio	−0.5331	−0.4837	−0.4076	−0.3948	−0.6035	0.0279
VaR (at 1%)	0.0840	0.0932	0.1090	0.0472	0.0722	0.0011
Panel b: Increasing IEPU state						
	Top three weights					
Sector-country	MAT-CH	TEC-CH	OIL-CH	TEL-IND	CONGD-CH	CONGD-CH
	TEL-UK	UTI-IND	HC-CH	UTI-IND	MAT-CH	MAT-UK
	OIL-CH	OIL-CH	MAT-CH	OIL-CH	FIN-CH	OIL-CH
Portfolio return	0.0018	0.0032	0.0118	−0.0008	0.0368	0.0076
Portfolio risk	0.1115	0.0172	0.0623	0.0046	0.0356	0.0097
Portfolio Sharpe ratio	−0.1560	−0.0140	−0.1188	−4.348	0.4944	−1.1960
Portfolio VaR (at 1%)	0.2574	0.0368	0.1331	0.0116	0.0461	0.0149
	Benchmark Portfolio					
Sharpe ratio	−0.6944	−0.8840	−0.7465	−0.7891	−1.2256	1.0531
VaR (at 1%)	0.0897	0.1009	0.1075	0.1457	0.0874	0.0012
Panel c: Decreasing IEPU state						
	Top three weights					
Sector-country	OIL-CH	TEC-US	TEL-UK	CONGD-UK	CONSV-US	TEC-US
	TEC-UK	OIL-US	CONGD-UK	OIL-UK	HC-UK	HC-CH
	MAT-CH	OIL-CH	OIL-CH	OIL-CH	OIL-CH	CONGD-CH
Portfolio return	0.0196	0.0364	0.0276	0.0808	−0.0302	0.0541
Portfolio risk	0.0871	0.0882	0.0522	0.0957	0.0509	0.0004
Portfolio Sharpe ratio	0.0050	0.1950	0.1609	0.6437	−0.9705	87.25
Portfolio VaR (at 1%)	0.1830	0.1688	0.0938	0.1418	0.1486	0.0001
	Benchmark Portfolio					
Sharpe ratio	−0.3981	−0.1921	−0.2160	−0.0658	−0.1101	−0.1212
VaR (at 1%)	0.0712	0.0783	0.0854	0.0868	0.0407	0.0002

Notes: The end of 2019 10-year treasury rate of 1.92 % is used as a risk-free rate in all the portfolios. The Sharpe ratio is calculated by deducting the risk-free rate from the return of the portfolio and dividing the value over the portfolio risk. The benchmark portfolio comprises equal weights across all stocks all over time. The full sample is from 02/2003 to 04/2019. Each portfolio (in any of the three panels) comprises 24 stocks from China, India, the UK, and the US. OIL, MAT, IND, CONGD, CONSV, FIN, HC, UTI, TEC, TEL denote the oil and gas, basic materials, industrial, consumer goods, consumer services, financial, health care, basic utilities, technology, and telecommunication sectors, respectively.

Table 3.b Multiscale portfolio optimization: the US only

	[2–4] months	[4–8] months	[8–16] months	[16–32] months	[32–64] months	[64–128] months
Panel a: Full sample						
Sector	**Top three weights**					
	TEL	IND	UTI	TEC	TEL	MAT
	UTI	CONGD	TEL	UTI	CONGD	CONGD
	OIL	OIL	OIL	OIL	OIL	OIL
Portfolio return	0.0001	0.0004	0.0008	−0.0004	0.0003	0.0365
Portfolio risk	0.0466	0.0539	0.0415	0.0623	0.0575	0.0034
Portfolio Sharpe ratio	−0.4098	−0.3488	−0.4433	−0.1894	−0.3286	5.088
Portfolio VaR (at 1%)	0.0765	0.0884	0.0674	0.1035	0.0942	0.0001
	Benchmark Portfolio					
Sharpe ratio	−0.0192	−0.4120	−0.3963	−0.3631	−0.4134	9.3475
VaR (at 1%)	0.0717	0.0773	0.0808	0.0996	0.0773	0.0003
Panel b: Increasing IEPU state						
Sector	**Top three weights**					
	UTI	TEL	TEL	UTI	TEC	MAT
	CONSVS	UTI	CONSVS	CONGD	CONGD	CONGD
	OIL	OIL	OIL	OIL	OIL	TEC
Portfolio return	0.0001	−0.0054	−0.0050	−0.0033	0.0032	0.0352
Portfolio risk	0.0419	0.0349	0.0322	0.0406	0.0325	0.0021
Portfolio Sharpe ratio	−0.4558	−0.3954	−0.7516	−0.5542	−0.4923	7.6190
Portfolio VaR (at 1%)	0.0688	0.0627	0.0595	0.0701	0.0502	0.0001
	Benchmark Portfolio					
Sharpe ratio	−0.4195	−0.4686	−0.4192	−0.3589	−0.8810	1.3219
VaR (at 1%)	0.0754	0.0679	0.0776	0.0976	0.0719	0.0020
Panel c: Decreasing IEPU state						
Sector	**Top three weights**					
	MAT	TEC	MAT	FIN	OIL	MAT
	TEC	OIL	UTI	TEC	CONSVS	TEC
	IND	MAT	OIL	OIL	MAT	OIL
Portfolio return	0.0131	0.0250	0.0241	0.0371	0.0616	0.0538
Portfolio risk	0.0562	0.0550	0.0857	0.0704	0.0423	0.0022
Portfolio Sharpe ratio	−0.1085	0.1055	0.0572	0.0179	1.0023	15.7272
Portfolio VaR (at 1%)	0.0796	0.0655	0.1168	0.0788	0.0079	0.0001
	Benchmark Portfolio					
Sharpe ratio	−0.4651	0.0412	−0.1436	−0.3315	−0.6463	6.9455
VaR (at 1%)	0.0678	0.0675	0.0666	0.0872	0.0495	0.0010

Notes: see notes on Table 3.a.

Figure 1. Wavelet Coherence: the EPU-Return relationships in China

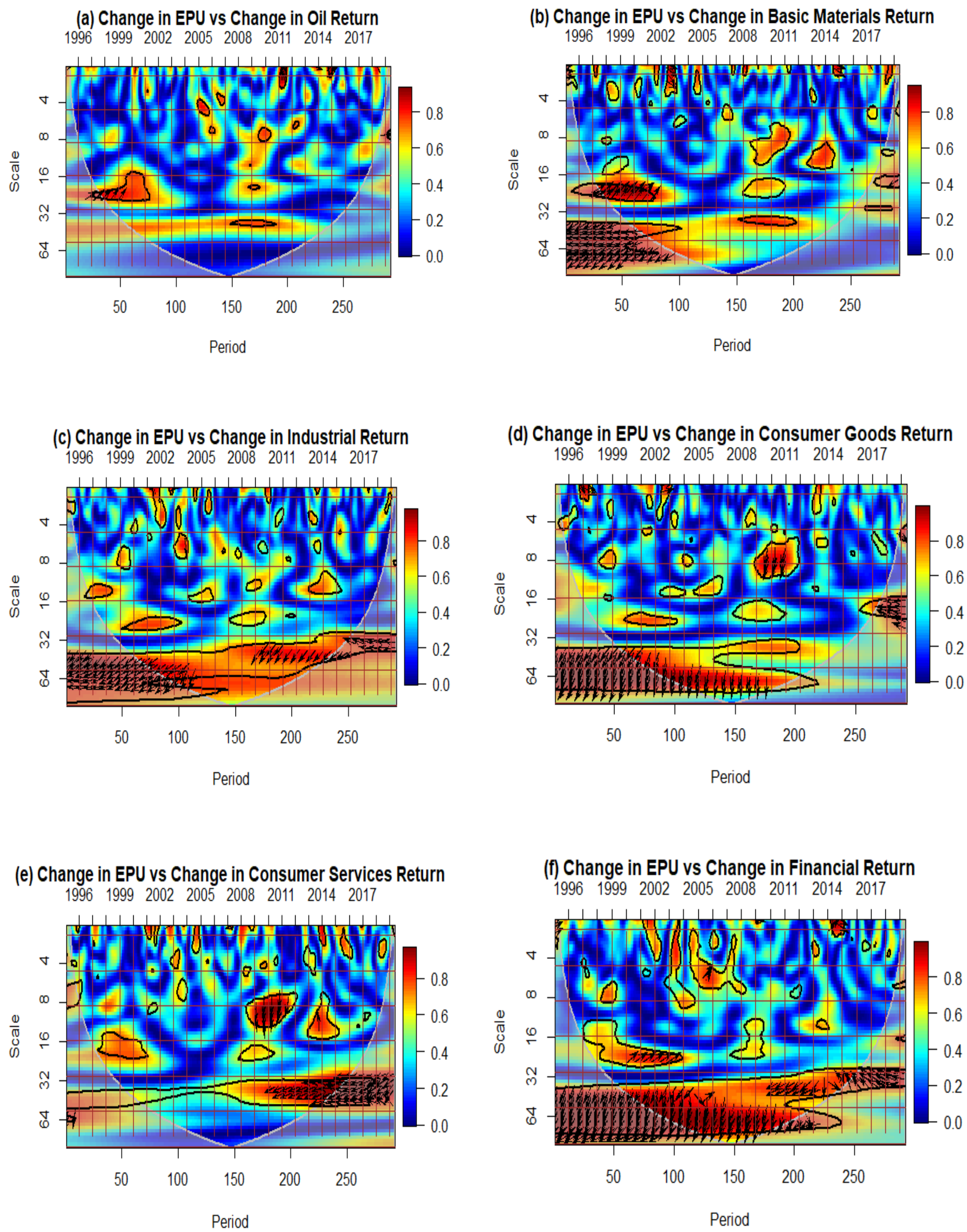


Figure 1. *Continued*.

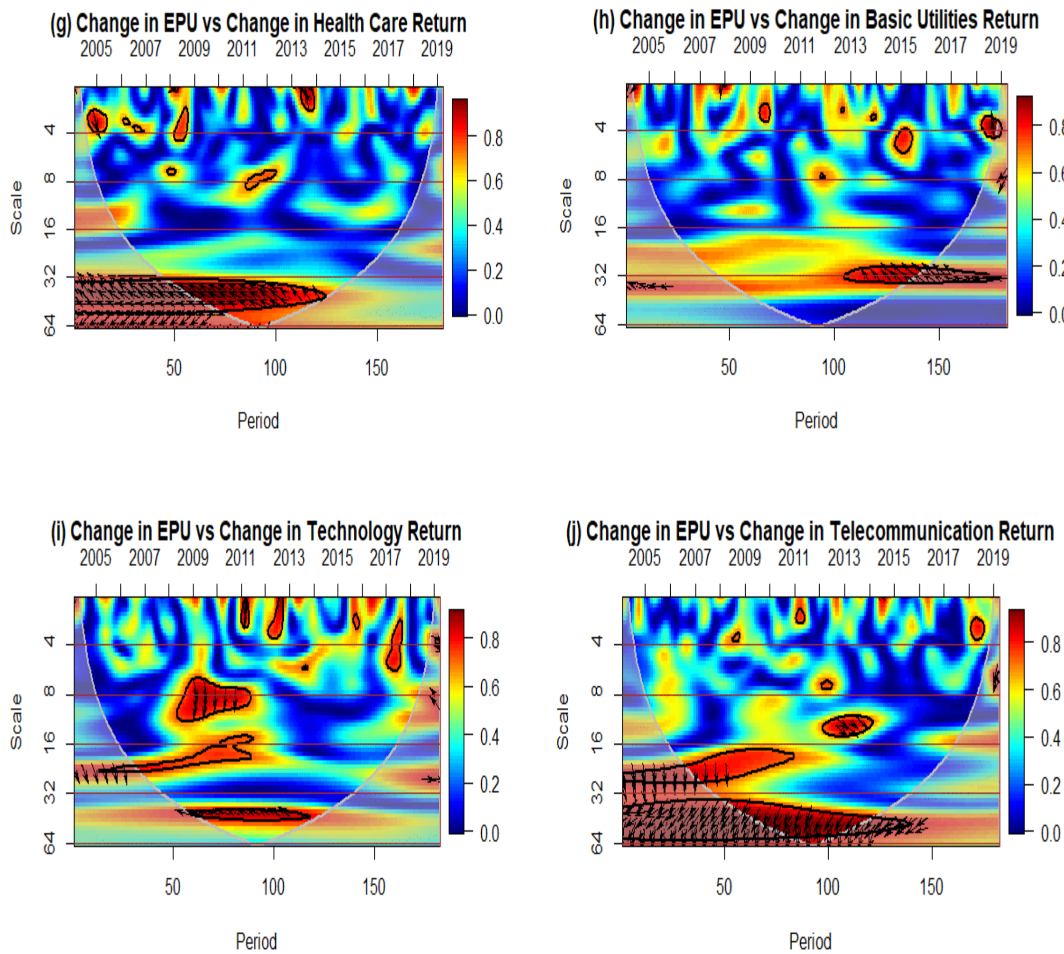
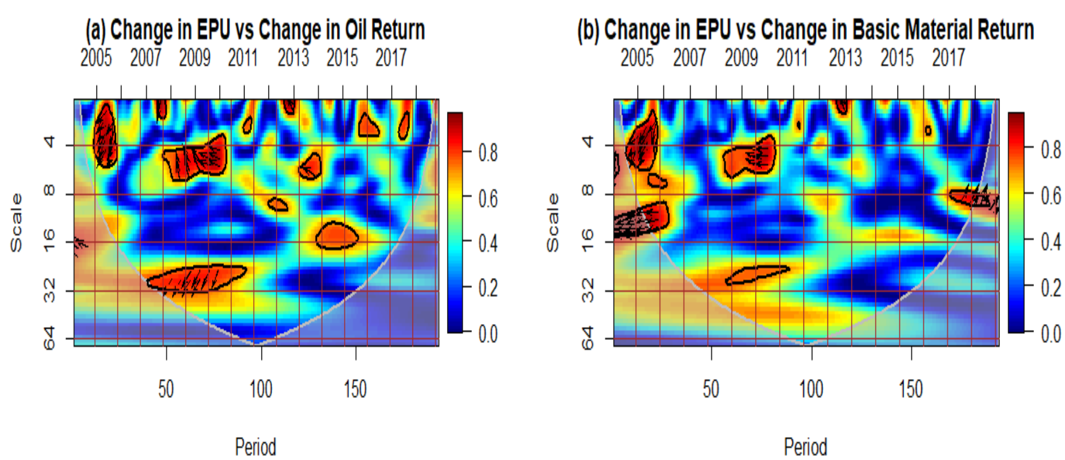


Figure 2. Wavelet Coherence: the EPU-Return relationships in India



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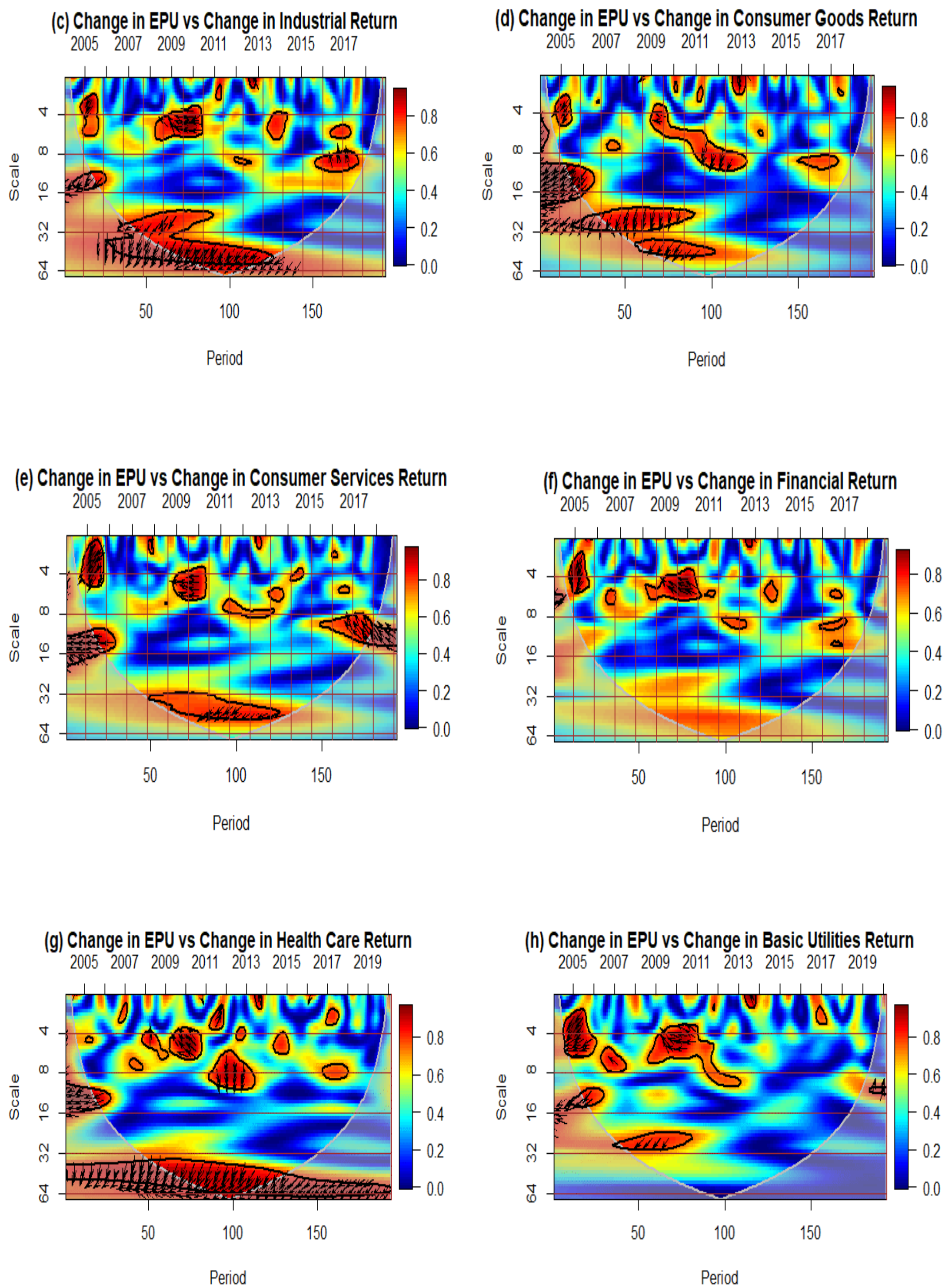

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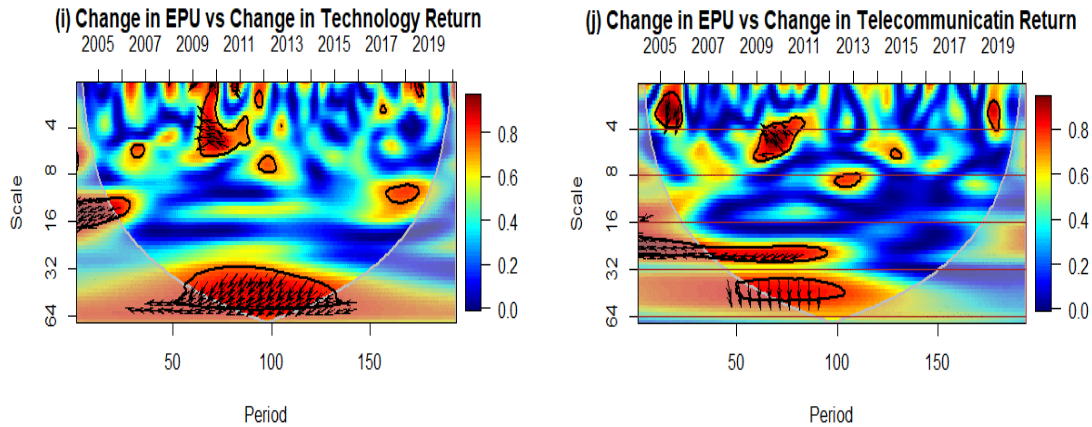
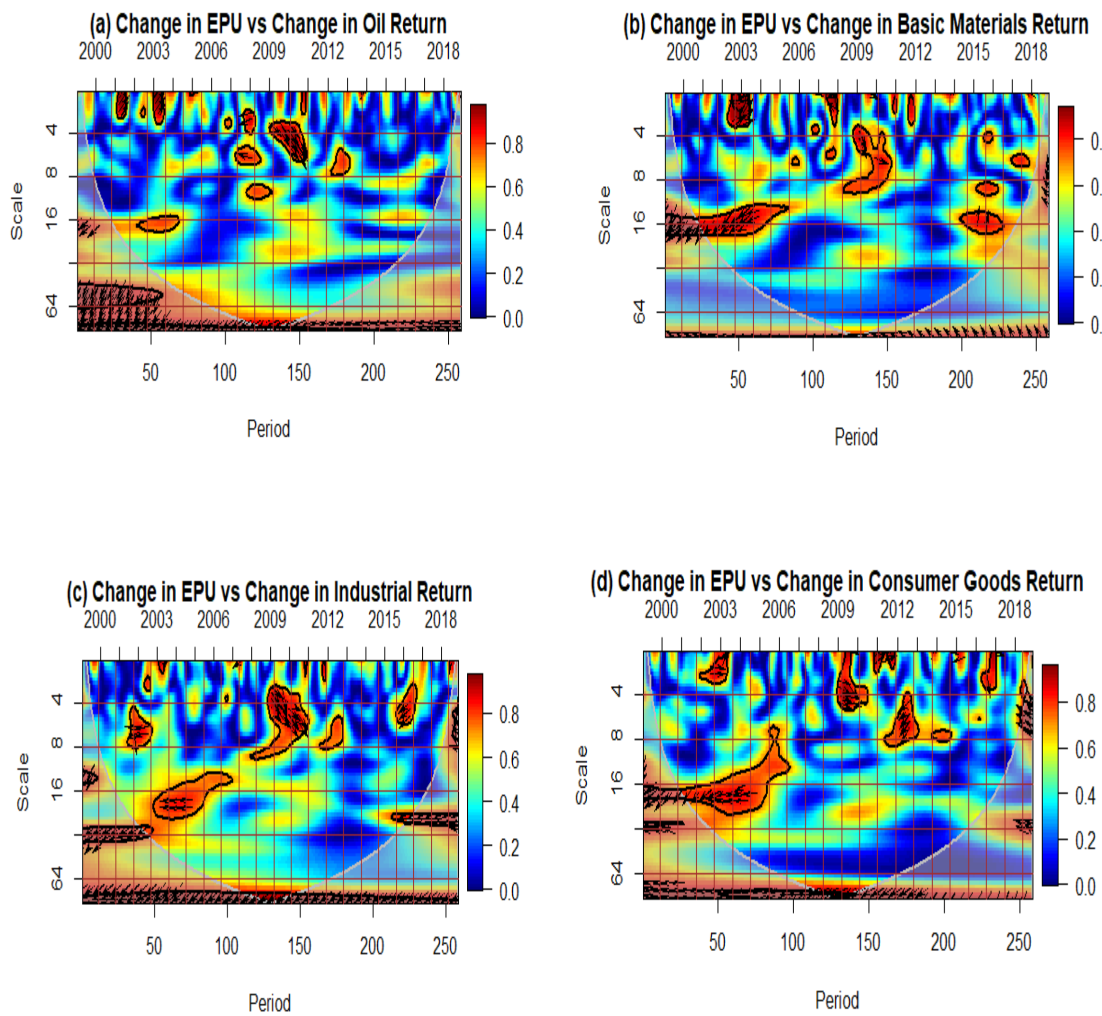


Figure 3. Wavelet Coherence: the EPU-Return relationships in the UK



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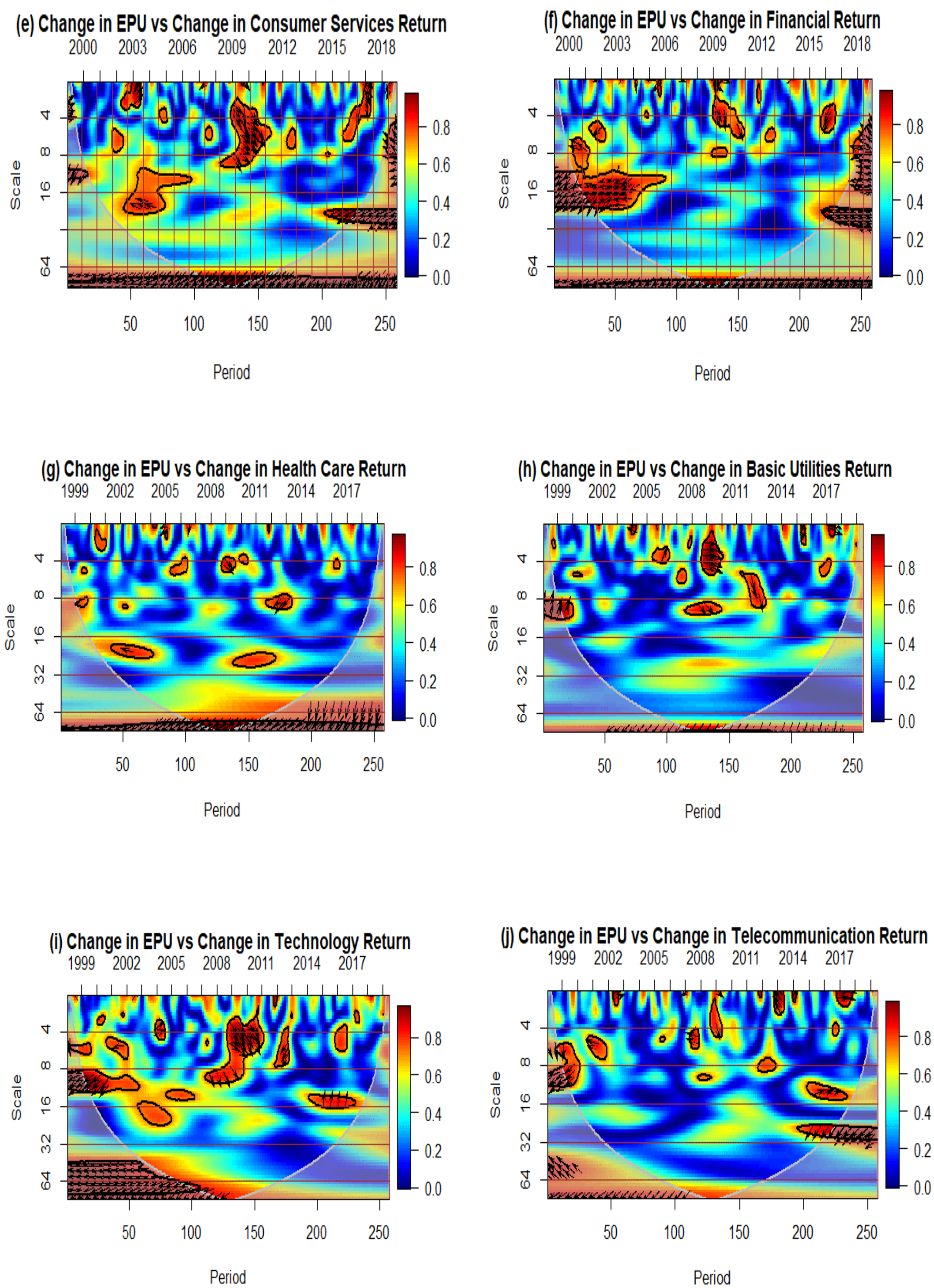
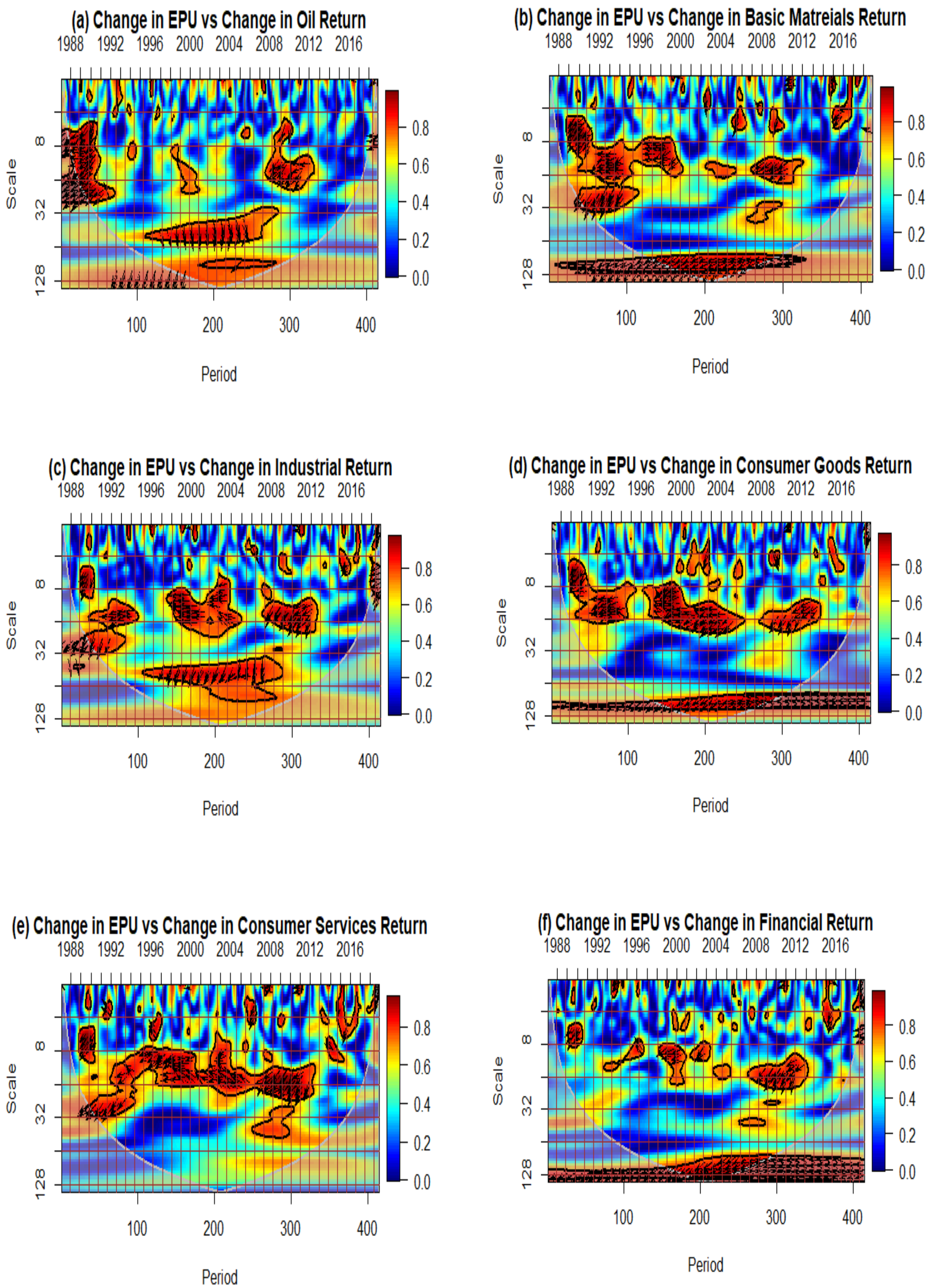


Figure 4. Wavelet Coherence: the EPU-Return relationships in the US



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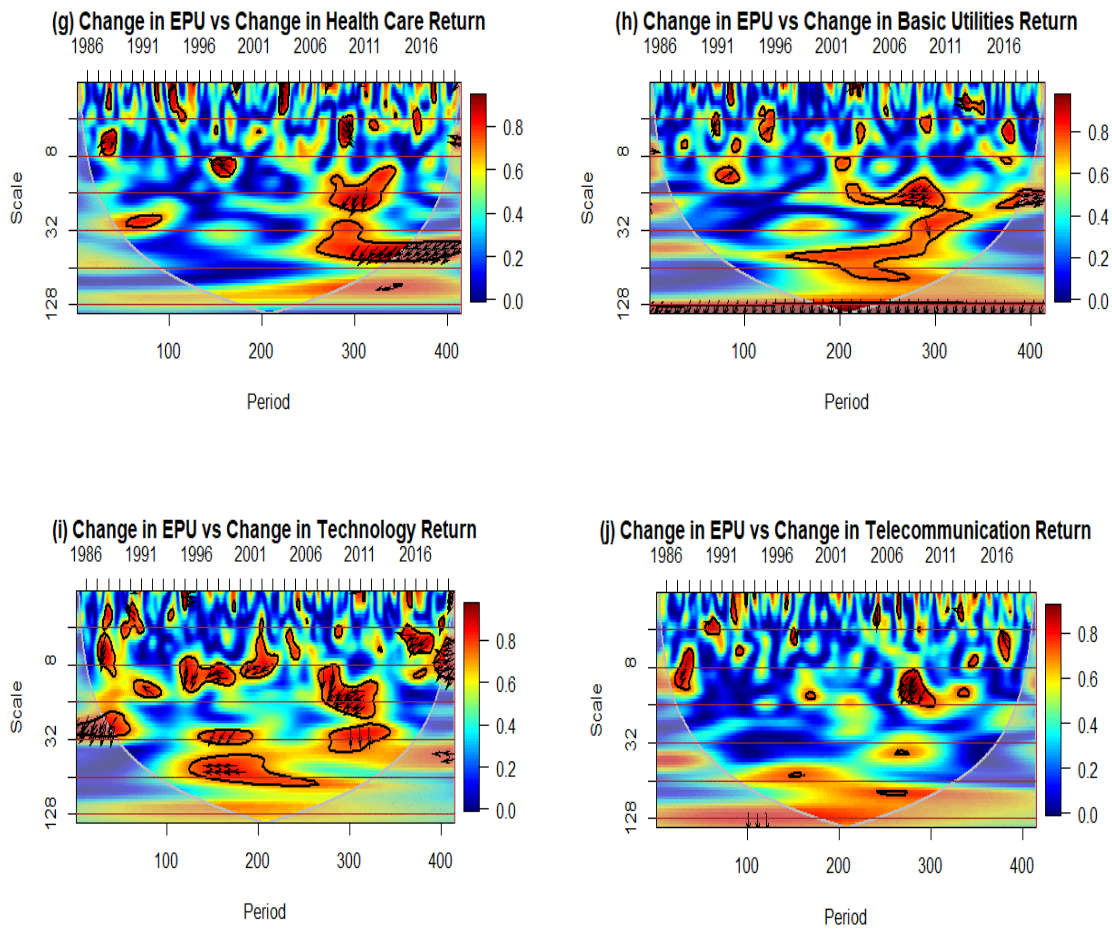
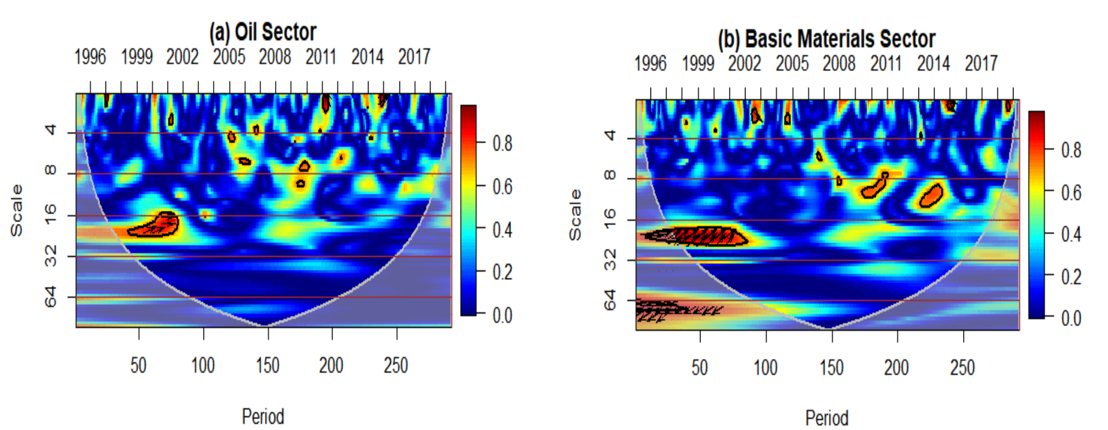


Figure 5. Partial Wavelet Coherence: The Chinese EPU and Sectoral Return | IEPU



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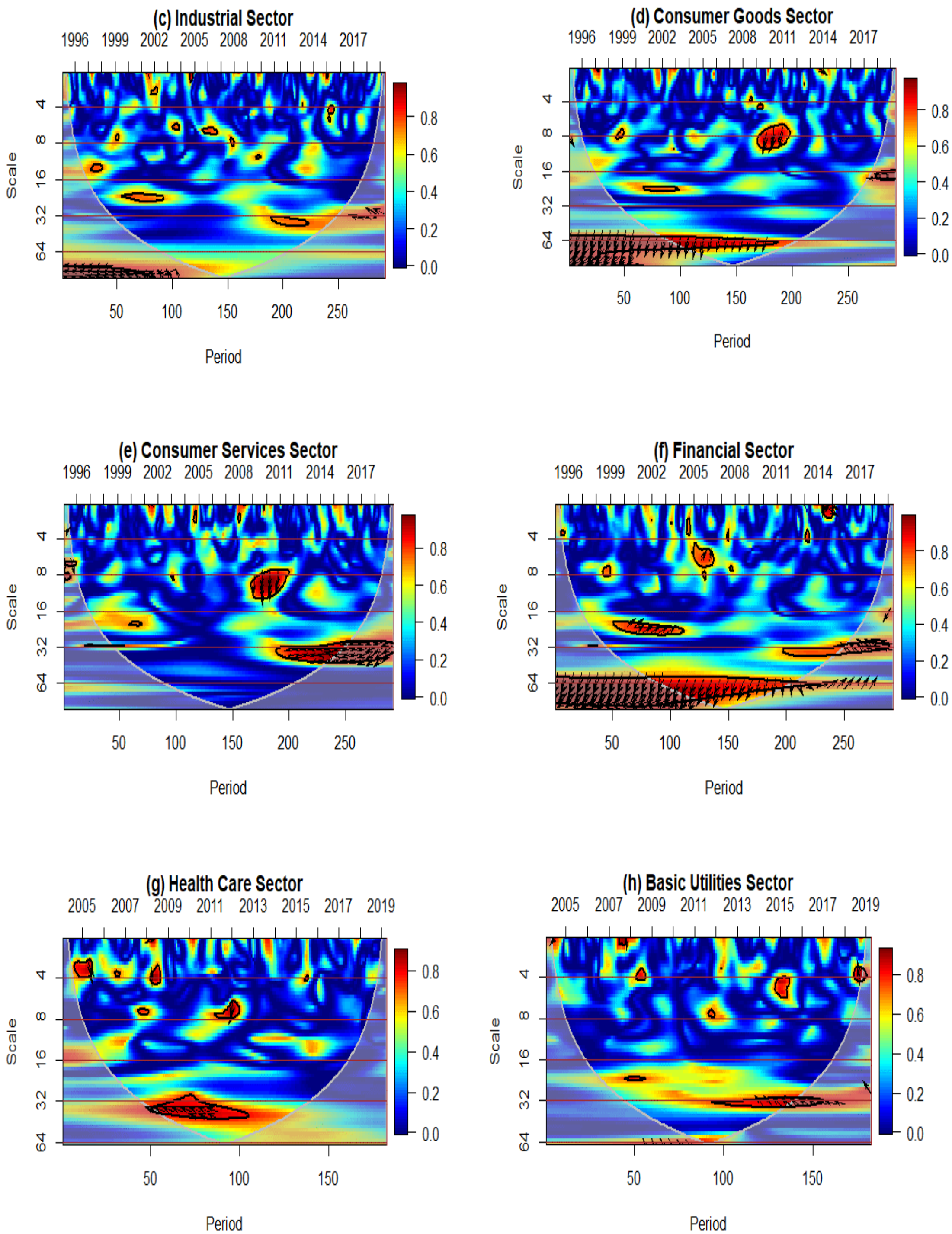


Figure 5. *Continued*

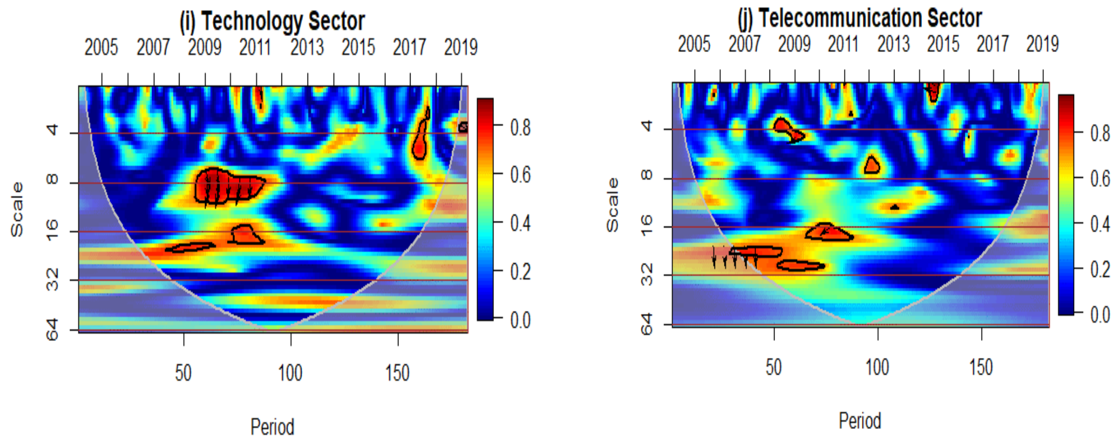


Figure 6. Partial Wavelet Coherence: The EPU of the UK and Sectoral Return | IEPU

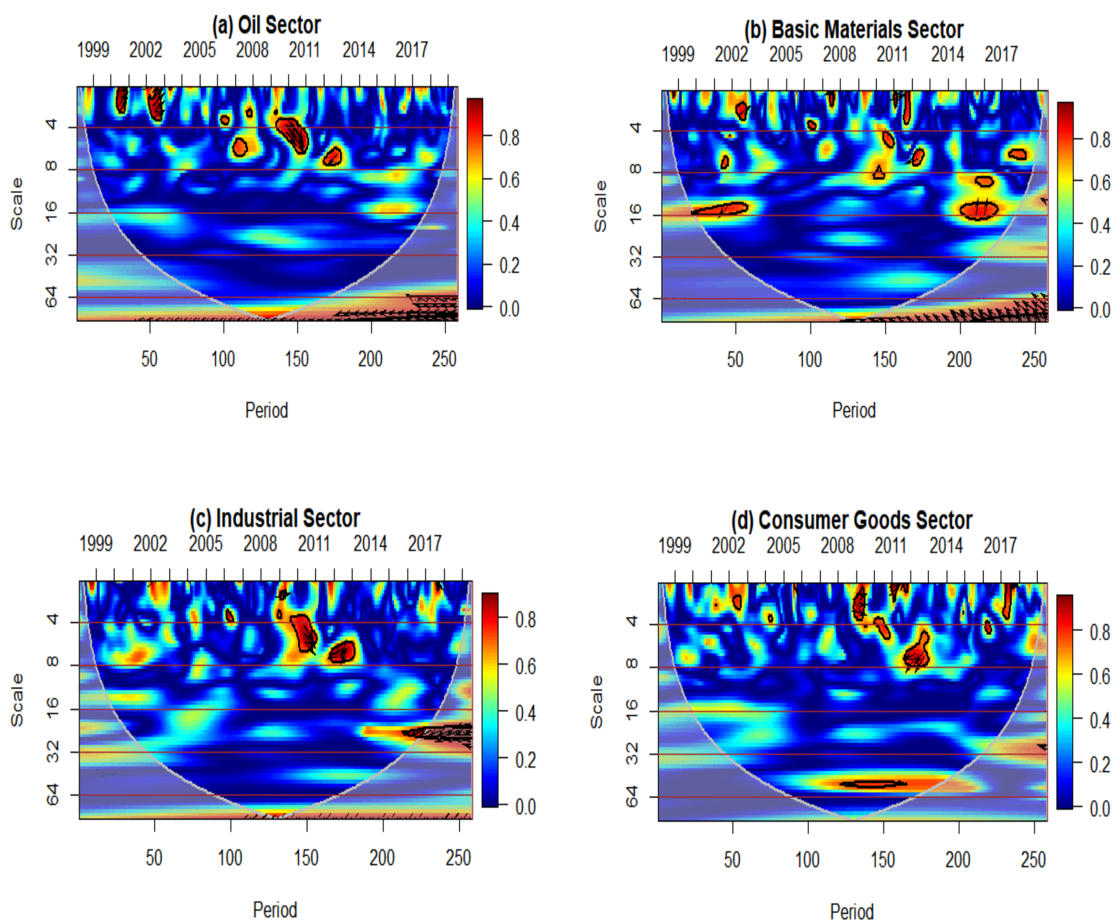


Figure 6. ***Continued*****.**

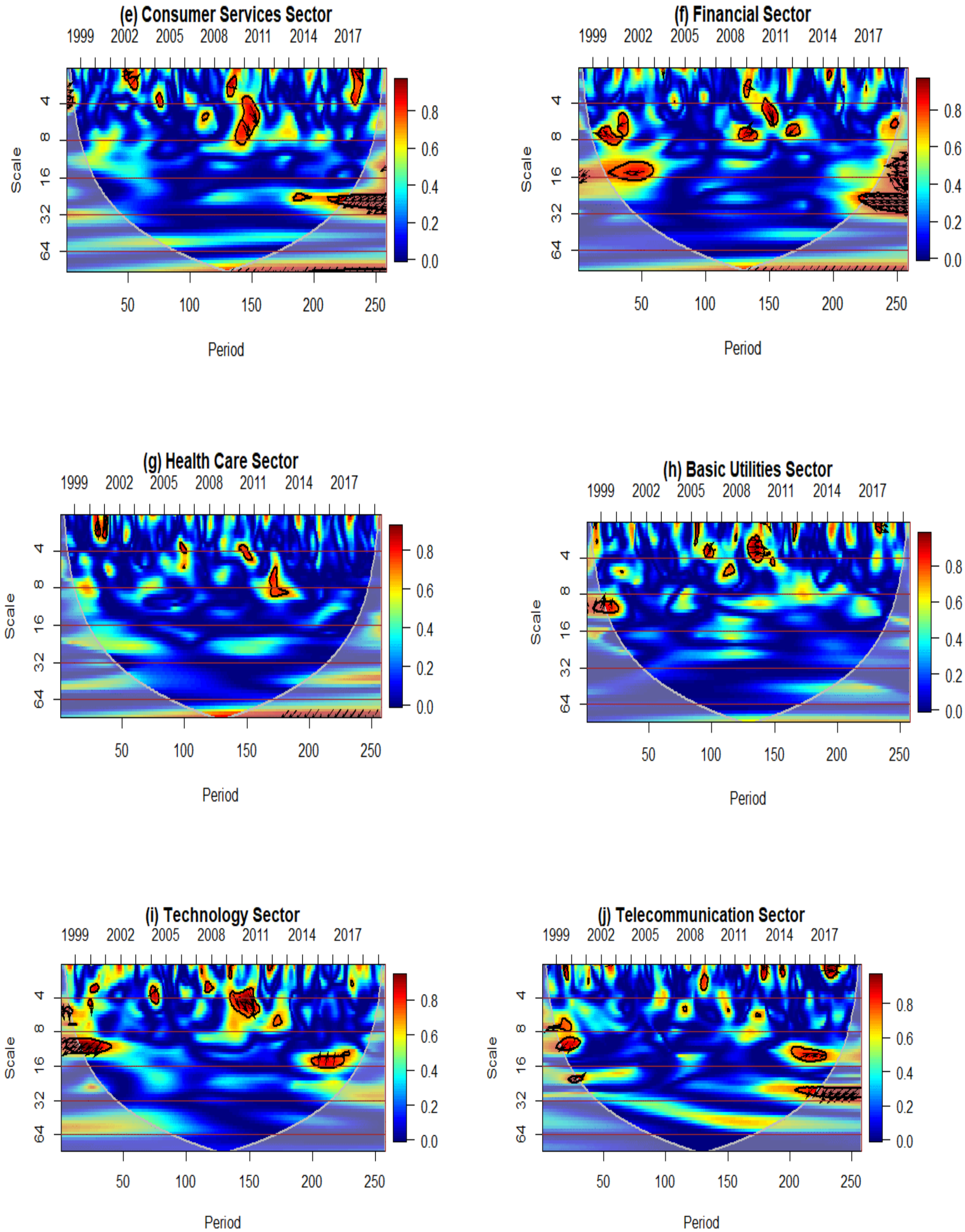
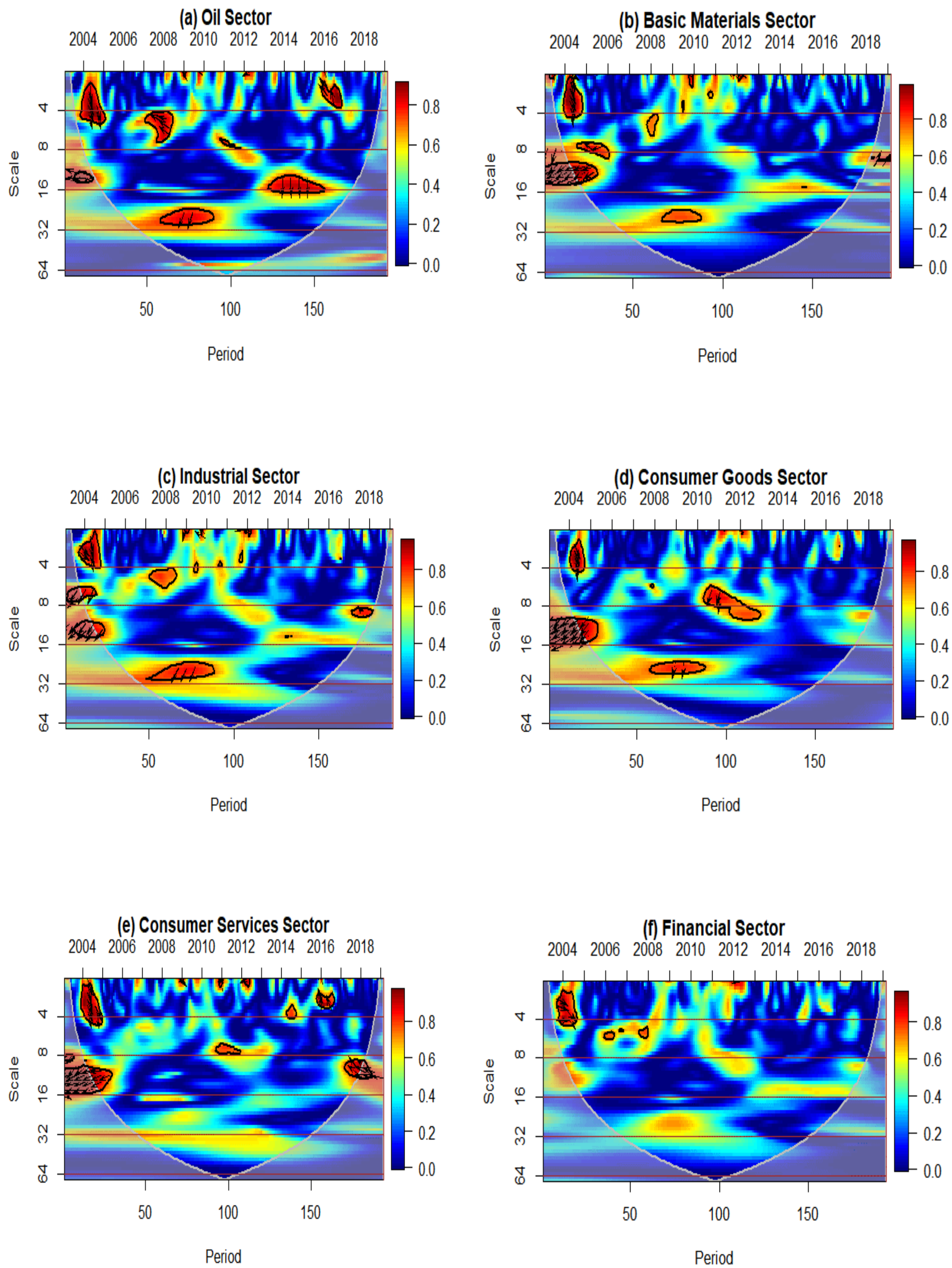


Figure 7. Partial Wavelet Coherence: The Indian EPU and Sectoral Return | IEPU



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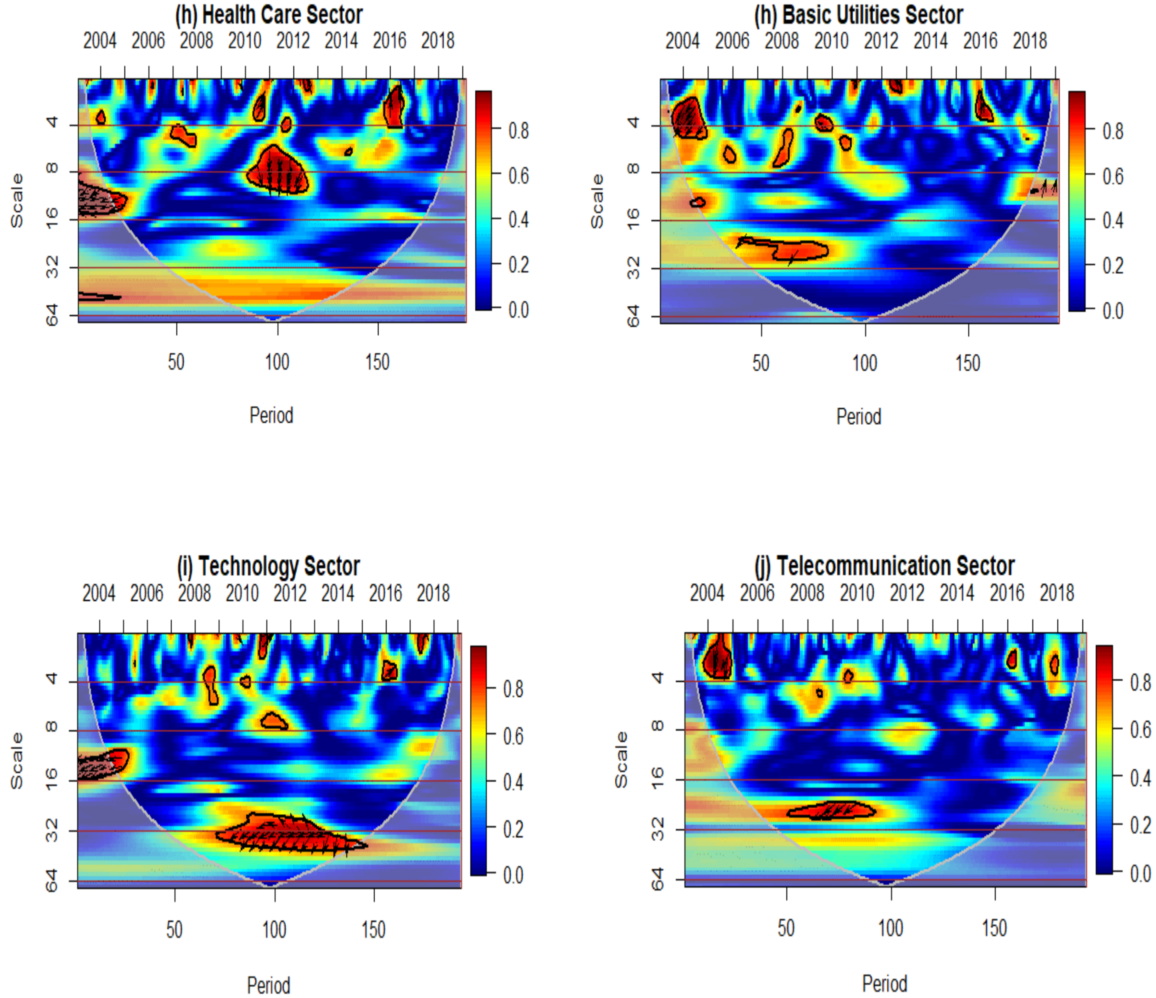


Figure 8. Multiple Wavelet Coherence: The UK EPU, Sectoral Return, and IEPU

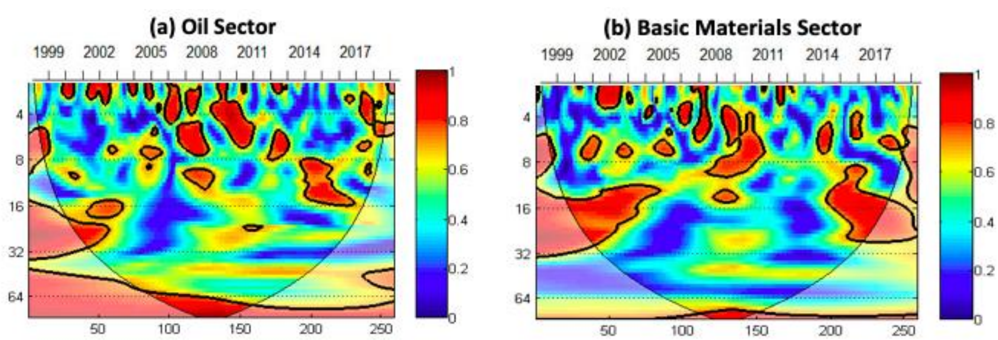


Figure 8. *Continued*.

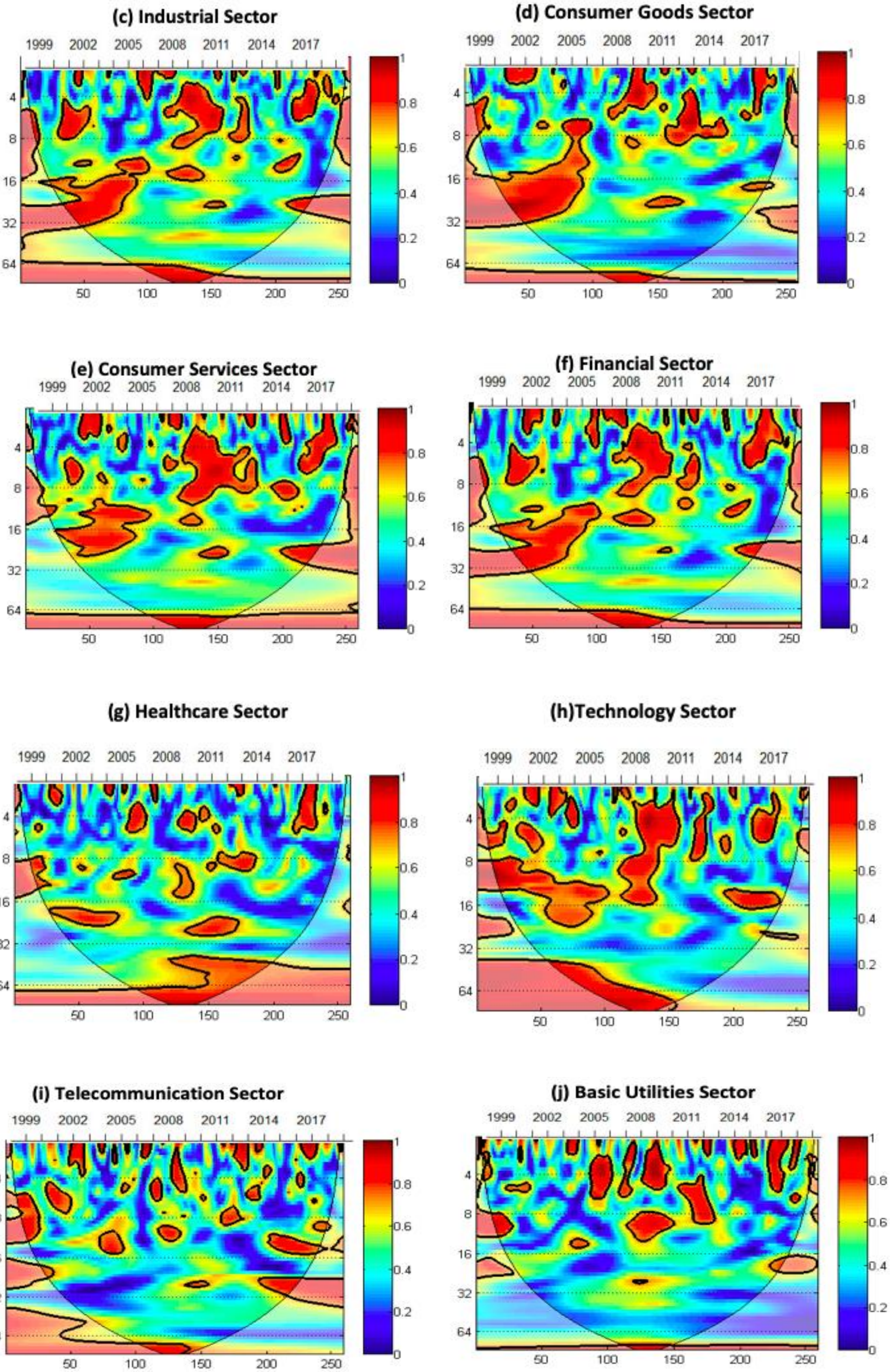


Figure 9. Multiple Wavelet Coherence: The INDIA EPU, Sectoral Return, and IEPU

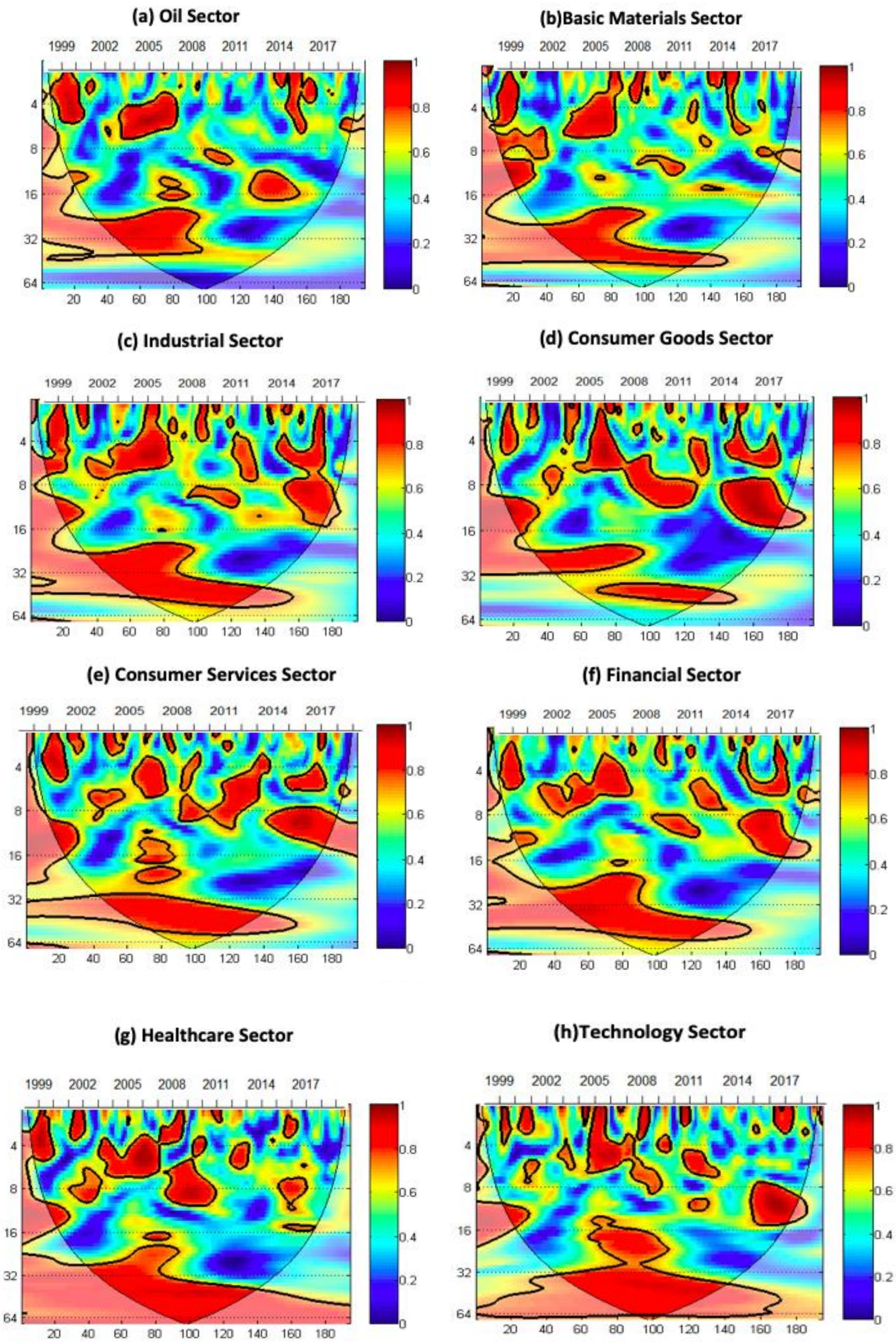
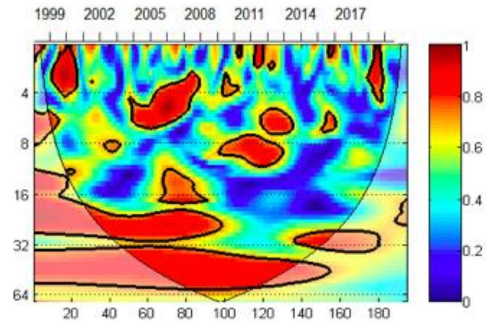


Figure 9. *Continued*.

(i) Telecommunication Sector



(j) Basic Utilities Sector

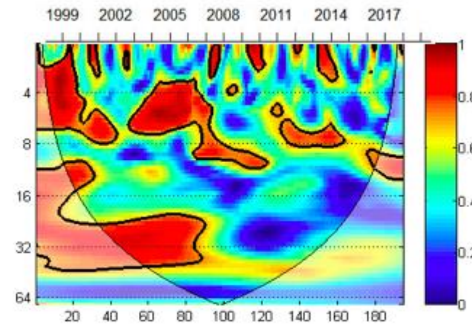
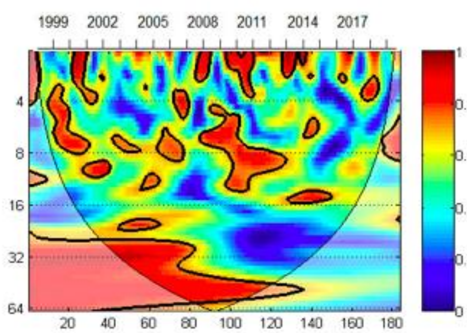
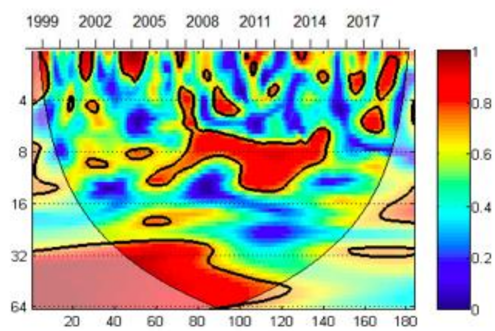


Figure 10. Multiple Wavelet Coherence: The CHINA EPU, Sectoral Return, and IEPU

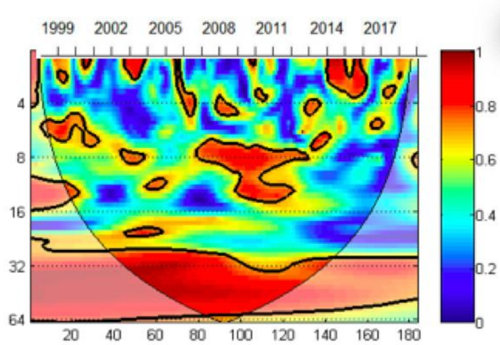
(a) Oil Sector



(b) Basic Materials Sector



(c) Industrial Sector



(d) Consumer Goods Sector

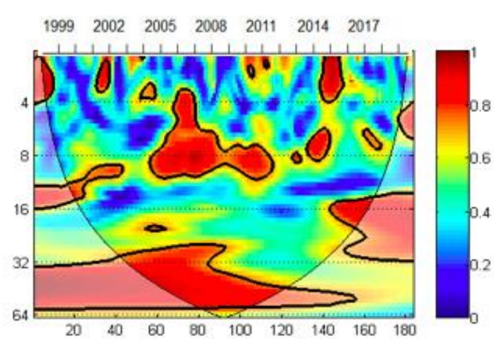
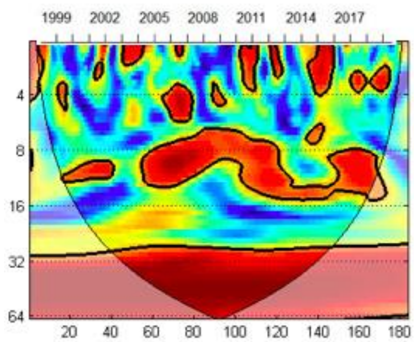
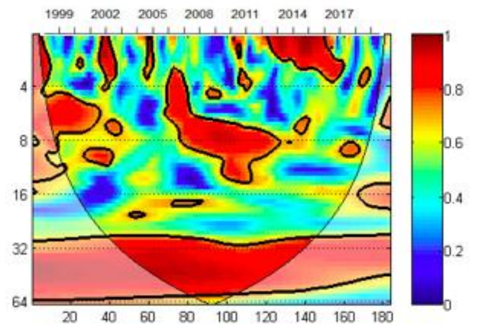


Figure 10. *Continued*

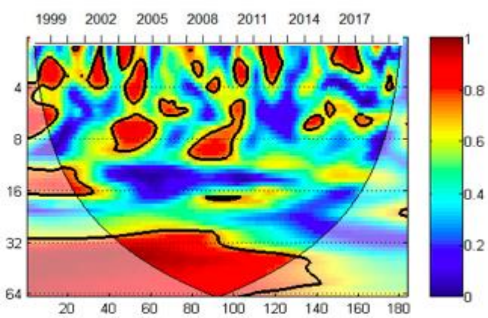
(e) Consumer Services Sector



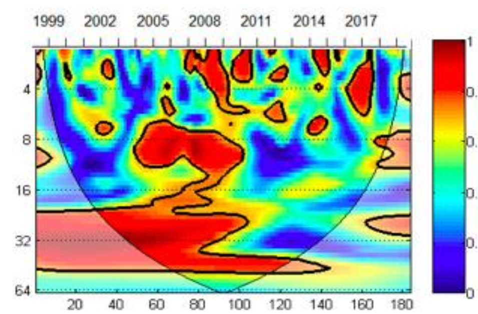
(f) Financial Sector



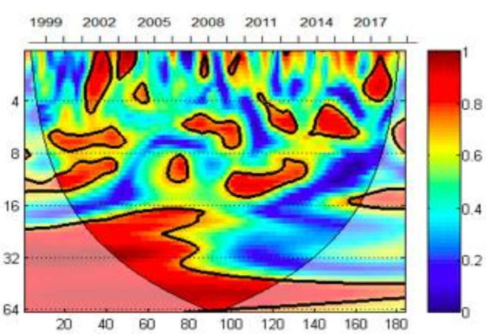
(g) Healthcare Sector



(h)Technology Sector



(i) Telecommunication Sector



(j) Basic Utilities Sector

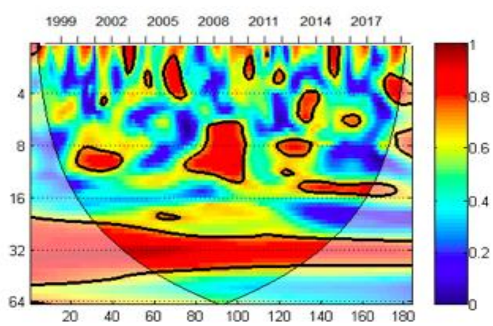


Figure 11. Wavelet VaR: The UK sectoral returns and EPU

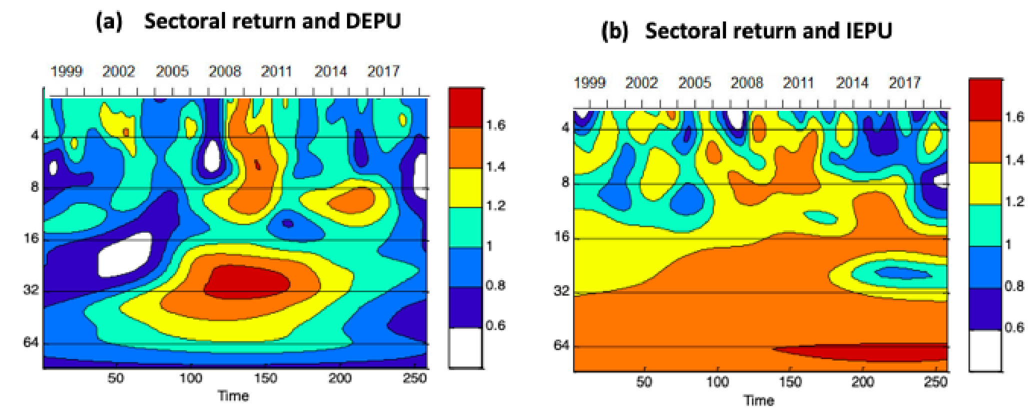


Figure 12. Wavelet VaR: The US sectoral returns and EPU

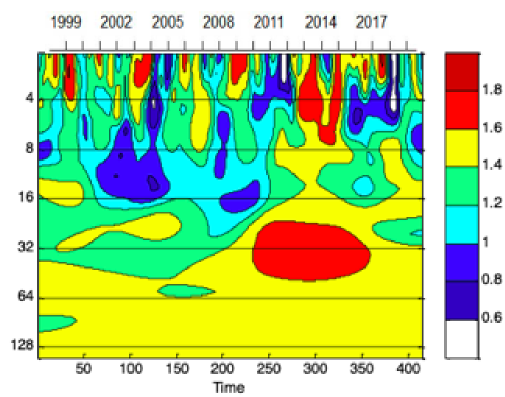


Figure 13. Wavelet VaR: The Indian sectoral returns and EPU

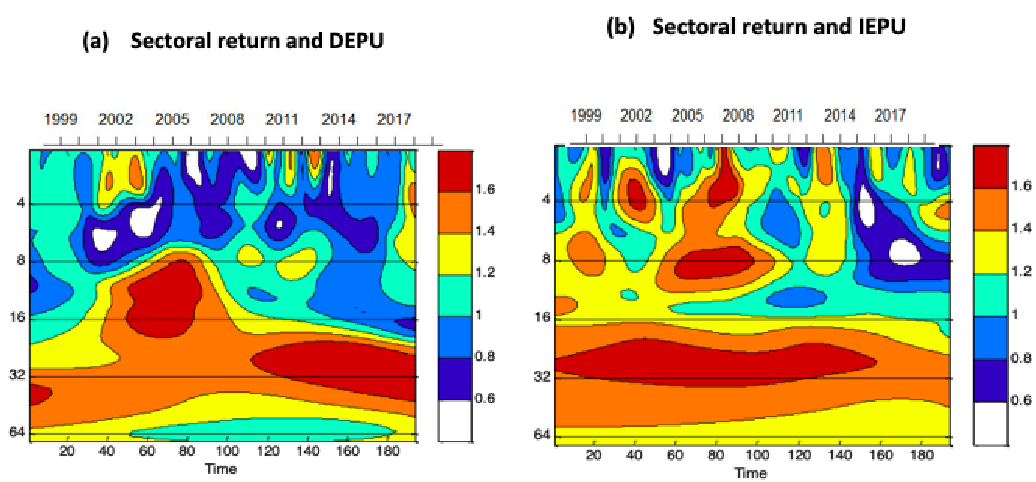


Figure 14. Wavelet VaR: The Chinese sectoral returns and EPU

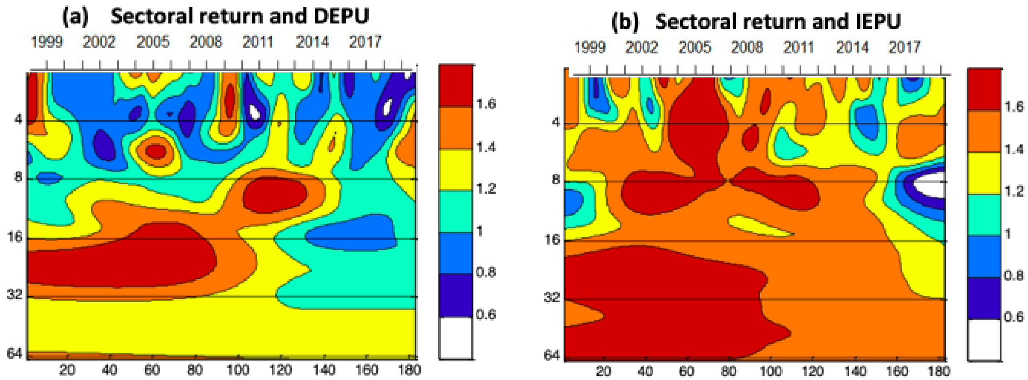
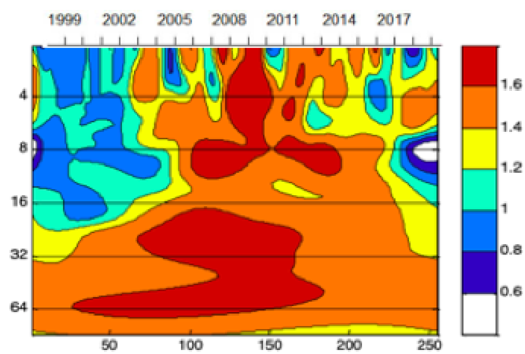


Figure 15. Wavelet VaR: All countries' global portfolio and IEPU



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