The Relationship between Monetary Policy and Uncertainty in Advanced Economies: Evidence from Time- and Frequency-Domains

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Highlights

- A wavelet approach is used to analyze the comovement of economic uncertainty and (shadow) interest rates.
- The study focuses on four advanced economies (Canada, Euro Area, Japan, UK and US).
- The results suggest that there is significant comovement over time and frequencies.
- For Canada, UK and US economic and uncertainty are mostly anti-phase while for the Euro Area and Japan, they are mostly in-phase.
- Granger causality test suggests that there is substantial time-variation.

Abstract

In this work we offer new insight into the relationship between interest rates and uncertainty for several advanced economies (Canada, EU, Japan, UK, US) for the period 2003-2018. For this purpose, we utilize wavelets, which allow us to analyze how the relationship changes over time and across different frequencies, and to make inference about causality. We also use the daily shadow interest rate measure of Krippner (2012, 2013) to capture the stance of monetary policy making at the zero lower bound, and the uncertainty measure by Scotti (2016) to measure uncertainty related to the real economy. Our findings suggest that there is significant co-movement over time and across different frequencies in all the countries we analyze. Corresponding to the similar, yet different conduct of monetary policy, we also find that the relationship exhibits different characteristics and causality in all the economies we analyze, implying that one must be careful not to draw generalized conclusions.

Keywords: Interest Rate, Uncertainty, Advanced Economies, Wavelet

JEL Codes: C22, E52, E58

1. Introduction

The topic of uncertainty has been a subject of interest in the macroeconomic literature for several decades. In some of the earlier works, authors such as Dixit (1989) focused on the analysis of investment decisions of firms when faced with macroeconomic uncertainty, whereas others such as Baldwin and Krugman (1989) analyzed the effect of uncertainties surrounding exchange rate movements on trade flows. While many works followed these authors and explored the channels through which uncertainties affect the economy in the following years[1], Bloom (2009) stands out. In this influential work, the author used firm-level data within a structural framework with time-varying volatility and an uncertainty measure based on stock market volatility to show that macroeconomic uncertainty can lower productivity growth. More recently, Bloom (2014) argued that uncertainty is countercyclical and that recessions increase uncertainty, which in turn can exacerbate the effects of the business cycle, implying – as in Bloom (2009) - an endogenous link between economic activity and uncertainty. In yet another contribution aimed at disentangling the causality and endogeneity of uncertainty and real economic activity, Ludvigson et al. (2015) argue within a structural VAR (SVAR) setup that financial uncertainty likely is a trigger of recessions and that uncertainty of real activity is an endogenous response of the cyclical movement.

As is apparent from these contributions, there is a growing number of works analyzing the link and causality between uncertainty and business cycles. A topic that has received similar attention is the relationship between uncertainty and the conduct of monetary policy. As discussed by Brainard (1967), the principle of attenuation suggests that central banks' response is dampened when they are faced with uncertainty associated with the effect of rate changes. In contrast, others such as Giannoni (2002) or Söderström (2002) have suggested that monetary authorities may react more aggressively under uncertainty. Following these discussions, several authors incorporated uncertainty measures into monetary policy reaction functions to analyze whether and to which extent uncertainty plays a role. Estimating a Taylor rule augmented with principal components and uncertainty, Ma et al. (2018) find that the Federal Reserve reacted to uncertainty by decreasing the policy rate. In a similar study, Christou et al. (2018) examine the reaction of the central banks of several advanced economies to uncertainty using a quantile regression approach. They find that central banks in advanced economies react more aggressively to uncertainty at lower quantiles, suggesting an aggressive monetary policy stance as the zero lower bound is approached. While these studies focus on a subject that is similar to ours – the relationship between the conduct of monetary policy and economic uncertainty – there are several important differences between their

[1]See Dixit and Pindyck (1994) for a review of the literature.

work and the present study. The econometric approach taken by Ma et al. (2018) and Christou et al. (2018), threshold regression and quantile regression, implies a causal direction from uncertainty to interest rates whereas the opposite could also hold true, i.e. that interest rate decisions drive economic uncertainty. Also, the methodologies used in these studies are not able to take into account differences in co-movement that arise at different frequencies. Time variation is also a feature that is not explicitly taken into account by these studies, but considering that several significant events took place in advanced economies that could influence the conduct of monetary policy (e.g. Great Recession, eurozone crisis, Brexit etc.), it is important to take into account this feature as well. Wavelets on the other hand allow for the time-varying analysis of dynamic relations at different frequencies.

Considering the shortcomings of the above mentioned works, we aim to contribute to the literature by analyzing the relationship between interest rates and uncertainty with wavelets using the uncertainty measure as constructed by Scotti (2016) and daily shadow interest rates as in Krippner (2013)[2] for US, EU, UK, Canada and Japan. We believe that with our approach we can address several important questions: is there co-movement between the series, and if yes, what is the nature of the co-movement? Does the co-movement exhibit time variation and if yes, does it differ across different frequencies? Is there causality between the variables considered and if yes, does it vary over time?

The use of Wavelets is suited for this type of analysis as it allows for time-variation across different frequencies. We further believe that our uncertainty measure is appropriate for our analysis: while there are many different proxies for uncertainty such as the VIX index, disagreement in professional forecasts, stochastic volatility or the variance of innovations in GARCH models, the index of Scotti (2016) is particularly useful as it proxies for the uncertainty of real economic activity as perceived by economic actors in *real time*. This is in line with the growing recognition that perception of economic agents matters for general economic sentiment (see e.g. Alexopoulos & Cohen, 2015 or Donadelli, 2015).

For the purpose of analyzing causality between interest rates and uncertainty measures for the respective economies, we use the time-varying rolling Granger causality methodology of Shi et al. (2016). Our contribution lies in focusing this often disparate research question to analyze

[2] While other shadow rate measures such as Wu & Xia (2016) are available, we choose the measure of Krippner (2013) because it is available at a daily frequency and because three-factor shadow term structure models such as the one employed by Wu & Xia (2016) are not always robust as shown in Krippner (2016).

comovements of the above-mentioned relationship across time and frequencies for advanced economies for the period 2003-2018. This time window also includes the global financial crisis which is a period of high economic uncertainty, and consequently, we discuss the nature and causality of the relationship before and after the crisis. Our results indicate that there is substantial time-variation across different frequencies for all countries that we examine. Specifically, we find that for the US, UK and Canada interest and uncertainty mostly move in opposite directions (i.e., are in anti-phase), whereas for the EU and Japan the two measures mostly comove positively (i.e., are in phase). Especially considering the increased understanding of the importance of uncertainty for the economy, we believe these results carry relevance for the growing literature of the effects of macroeconomic uncertainty. The findings of our study also offer some endorsements regarding the policies that could be implemented to attenuate the long-term uncertainty spillover to the banking system. It is suggested that economies can reduce their vulnerability to monetary policies through the development of financial markets and guaranteeing fiscal space (Georgiadis and Zhu, 2019). In this respect, transparent monetary policy may diminish speculation and uncertainty about long-interest rates.

Our paper is organized as follows: section 2 details the methodology, section 3 presents the data used for the analysis, while section 4 discusses the results, with section 5 providing implications of the results obtained, and section 6 concluding the paper.

2. Methodology

The wavelet approach allows one to examine the behavior of time series jointly in frequency and time spaces. In our paper, we use wavelet coherence under the Morlet specification to assess the co-movements between uncertainty and interest rates within different contexts. Used by a growing number of researchers, the wavelet analysis has demonstrated its ability to explicitly expose and follow the time-scale varying outlines of time series. According to Aguiar-Conraria et al. (2008), the wavelet approach performs the estimation of the spectral characteristics of a time series as a function of time, revealing how the different periodic components of the time series change over time. More explicitly, this approach stretches to isolate slow and persistent movements. The wavelet approach allows us to describe the local behavior of heterogeneous markets participants. Indeed, some participants have an investment horizon of several minutes or hours to several days (e.g. when considering short-term movements of stock markets) while others may have an investment horizon of several weeks or months (e.g. with medium-term movements of the stock markets) or an investment horizon of several years (e.g. with long-term movements of the stock markets). Corresponding to this diversity, policymakers may need to understand comovements of policy-relevant time series at different horizons. It is further possible that interest rate or uncertainty shocks have short-term and long-term effects, owing to the transitory or permanent nature of shocks.

In addition, the Wavelet approach is an appropriate tool to analyze the behavior of time series jointly in both the frequency and time spaces. Specifically, the wavelet coherence is employed under Morlet's specification. The wavelet is defined as $\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right)$. First, one should recall that a wavelet is a real-valued or a complex valued function $\psi(.)$ defined over the real axis. Moreover, it is assumed that the wavelet is a square integrable function $\psi(.) \in L^2(\mathbb{R})$. In the above equation, $\frac{1}{\sqrt{s}}$ is the normalization factor, ensuring that the unit variance of the wavelet satisfies $\|\psi_{u,s}\|^2 = 1$ and u denotes the location parameter, providing the exact position of the wavelet. s is the scale dilatation parameter of the wavelet. It defines how the wavelet is stretched or dilated. In this regard, a higher scale implies a more stretched wavelet, which is appropriate for detection of lower frequencies. Formally, the Morlet's wavelet is given by $\psi^M(t) = \frac{1}{\pi^{1/4}}e^{i\omega_0 t}e^{-t^2/2}$where $\psi^M(t)$ is the wavelet value at non-dimensional time t and ω_0 is the central frequency of the wavelet which is equal to 6.

2.1. The continuous wavelet transform

As in Rua and Nunes (2009) and Baruník et al. (2011), the continuous wavelet transform is given by $W_x(u,s) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{s}}\overline{\psi(\frac{t-u}{s})}dt$. Specifically, $W_x(u,s)$ is obtained by projecting the specific wavelet $\psi(.)$on the selected time series. The main advantage of the wavelet transform is the aptitude to decompose and then consequently reconstruct the function $x(t) \in L^2(\mathbb{R})$:

$$x(t) = \frac{1}{C_\psi}\int_0^{\infty}\left[\int_{-\infty}^{\infty} W_x(u,s)\psi_{u,s}(t)du\right]\frac{ds}{s^2}, \quad s > 0 \tag{1}$$

One should note that the main feature of the wavelet transform is the energy preservation of the selected time series. This property is employed for the power spectrum analysis which specifies the variance as follows: $\|x\|^2 = \frac{1}{C_\psi}\int_0^{\infty}\left[\int_{-\infty}^{\infty}|W_x(u,s)^2|du\right]\frac{ds}{s^2}$.

*2.1.1.**Wavelet power spectrum***

Analogous to Torrence and Compo (1998) and Aguiar-Conraria et al. (2008), the wavelet power spectrum can simply be defined as $|W_n^x|^2$and this measure assesses the local variance of each variable. The statistical significance, according to Grinsted et al. (2004), can be assessed relatively to the null hypothesis that the variable under consideration has a significant power spectrum, i.e., the signal is generated by an *AR (0)* or *AR(1)* stationary process with mean background power spectrum (P_f). Based on Monte Carlo simulations through computing the white-noise and red-noise wavelet powers, Torrence and Compo (1998) show that, at each time n and scale s, the corresponding distribution for the local wavelet power spectrum can be written as

$$D\left(\frac{|W_n^X(s)|^2}{\sigma_X^2} < p\right) \Rightarrow \frac{1}{2} P_f \chi_v^2 \tag{2}$$

whereP_k is the mean of spectrum at the Fourier frequency f that corresponds to the wavelet scale s $\left(s \approx {}^{1}/_{f}\right)$, and v takes the values of 1 or 2 for real or complex wavelets, respectively.

2.1.2. Cross-wavelet power, wavelet coherence, and phase differences

The cross-wavelet power shows the area in the time-scale space where the time series exhibit high common power. As noted by Aguiar-Conraria et al. (2008), the cross-wavelet power captures the local covariance of two time series in each frequency and shows the quantitative similarities of power between them. It is also interesting to note that low (high) scales are compressed wavelets allowing us to examine rapidly changing details related with high (low) frequencies, respectively. According to Hudgins et al. (1993), for each signal X and Y, the individual wavelet spectra are specified as $W_n^X(s)$and $W_n^Y(s)$, respectively. In the time-frequency analysis, the cross-wavelet between two signals is represented by the cross-wavelet spectrum $W_n^{XY}(s)$which is defined as in Eq. (3)[3]

$$W_n^{XY}(s) = W_n^X(s) W_n^{Y^*}(s) \tag{3}$$

where $W_n^{Y^*}(s)$ is the complex conjugate of $W_n^Y(s)$ and $*$ denotes complex conjugation. The cross-wavelet power is therefore given by $|W_n^{XY}|$ and it measures the local covariance of two variables at each scale. Torrence and Compo (1998) show that the theoretical distribution of the cross-wavelet power of two signals with background power spectra P_k^X and P_k^Y acquires the following form:

$$D\left(\frac{|W_n^X(s) W_n^{Y*}(s)|}{\sigma_X \sigma_Y} < p\right) = \frac{Z_v(p)}{v} \sqrt{P_k^X P_k^Y} \tag{4}$$

Where σ_X and σ_Y designate the standard deviations of x and y, respectively. $Z_v(p)$ is the confidence interval level related to the probability p for a *pdf* (probability density function), defined by the square root of the product of two χ^2 distributions.

On the other hand, the wavelet coherency of two time series $x = \{x_n\}$ and $y = \{y_n\}$ is defined as the localized correlation coefficient between these series in the time-frequency space

[3]See Torrence and Compo (1998) for more details about cross-wavelet spectrum hypothesis and confidence levels.

(Torrence and Compo, 1998). It is thus a very useful tool for detecting time series' co-movements. Following Torrence and Webster (1999), the wavelet coherence is computed as the squared absolute value of the smoothed cross-wavelet spectra, normalized by the product of the smoothed individual wavelet power spectra of each time series:

$$R^2(u,s) = \frac{\left|S(s^{-1}W_{xy}(u,s))\right|^2}{S(s^{-1}|W_x(u,s)|^2)S(s^{-1}\left|W_y(u,s)\right|^2)} \tag{5}$$

Where S denotes the smoothing parameter. In the no-smoothing case, the wavelet coherence will be equal to one. Additionally, the squared wavelet coherence coefficient satisfies this inequality $0 \leq R^2(u,s) \leq 1$. A value close to zero indicates weak correlation, while a value close to one signifies the presence of high correlation.

While the phase of a wave is defined as a fraction of a complete cycle which oscillates around a time-axis, the phase difference is a difference of the phase between two time series. In addition, the phase difference provides ideas about the lateness of the oscillations between two variables as a function of frequency. The phase difference of two time series, noted as $\phi_{x,y}$, characterizes the phase relationships between them. It effectively gives us information about the time series' positions in the pseudo-cycle. The phase difference is given as;

$$\phi_{x,y} = tan^{-1}\left(\frac{\Im\{W_n^{xy}\}}{\mathcal{R}\{W_n^{xy}\}}\right)\text{with } \phi_{x,y} \in [-\pi, \pi]. \tag{6}$$

For a more detailed understanding of this issue, we will consider two ideal cyclical time series X and Y, where both are sine functions with different phases[4]. The interpretation of the phase as a lead or a lag has to be done relative to the phase difference. Based on Eq.6, we can identify the lead-lag relationship between the two time series. Therefore, when the difference phase is given by $\phi_1 \in [0, \pi/2]$, X leads Y by ϕ_1 and when $\phi_2 \in [\pi/2, \pi]$, X lags Y by ϕ_2 (or Y leads X by ϕ_2) by $\pi - \phi_2$. In addition, when the phase difference is $\phi_3 \in [-\pi, -\pi/2]$, X leads Y by ϕ_3, or in another words, X leads Y in anti-phase relationship by $\phi_3 - \pi$ and when $\phi_4 \in [-\pi/2, 0]$, Y leads X in anti-phase relationship by $2\pi - \phi_4$. However, the relationship between the two time series is unclear when the phase difference is equal to $\pi/2$ or $-\pi/2$. According to Ho et al. (2010), to better recognize the lead/lag relation between time series, when the phase difference is $\in [\pi/2, -\pi/2]$, it is important to transform each phase of each specified

[4] We refer the reader to Ho et al. (2010) for definition of these technical issues.

band wavelet into a sine function and make the pseudo cycle, making possible to judge the lead/lag relationship of the two time series at specified band.

In addition, the phase difference, which is given by the relative lag between the two time series, is interpreted as a lead or a lag between the time series. In this sense we can interpret the phase difference in terms of the arrow's direction. Arrows pointed to the right (left) indicate that variables are in phase (out of phase or anti-phase). If arrows move to the right and up (down), the first variable X is leading (lagging). By contrast, if arrows move to the left and up (down), the variable X is lagging (leading).

Despite its usefulness, the phase difference only serves as a heuristic regarding causality of the variables. Because it is also our interest to analyze causality issues, we used the rolling Granger causality measure of Shin et al. (2016) for this purpose which utilizes time-varying bivariate VAR setup. We choose this measure because it allows for the analysis of causality while allowing for time variation[5].

3. Data

As mentioned in the introduction, we use the daily index of Scotti (2016) to measure uncertainty.[6] The index captures uncertainty related to the real economy as perceived by economic agents using Bloomberg expectations and realizations of several macro variables. Further, the measure, which relies on a factor model using macroeconomic variables, can isolate uncertainty about the economy from other measures that can potentially bias the uncertainty measure and is more preferable to competing uncertainty measures such as the news based measure of Baker et al. (2016). To compile the index, the author uses a dynamic factor model which is estimated to construct business conditions index and forecasting weights. Using these, uncertainty is then a weighted average of squared surprises from the macroeconomic variables. The data is constructed with daily frequency and is provided for the United States, Euro Area, United Kingdom, Canada and Japan for the period 15th May, 2003-2nd October, 2017.

[5] We refer the reader to Shin et al. (2016) for technical details of the procedure.

[6] The data is available for download from: https://drive.google.com/file/d/1KkrQSXOxJMqb9eTEkQuGY7VlVsQomuU4/view.

Figure 1 (Figures 1a and 1b)

Shadow interest rate and uncertainty index for the US

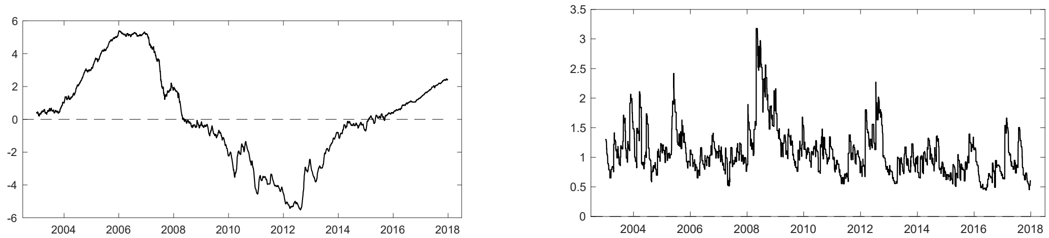


Figure 2 (Figures 2a and 2b)

Shadow interest rate and uncertainty index for the Euro Area

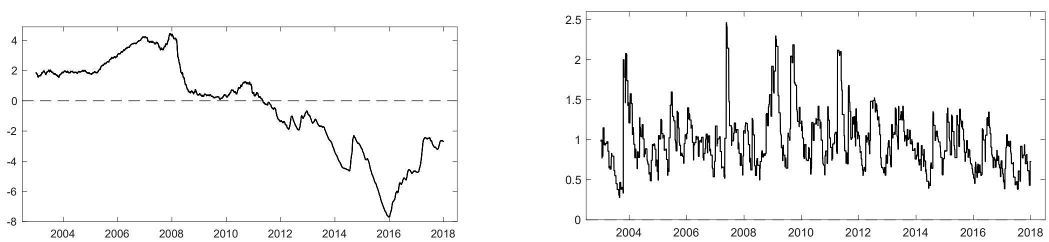


Figure 3 (Figures 3a and 3b)

Shadow interest rate and uncertainty index for the UK

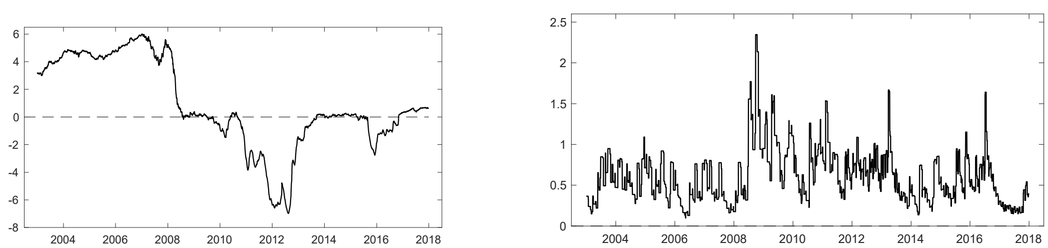


Figure 4 (Figures 4a and 4b)

Repo rate and uncertainty index for the Canada

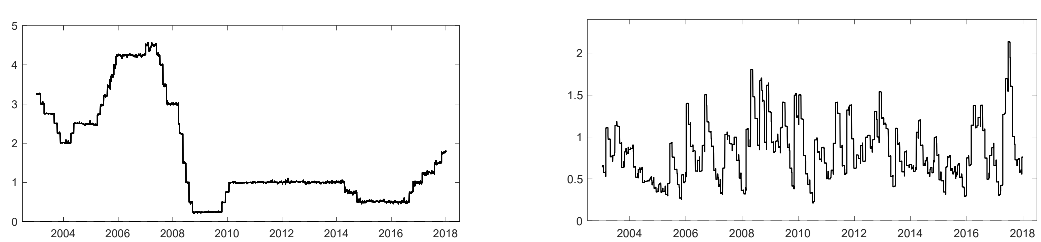
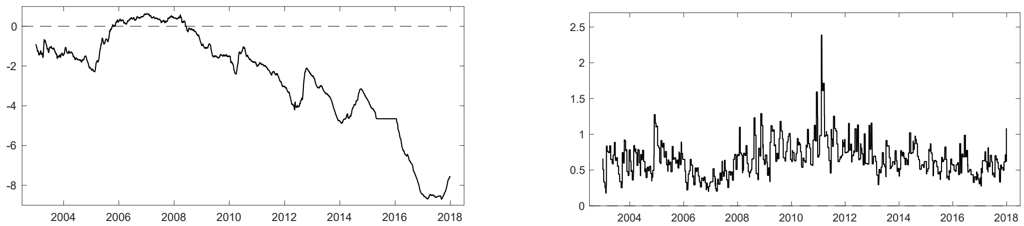


Figure 5 (Figures 5a and 5b)

Shadow interest rate and uncertainty index for the Japan



In addition to the uncertainty index, we use the daily shadow interest rate measure as introduced in Krippner (2012, 2013) for the US, Euro Area, UK and Japan. This option-based measure is a product of the estimation of a dynamic term-structure model that is an extension of a Gaussian affine term structure model which allows for negative rates. There are several reasons why we choose this measure: first, the countries we consider are all major developed countries and substantially decreased interest rates after the 2008 financial crisis. Because interest rates are constrained by the zero lower bound, we believe that shadow interest rates represents stance of monetary policy more appropriately, especially for those countries that implemented quantitative easing measures.[7] Second, the interest rate measure is available at daily frequency and hence matches the daily uncertainty measure of Scotti (2016). Also, while other shadow rate measures such as Wu & Xia (2016) are available, we choose the measure of Krippner (2013) because three-factor shadow term structure models such as the one employed by Wu & Xia (2016) are not always robust as shown in Krippner (2016). For Canada we use the daily repo rate, obtained from the Bank of Canada[8], since it is the only country in our sample not to have pursued unconventional monetary policy (see Fontaine et al., 2017).The use of daily data for interest rates and uncertainty is specifically suited for our purpose since wavelets allow us to examine the dynamic relationship between interest rates and uncertainty for different frequencies over time.[9]

[7]The data can be downloaded from: https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy/comparison-of-international-monetary-policy-measures.

[8]The data is available at: https://www.bankofcanada.ca/rates/interest-rates/.

[9]As a prelude to the wavelet analysis, Figures A1 to A5 in the Appendix of the paper present quantiles-based coherency (as developed by Baruník and Kley, 2015) between uncertainty and interest rate across various quantiles. The figures in the left panel correspond to Real (Re) and the right panel for imaginary (Im) parts of the quantile coherency estimates for weeks (W), months (M) and years (Y), along with the 95 percent confidence intervals. Note, quantiles provide an indirect way of studying the time-varying nature of the relationship between the two variables, as they correspond to different states of uncertainty and interest rates. As can be seen, in general, the relationship between these two variables tend to be negative.

4. Results

4.1. Wavelet coherency, phase difference analysis for US

In this section we discuss our empirical findings. As pointed out above, to analyze the wavelet plots, we will base our interpretation on two factors; the arrow's direction and the plot's color bars. More precisely, as noted by (Vacha et al. 2013), the phase differences presented by black arrows allow us to distinguish between negative and positive correlations, indicating delay in the oscillation between two time series. When the arrows are directed to the right, the investigated time series are in phase and move together, i.e. are positively correlated. If, contrary, the examined time series are negatively correlated, they are anti-phase. Furthermore, alluding to Ben-Salha et al. (2018), the intensity of correlation between two time series is revealed by colored areas. The plot's color bars demonstrate many colors ranging from blue to red. While blue color indicates that there is no correlation between the investigated time series (blue islands), the red color indicates high level of co-movement (correlation) between time series. On the other hand, the co-movement (the correlation) between studied time series vary in time and across frequency. Time and frequency are represented on the horizontal and the vertical axis, respectively. More precisely, the time series are decomposed to scales ranging from high (low scales) to low frequencies (high scales). In addition, the thick black contour encloses regions where the wavelet coherence is significant at the 5% level against the red noise estimated from Monte Carlo simulations using phase randomized surrogate series. In our plots, the cone of influence (COI) is graphically represented by the lighter shade which delimits the important power regions.

The following plots correspond to wavelet coherence between uncertainty and interest rate and the phases' differences in different countries. Figure 6 (Fig. 6a and Fig. 6b respectively) reports the cross-wavelet power coherency between uncertainty index and interest rate over time and across frequencies and the phase differences for the US case.

Figure 6. Wavelet and phase plots for US

Fig 6a. Wavelet coherence between uncertainty and interest rate

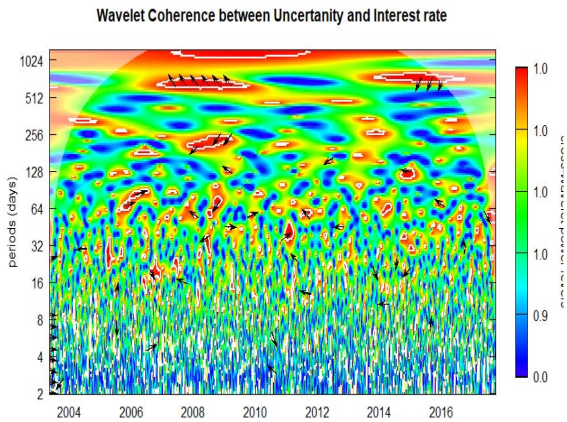


Fig 6b. Global pattern of averaged phase difference

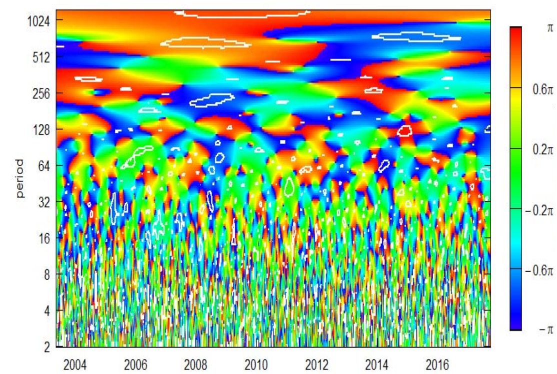
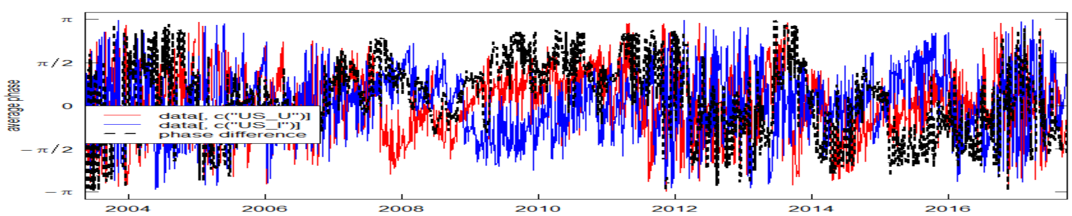


Fig 6c. phases and Time-Lag



Note: a) wavelet coherency between uncertainty index and interest rate, b) Global pattern of averaged phase difference, c) The phases and Time-Lag. The white contour identifies the regions in which the spectrum is significant at the 5%level against red noise. The cone of influence (COI), indicated by the lighter shade which delimits the high power regions. Time and frequency (daily) are represented on the horizontal and vertical axes, respectively.

Fig. 6a presents the wavelet coherence between uncertainty and interest rate from 2004 to 2016. Excluding the unsteady co-movement at frequencies around 2-128 days, we find a significant long-run co-movement at low frequencies, especially between 256 and 1024 days. However, we are careful to interpret this co-movement for two reasons. Firstly, this co-movement was mostly localized at high scales (512-1024 band of days) and secondly it is scattered over two sub-sample periods; from 2006 to the end of 2010 and from 2013 to the end of 2016. For the first sub-sample period (2006-2010), the uncertainty index and the US interest rate are anti-phase (move oppositely) as the arrows are pointed to the left and the uncertainty index is lagging. We note that this period corresponds to the US financial crisis where policy uncertainty was very high. For the second subperiod (2013-2016) and for the same frequency-band, the uncertainty index and the US interest rate move conversely as the arrows are pointed to the left and down indicating that they are anti-phase and the uncertainty index is leading.

In Fig. 6b, we present the global pattern of averaged phase difference to check whether the two time-series (US uncertainty index and the interest rate) exhibit phase or anti-phase characteristics and especially whether they exhibit the lead-lag relationship. While this figure exhibits patterns that confirm our previous finding revealing that the two series comove within 64-256 and 512-1024 day cycles, the cyclical relationship (in phase/anti-phase) is not easily understood at average level. This is why we will rely on Fig. 6c to analyze the pattern of average phase differences. Fig. 6c corresponds to the average phase difference (1-1012 day of frequency). Note that Phases and Phase-Difference (Phase.x- Phase.y) are also computed for different frequency bands[10]. For Fig. 6c, the blue line represents the US interest rate index phase, the red line represents the US uncertainty index phase, and the black dotted line represents the phase difference. It is interesting to note that, when the phase-difference is converted to an angle in the interval $[-\pi, \pi]$, an absolute value less (larger) than $\pi/2$ indicates that the two series move in phase (anti-phase). In addition, the sign of the phase-difference indicates which series leads (lags) in the relationship. In this plot, we can analyze the relationship within three episodes: In the first two episodes, the interest rate index leads the US uncertainty index (on average) in anti-phase relationship $[-\pi, -\pi/2]$ for the periods 2004-2006 and 2012-2016, implying a negative relationship between the two time-series. The third episode of the relationship corresponds to the period 2007-2011, where the phase plunges to the interval $[0, \pi/2]$, indicating that the uncertainty index leads the interest rate index in anti-phase relationship. This result indicates that the uncertainty is negatively correlated with the interest rate in the US. This is not surprising as, during turmoil periods, uncertainty is high and considerably slows US bank credit growth (Bordo et al. 2016), or put alternatively interest rate is low, as observed particularly during the Great Recession.

4.2. Wavelet coherency, phase difference analysis for Euro Area

Figure 7 (Fig. 7a to Fig. 7c) reports the wavelet coherency between uncertainty and the interest rate for the period 2004 to 2016 for the European case. Looking at high and medium scales, especially the 256-1024 day and 64-256 frequencies bands, the two time-series have a common and high

[10]More precisely, we compute the phases for the 2-4 day, 4-8 day, 8-16 day, 16-32 day, 32-64 day, 64-128 day, 128-256 day, 256-512 day and 512-1024 day frequency bands. Plots are not reported to conserve space, but are available upon request addressed to the corresponding author.

coherency level, where the interest rate leads in the second quarter (2007-2011) and the European uncertainty index leads in the second half of the sample.

Figure 7. Wavelet and phases plots for Europe

Fig 7a. Wavelet coherence between uncertainty and interest rate

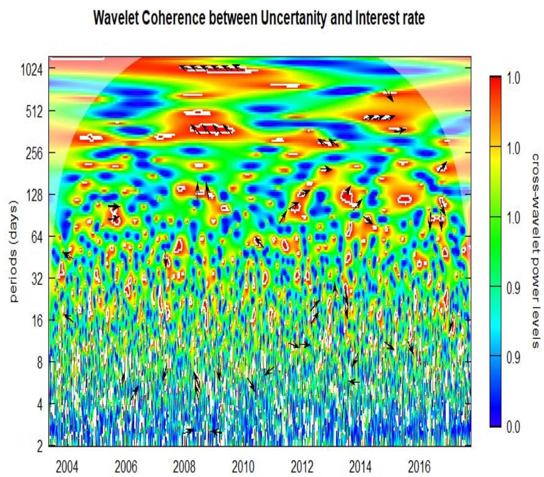


Fig 7b. Global pattern of averaged phase difference

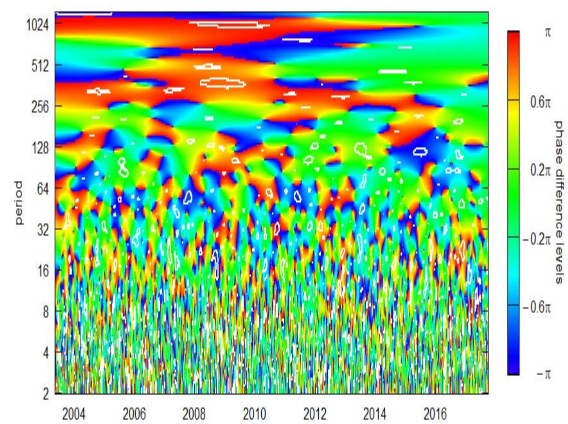
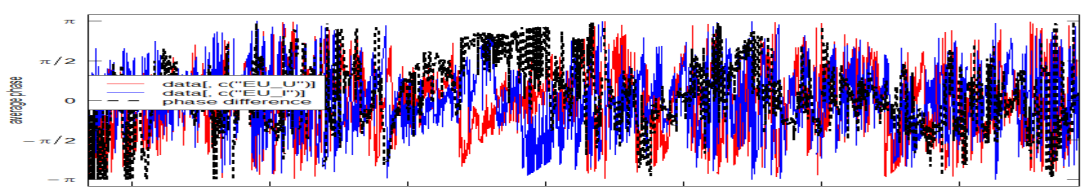


Fig 7c. Phases and Time-Lag



Note: a) Wavelet coherency between uncertainty index and interest rate, b) Global pattern of averaged phase difference, c) The phases and Time-Lag. The white contour identifies the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence (COI), indicated by the lighter shade which delimits the high power regions. Time and frequency (daily) are represented on the horizontal and vertical axes, respectively.

The global phase difference is given in Fig. 7b and reveals a strong relationship between the two series, especially localized in low frequencies and in general dispersed over all the sample period. However, it will be more interesting to understand the phase or anti-phase relationship from the average phase differences (Fig.7c). Looking to Fig. 7c, it is understandable that for the period 2009-2010 the phase difference is localized between $[0, \pi/2]$. This reveals that the European interest rate leads the uncertainty index in a phase movement. In addition, for the periods 2004-2008 and 2011-2016, the phase plunges mostly to the interval $[\pi/2, -\pi/2]$, indicative of aphase relation in which the uncertainty index leads the interest rate in general. Our findings indicate a positive relationship between uncertainty policy and interest rate.

4.3. Wavelet coherency, phase difference analysis for United Kingdom

Figure 8 (Fig. 8a to Fig. 8c) reports plots of wavelet coherency and phase differences between economic uncertainty index and interest rate for the United Kingdom. Fig. 8a presents result of wavelet coherency between the uncertainty index for the UK and the interest rate and indicates a strong relationship between the two time-series, especially localized at high scales during the period 2006-2017, indicating the occurrence of extreme events at the middle and the end of the period. Noting that the vote to exit the European Union, known as Brexit, took place in 2016, it is why not surprising that this event lead to high economic and policy uncertainty in the UK. During this period, the arrows are directed to the left and up, revealing that the interest rate index is leading. While small islands of orange color are spread over the sample period, the lead-lag relationship is no longer clear. This result does not neglect the presence of some scenarios which inspire the relationship between the two time-series. We assume that the global power average phase difference (ranged between $[-\pi, \pi]$ given in (Fig. 8b) and the outline of average phase differences(shown in (Fig 8c)) allow us to understand the accurate lead/lag relationship between the two time-series. Visual inspection for these plots reveals big areas of dark red color, mostly concentrated at low frequencies, indicating that the two time-series comove strongly around these scales. In addition, Fig. 8c gives more information about the phase (anti-phase) and the lead (lag) relationships of the two respective time series. This plot reveals that UK Uncertainty index and the corresponding interest rate are, in general, in anti-phase $[\pi/2, -\pi/2]$from the beginning of the period to the end of 2012, with the interest rate leading the uncertainty index. From 2013 to the end of the sample period, the two time-series move in phase $[0, \pi/2]$, where again the interest rate leads the uncertainty index.

Figure 8. Wavelet and phases plots for United Kingdom

Fig 8a. Wavelet coherence between uncertainty and interest rate

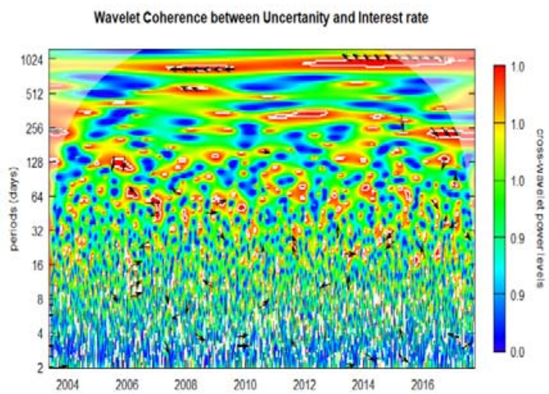


Fig 8b. Global pattern of averaged phase difference

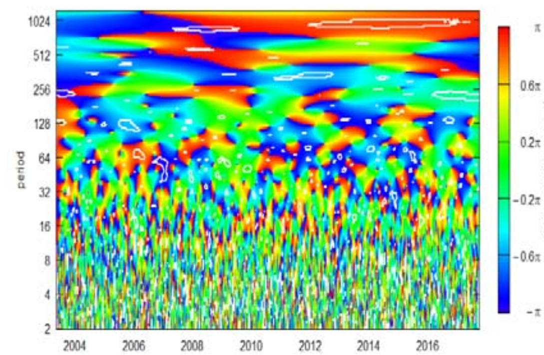
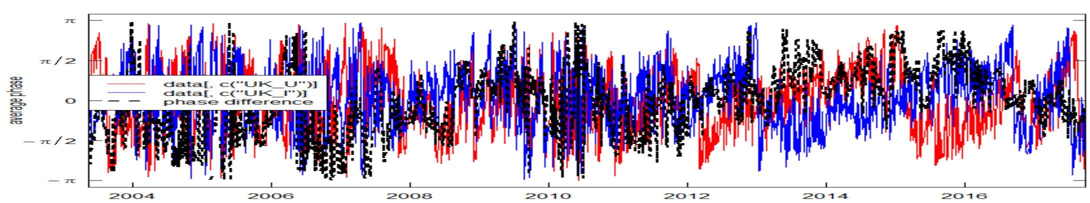


Fig 8c. Phases and Time-Lag



Note: a) Wavelet coherency between uncertainty index and interest rate, b) Global pattern of averaged phase difference, c) The phases and Time-Lag. The white contour identifies the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence (COI), indicated by the lighter shade which delimits the high power regions. Time and frequency (daily) are represented on the horizontal and vertical axes, respectively.

4.4. Wavelet coherency, phase difference analysis for Canada

A visual inspection of figures Fig. 9a; Fig. 9b and Fig. 9c, corresponding respectively to the wavelet coherence, the global phase difference and the phase differences plots, reveals a strong co-movement between the Canadian uncertainty index and the interest rate. The highest level of co-movement is concentrated within the 32-256 frequency band (medium scales) over the sample period where the arrows generally point right and down (in anti-phase), indicating that the uncertainty index leads the interest rate in Canada. We also find strong localized co-movement at high scales during the period 2011-2013, where the arrows point to the left, indicating that the two series are in phase. The phase differences plot shown in Fig. 9c indicates that the two time-series broadly exhibit anti-phase characteristics. In addition, the plots specifically show that the patterns of the two phases vary over the sample period. First, an anti-phase relation between uncertainty index and interest rate is exhibited for the period 2004-end of 2011, where the phase difference is $\in [\pi/2, -\pi/2]$,demonstrating that the uncertainty index leads the interest rate. For the period 2011-2013 where the interest rate leads the uncertainty index in anti-phase relationship, the phase difference is $\in [\pi/2, \pi]$.

Figure 9. Wavelet and phases plots for Canada

Fig 9a. Wavelet coherence between uncertainty and interest rate

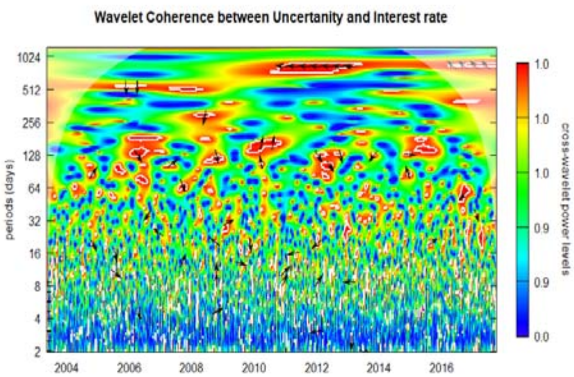


Fig 9b. Global pattern of averaged phase difference

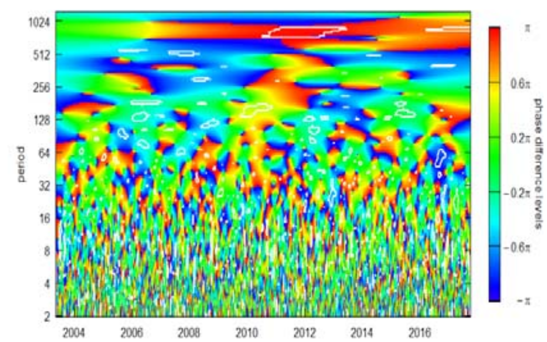
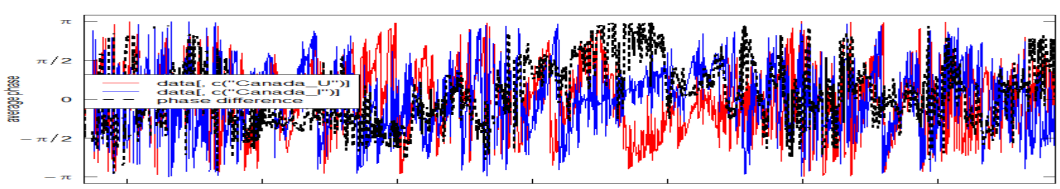


Fig 9c. Phases and Time-Lag



Note: a) Wavelet coherency between uncertainty index and interest rate, b) Global pattern of averaged phase difference, c) The phases and Time-Lag. The white contour identifies the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence (COI), indicated by the lighter shade which delimits the high power regions. Time and frequency (daily) are represented on the horizontal and vertical axes, respectively.

4.5. Wavelet coherency, phase difference analysis for Japan

Figures 10a, 10b and 10c represent the wavelet coherence, the global phases difference pattern and the average phase differences, respectively. Fig. 10a reveals small areas of red colors dispersed over the sample period and mostly concentrated within the 64-256 frequency band. The arrows are generally pointed to the right and down between 2004 and 2011 and are directed to the left and up during 2015-2016 for the same frequency band. These results indicate the existence of remarkable events at the beginning and the end of the sample period and also a change in the lead-lag relation between the uncertainty index and the interest rate for Japan. The average phase difference shows that, in general, the two time-series are in phase $[\pi/2, -\pi/2]$ and the interest rate leads the uncertainty index. The change in lead-lag relation is also apparent in the average phase difference for the period (2015-2016) and the two time-series are in phase $[0, \pi/2]$ and the uncertainty index leads the interest rate.

Figure 10. Wavelet and phases plots for Japan

Fig 10a. Wavelet coherence between uncertainty and interest rate

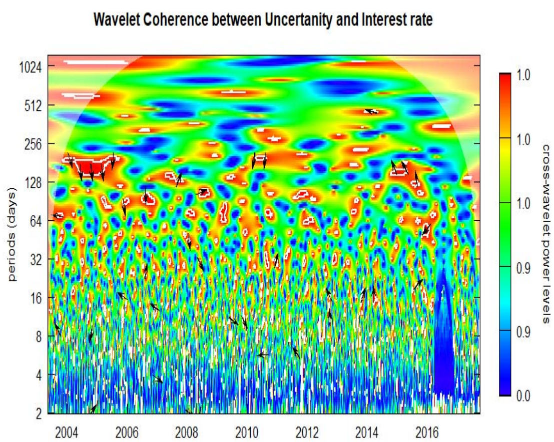


Fig 10b. Global pattern of averaged phase difference

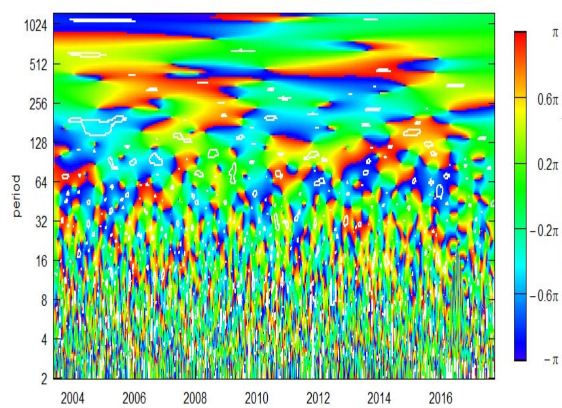
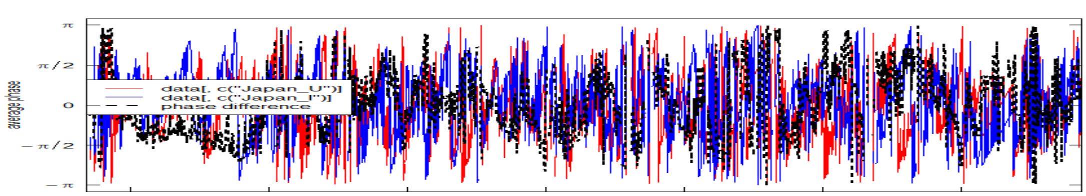


Fig 10c. Phases and Time-Lag



Note: a) Wavelet coherency between uncertainty index and interest rate, b) Global pattern of averaged phase difference, c) The phases and Time-Lag. The white contour identifies the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence (COI), indicated by the lighter shade which delimits the high power regions. Time and frequency (daily) are represented on the horizontal and vertical axes, respectively.

From the previous findings, we can conclude that, around the financial crisis, the US uncertainty jumped up and remained high impacting the economic policy and macroeconomic variables. In addition, our results indicate that for Europe and Canada uncertainty exhibits similar tendencies in comparison to the US, suggesting that uncertainty hikes in general, during periods of deep recessions are global in nature, given interlinkages of countries. As well, overall, the findings disclose that uncertainty index and interest rate exhibit a long-term relationship as the co-movements are mostly localized at high scales, indicating that the impact of uncertainty in monetary policies are more likely to be stronger at long horizons.

5. Economic and Financial implications

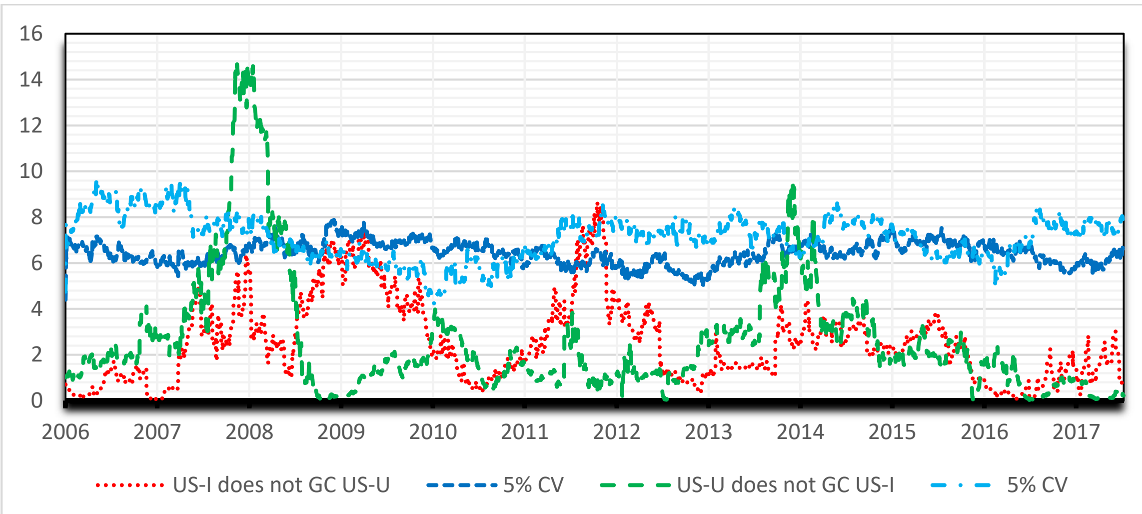
The results carry important implications for the literature that is concerned with causality of uncertainty and the real economy. In the following, we will detail some of the implications of our results for the countries that we considered for the period of analysis.

5.1 US

Figure 1 (Fig. 1a and Fig. 1b) depicts the uncertainty index and the shadow interest rates for the US. As one can see in Figure 1a, uncertainty in the US spiked around the years 2004, 2006, 2008, 2013 and 2016. In Fig. 1b, one can see the (shadow) interest rate. In 2004, the Federal Reserve decided to raise interest rates after conducting expansionary monetary policies for several years. This period, which also corresponds to the aftermath of the 2003 Gulf War appears to have raised uncertainty regarding the real economy. Similarly, in the midst of contractionary monetary policies in the following period, uncertainty reached high levels around November 2005. Not surprisingly, uncertainty reached a climax in the US around the collapse of Lehman Brothers in 2008 when the possibility of a financial meltdown became apparent. Before the financial crisis erupted in 2008, the Federal Reserve lowered interest rates after July 2007 when signs of the subprime mortgage crisis became apparent and continued with unconventional monetary policies until 2013. In the following period after 2013, uncertainty increased once more when the so-called “taper tantrum” started and the Federal Reserve announced it would end pursuing unconventional monetary policies. Uncertainty increased again after 2016 following concerns of trade and currency wars.

Against this background, we find that uncertainty and interest rates mostly exhibit an anti-phase relationship, where the interest rate leads for the periods 2004-2006 and 2012-2016, and uncertainty leads for 2007-2011. Also Figure 11 gives further information about the timing and direction of causality between the shadow interest rate and uncertainty for the US. As is visible, Granger causality from uncertainty to the interest rate is significant for the periods around 2008 and 2014, whereas the causality runs in the opposite direction only around 2012. These results support the finding of Gupta et al. (2018) that uncertainty shocks in the US lead to expansionary monetary policies. The finding also may indicate that during the financial crisis of 2008, when uncertainty was very high, interest rate decisions were a response to the increasing uncertainty that prevailed in the economy once the economy entered a recession, confirming the finding of Bloom (2014) that uncertainty may have accounted for one-third of the drop in GDP after the 2008 financial crisis.[11]

Figure 11. Time-varying rolling Granger causality test for the US



5.2 Euro Area

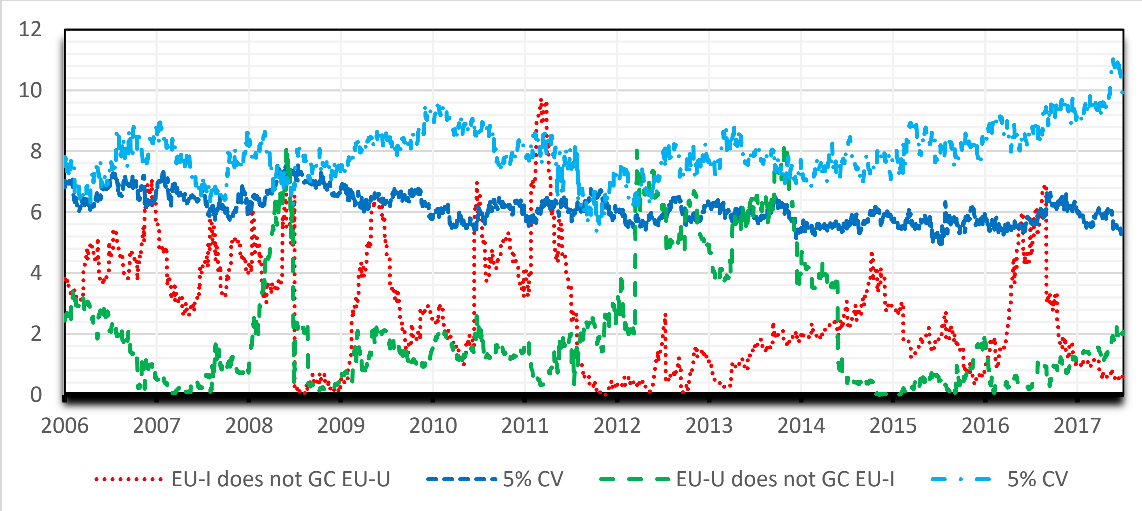
Figure 2 (Fig. 2a and Fig. 2b) depicts the uncertainty index and the interest rate for the Euro Area. As is apparent, uncertainty was especially high during the periods around 2007, 2009, 2010 and 2012. The year 2007 was marked by signs of instabilities in financial markets in several countries

[11]As a robustness check, we conducted the analysis for the US over the period of 25th November 1985 to 29th May 2018 using different measures for uncertainty and monetary policy. For uncertainty, we used the news-based daily data developed by Baker et al. (2016), which is a daily news-based Economic Policy Uncertainty Index based on newspaper archives from Access World News Bank service and is downloadable from: http://policyuncertainty.com/us_monthly.html. The primary measure for this index is the number of articles that contain at least one term from each of three sets of terms: "economic or economy"; "uncertain or uncertainty", and; "legislation or deficit or regulation or congress or federal reserve or white house". For monetary policy, we used the SSR and the expected monetary stimulus (EMS), which are both sourced from Krippner (2012, 2013) at: https://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy. Understandably, the SSR and EMS are negatively correlated. Based on the phase-difference results reported in figures A6 and A7, we find that the relationship between interest rates and uncertainty is mostly anti-phase, while that between EMS and uncertainty is in-phase, thus confirming the theory in general. In essence, over the common period of analysis, the uncertainty index of Scotti (2016) is qualitatively similar to the one obtained with the news-based index of Baker et al. (2016).

in and around the Euro Area: banks in Spain, Germany and the UK showed signs of instability and the subprime mortgage crisis in the US was starting to make headlines. Surprisingly, 2008 is marked by relatively low uncertainty, whereas in 2009 the index increased. As Scotti (2016) explains, this may indicate that economic actors in the Euro Area were more uncertain about the economy when it entered and exited the recession than during the crisis. Uncertainty once more increased in 2010 when Greece was bailed out after 2011 when the sovereign debt crisis affected several Euro Area economies.

During this period, interest rates also went through several stages. Interest rates fluctuated around the 2 percent band until 2005, after which they were raised until July 2008 when the financial crisis became apparent in the US. While coming close to the zero lower bound around May 2010 (during the Greece bail-out), interest rates slightly increased again until July 2011. The period after 2012 is marked by the effects of unconventional policies, especially after ECB president Mario Draghi announced in July 2012 that the ECB would do whatever it takes to preserve the currency. These events and movements suggest that the results of the wavelet analysis for the Euro Area may stay in contrast to the results for the US. Specifically, our results show that interest rates and uncertainty comove in a phase relationship, where the interest rate leads uncertainty for the period 2007-2011, and uncertainty leads the interest rate for the periods 2004-2008 and 2011-2016. The contrasting results are not surprising as the interest rate and the uncertainty index for the Euro Area exhibit different characteristics in comparison to US variables; interest rates were lowered following signs of the financial crisis of 2008 in the Euro Area, but the dramatic lowering of interest rates only following the sovereign debt crisis that encompassed several Euro Area economies after 2011. Similarly, while uncertainty reached a climax in the US around the time of the Lehman Brothers collapse and was relatively lower in the following period, uncertainty in the Euro Area reached high levels *before* and *after* the financial crisis, and around the time when the sovereign debt crisis erupted in Greece. These results are complemented by the Granger causality test (figure 12), which indicates that causality runs from uncertainty to the interest rate during the period 2011-2015 whereas the opposite is true for the periods 2010-2011 and around 2016, indicating that in the first few years of the eurozone crisis interest rate decisions were driving uncertainty, while after 2012 uncertainty drove interest rate decisions.

Figure 12. Time-varying rolling Granger causality test for the eurozone



5.3 UK

Figure 3 (Fig. 3a and Fig. 3b) displays interest rates and the uncertainty index for the UK. It is clear from the figure that uncertainty in UK was relatively low until the end of 2008. After this period, which corresponds to the immediate aftermath of the eruption of the financial crisis in the US, uncertainty reached a climax and remained relatively high. Events that might have contributed to subsequent rounds of uncertainty include the sovereign debt crisis surrounding the Euro Area, the Brexit vote of June 2016 and the triggering of Article 50 in March 2017 that would initiate the exit of United Kingdom from the European Union.

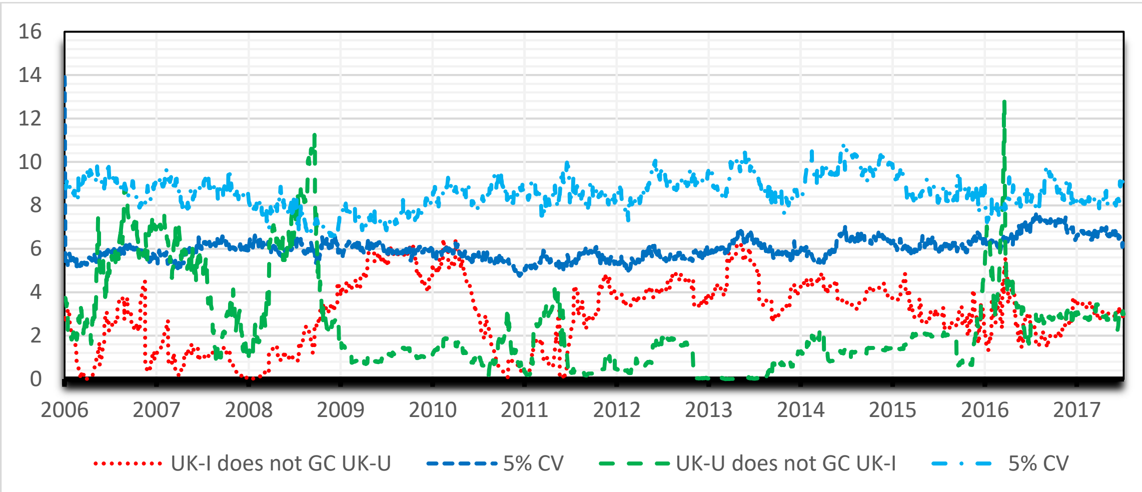
The conduct of monetary policy in the period of our analysis can be broken down into several subperiods. Interests were kept at relatively high levels until July 2008, i.e. the period preceding the financial crisis. During the first few months of the financial crisis, expansionary monetary policy measures pushed rates down to the zero lower bound. Following these measures, the Bank of England implemented successive rounds of quantitative easing in November 2009, October 2011, July 2012. While the shadow interest rate became positive in 2014, Bank of England announced another round of quantitative easing in August 2016 following the Brexit vote in June 2016, thereby pushing shadow rates into the negative territory once more. Finally, in November 2017 Bank of England raised interest rates.

Our results indicate that the shadow interest rate and uncertainty comoved in an anti-phase relationship from 2003 to the end of 2012, and in a phase relationship in the period 2013-2018..[12]

[12]As for the US, using the news-based daily data on uncertainty developed by Baker et al., (2016) athttp://policyuncertainty.com/uk_monthly.html, were-conducted the analysis over the period of 1[st]January,

The causality test in Figure indicates that Granger causality ran from the uncertainty measure to the interest rate around 2008 and 2016, whereas the opposite was the case for only a brief period around 2010. According to these results, the relationship between the interest rate and uncertainty was mostly "conventional" in that two series moved in opposite directions. They also imply that the uncertainty surrounding the global financial crisis after 2008 and the period following the Brexit vote in 2016 drove interest rate decisions.

Figure 13. Time-varying rolling Granger causality test for the UK



5.4 Canada

Figure 4 (Fig. 4a and Fig. 4b) depicts the uncertainty index and the repo rate of Canada. The uncertainty index in Canada saw several short-lived increases in 2007. Similar to other countries that we analyze, there is elevated uncertainty for several years following the eruption of the financial crisis in 2008. While uncertainty remained high in the following years, it spiked again and reached a climax after 2016, when uncertainties surrounding trade wars and renegotiation of the NAFTA deal affected the Canadian economy.

In our analysis Canada stands out with regard to the conduct of monetary policy since it did not implement quantitative easing policies. Interest rates, which hovered between 2-4 percent until

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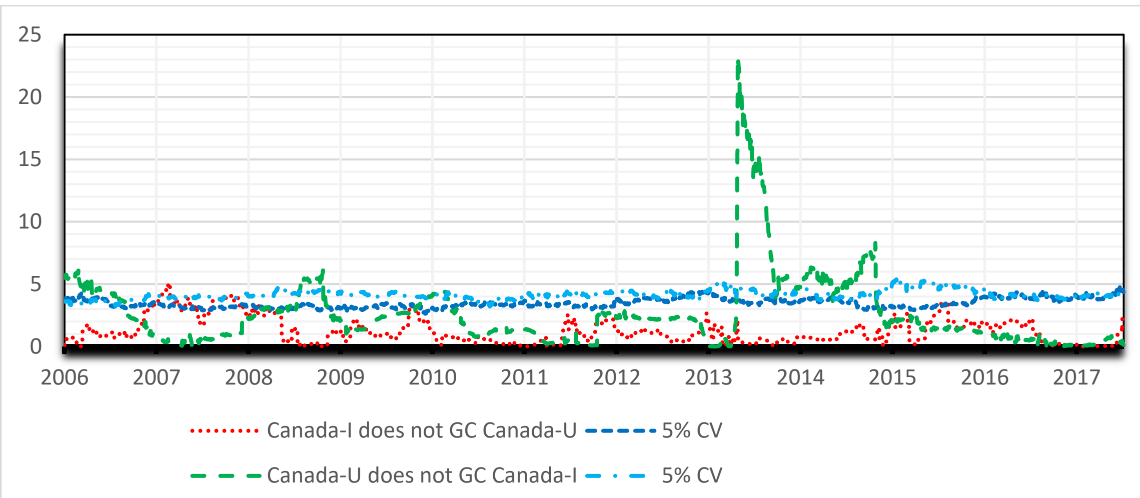
2001 to 29th May, 2018, and as measures of monetary policy, we use the SSR. Based on the phase-difference result reported in Figures A8, we find that the relationship between uncertainty and interest rates are mostly anti-phase. Again, as in the case of the US, over the common period of analysis compared to the uncertainty index of Scotti (2016) is qualitatively similar to those obtained with the news-based index of Baker et al., (2016).

2008, were decreased to 0.25 percent by April 2009 and kept at that level until the second quarter of 2010. Between September 2009 and January 2015, interest rates were kept at 1 percent decreased again until June 2017. After that, Bank of Canada successively raised interest rates. As described in the previous section, the relationship between uncertainty and interest rates comoved in an anti-phase relationship for the period of our analysis. The causality test, as presented in figure 14, indicates that causality ran from interest to uncertainty for a brief period around 2007, and that the opposite was true around 2008 and the period 2013-2015. While the first two results indicate that the interest rate decision of the Bank of Canada drove uncertainty prior to the crisis and uncertainty drove interest rate decisions after the start of the global financial crisis, the significant direction of causality around 2013 is likely due to uncertainty stemming from oil price fluctuations affecting Canada, an oil-exporting country.

Figure 14. Time-varying rolling Granger causality test for Canada

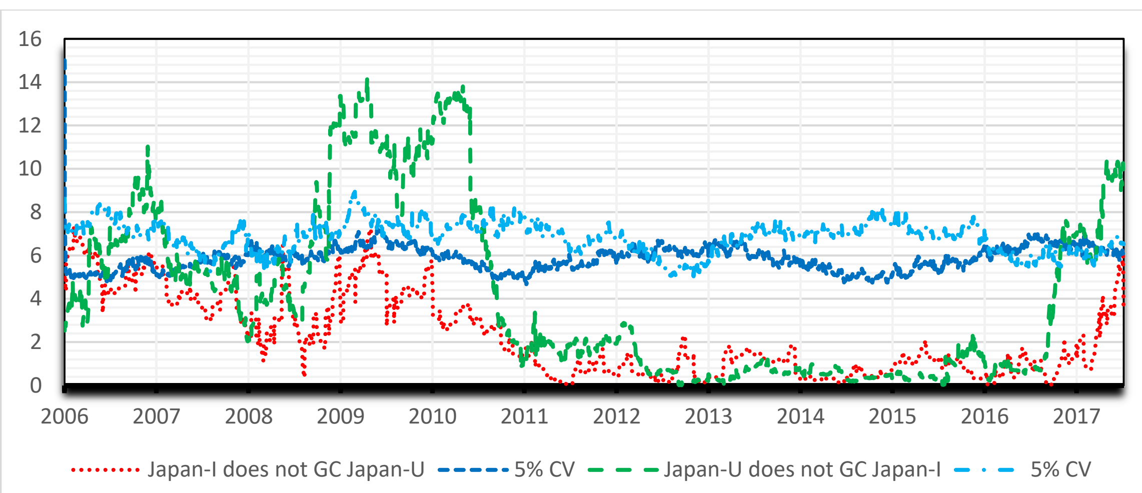


5.6 Japan

Figure 5 (Fig. 5a and Fig. 5b) shows uncertainty and the shadow interest rate for Japan. Japan's economy exhibited relatively low levels of uncertainty until the financial crisis of 2008. This event and other events such as the resignation of Prime Minister Fukuda in September 2008 and general elections in August 2009 caused uncertainty to be elevated for several years. Amid these developments, the index spiked in March 2011 and reached its highest level in our observation period when Japan was struck by a tsunami and a nuclear plant was affected as a result. In most of the following period, the index remained at levels that were prevalent after the financial crisis. Japan was also one of the countries that implemented unconventional monetary policy measures after the financial crisis. While Japan followed other countries in this, unconventional policies had been implemented several years prior to the financial crisis of 2008. In 1999, Bank of Japan had introduced a zero-interest rate policy to combat deflation and implemented quantitative easing measures between 2001-2006. This period was followed by moderate increases in the interest rate and reached 0.5 percent. Following the financial crisis, Japan followed other central banks and decreased interest rates once more. After the Bank of Japan started implementing additional rounds of quantitative easing, shadow interest rates went into the negative territory and remained there for the remaining period of our analysis (see Kuroda, 2016 for a brief account of unconventional policies implemented by Bank of Japan).

As explained above, our findings suggest that the shadow interest rate and the uncertainty index mostly move in a phase relationship. This may be indicative of Japan's position as the first country to have implemented quantitative easing measures and that monetary policy decisions are perceived to have significant consequences for the real economy. Further, our Granger causality test results indicate that causality ran from uncertainty to the interest rate for the periods 2007, 2009-2011 and after mid-2016. That causality runs from uncertainty to interest rates is a recurring pattern in our analysis and reflects the severity of the uncertainty that came with the global financial crisis. Further, the causality effect after 2016 is likely due to several events that were relevant for the Japanese economy such as discussions surrounding the tax hike and withdrawal of the US from the trans pacific partnership (TPP) and its implications for trade.

Figure 15. Time-varying rolling Granger causality test for Japan



5.7 Discussion

Our results show that while advanced economies implemented similar measures after the Great Recession, their monetary policy experience was more nuanced than put forth in earlier works.

Specifically, one can see that for the UK, US and Canada, the relationship between interest rates and uncertainty mostly moves in phase but anti phase during other times, whereas for the EU and Japan there is mostly an anti-phase relationship. The latter result for the EU and Japan which is seemingly puzzling – that interest rates and uncertainty mostly comove positively – is mostly likely due to the monetary policy environment in which these economies operate: the ECB conducts policy for the eurozone as a whole and not for individual member economies and hence, interest rate decisions may not be comparable to the decision-making of a "traditional" central bank. Indeed, this divergence was analyzed in the literature and some authors argue that ECB's policies were not always optimal for the needs of individual members (e.g. Moons and Van Poeck, 2008). Similarly, Japan's monetary policy experience is unique in the sense that the economy entered the "lost decade" in the 1990's and implemented its zero-interest rate policy and quantitative easing policies after 1999. Consequently, the data we utilize for Japan is in the negative range for almost all of the observation period. We believe that due to this idiosyncrasy of monetary policy, Japan's relationship is different in comparison to other advanced economies.

6. Conclusion

The relationship between uncertainty and interest rates is a subject of growing interest for the macroeconomics literature. The debate regarding the nature of the relationship and causality has still not been settled conclusively. In this work we contributed to this literature by analyzing this relationship for several advanced economies in an empirical setup using daily data and wavelets. Although in our analysis we consider only advanced economies, these faced different challenges for the observation period under consideration and applied different versions of unconventional policies[13]. Correspondingly we find that in some of the countries uncertainty and interest rates mostly comove positively (EU and Japan) while in others they comove negatively (Canada, UK, US). We also find that causality between uncertainty and interest rates is not linear and is subject to changes over time. These results carry importance for the ongoing debate since they imply that causality and the nature of the relationship are subject to changes over time and frequencies. Our findings also suggest that the relationship does not remain equal across countries and drawing generalized conclusions with regard to the relationship may not be correct. Comparing our results to Christou et al. (2018) who analyzed a related research question and find that advanced economies significantly react to economics policy uncertainty (with the exception of Japan), our results imply that the relation has a more nuanced nature and is subject to time variation. By using a wavelet

[13]See Dell'Ariccia et al. (2018) for a description of unconventional policies pursued by the Euro Area, Japan and the United Kingdom.

approach, our results complement these studies. Since daily data on interest rates and uncertainty are so far only available for few advanced countries, our analysis is limited to those economies. Future work could shed light on this subject for emerging and developing markets when data becomes available.

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APPENDIX:

Figure A1. Quantile Coherency between Uncertainty Index and Interest Rate in the US

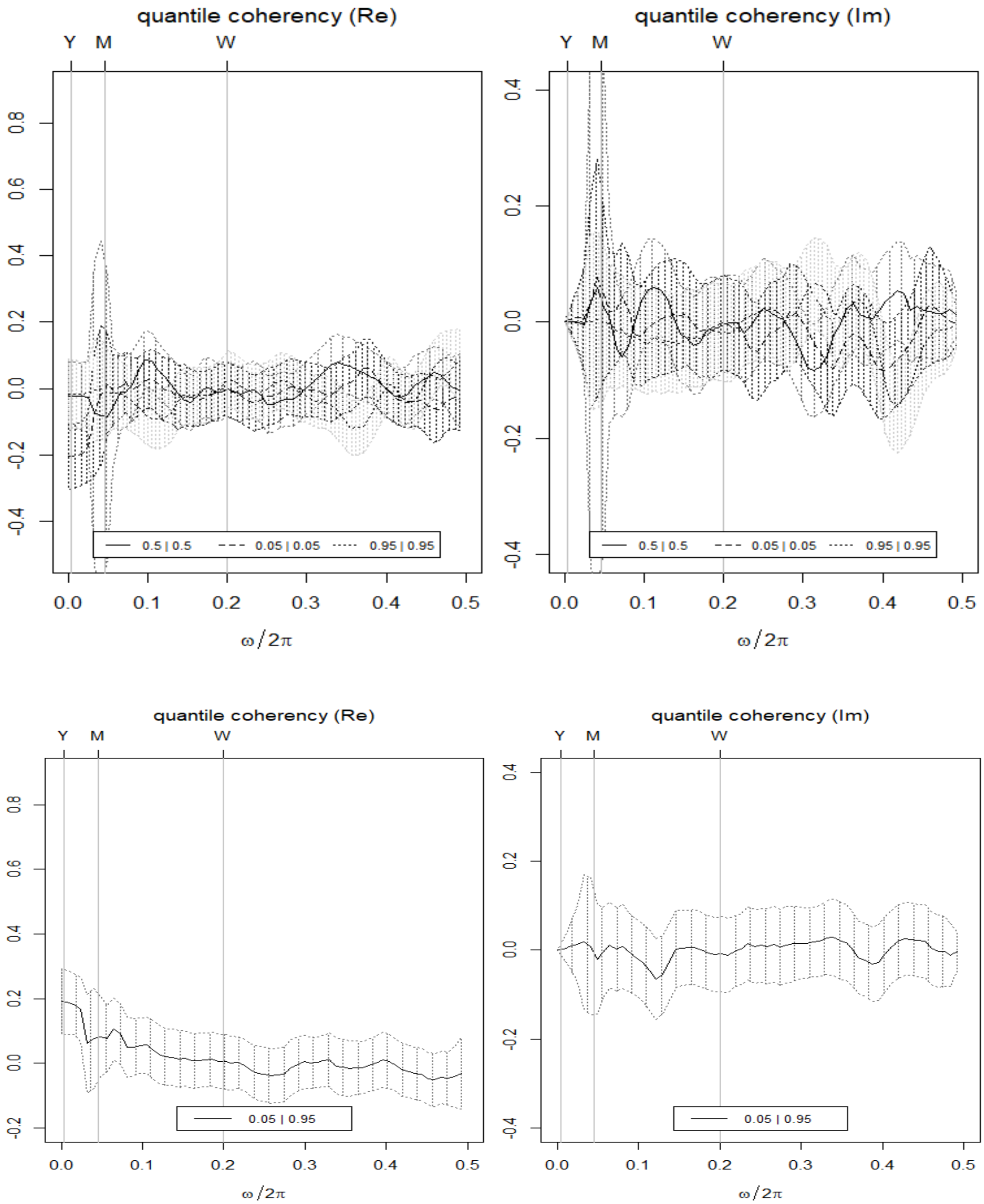

Figure A2. Quantile Coherency between Uncertainty Index and Interest Rate in Europe

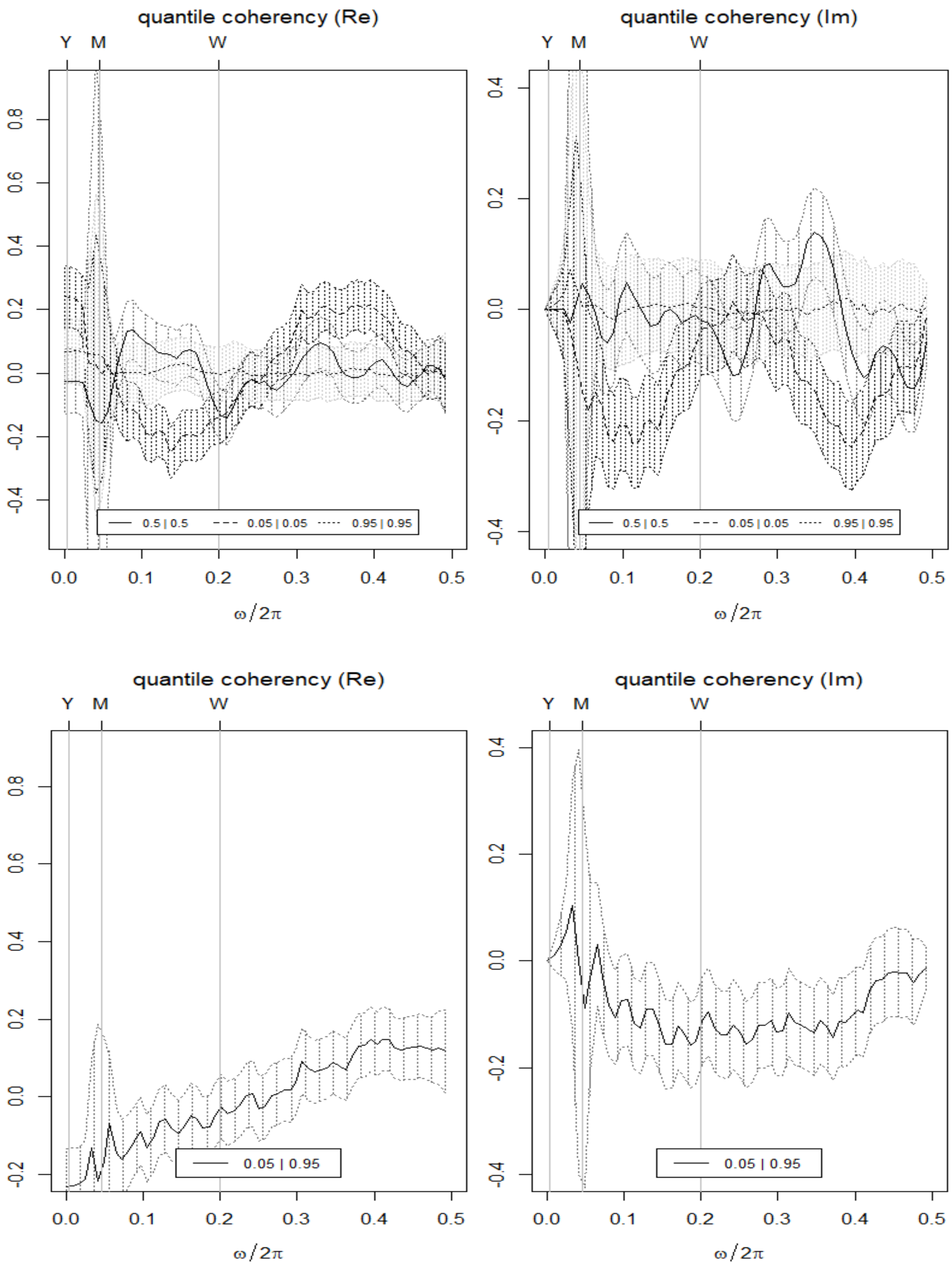

Figure A3. Quantile Coherency between Uncertainty Index and Interest Rate in the UK

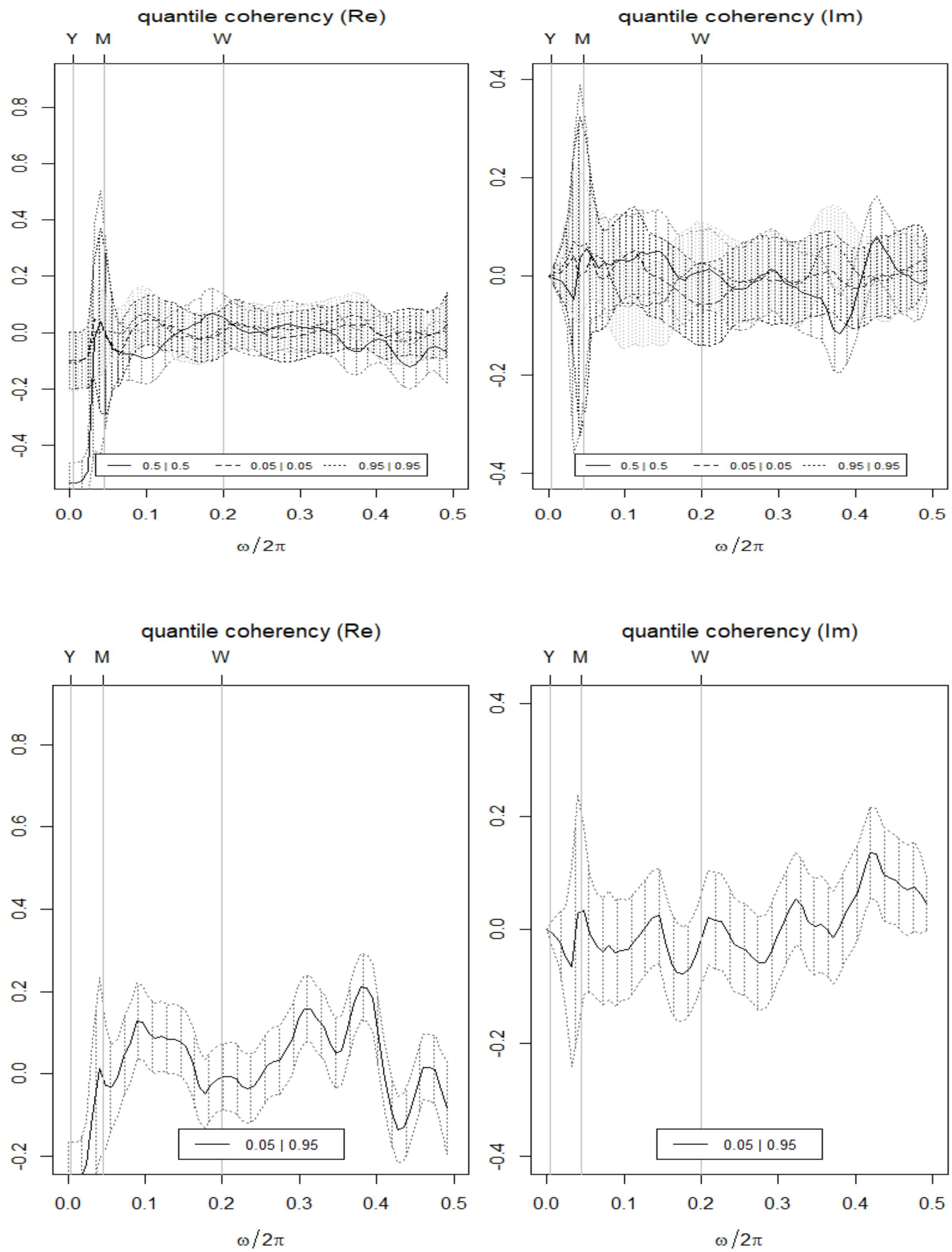

Figure A4. Quantile Coherency between Uncertainty Index and Interest Rate in Canada

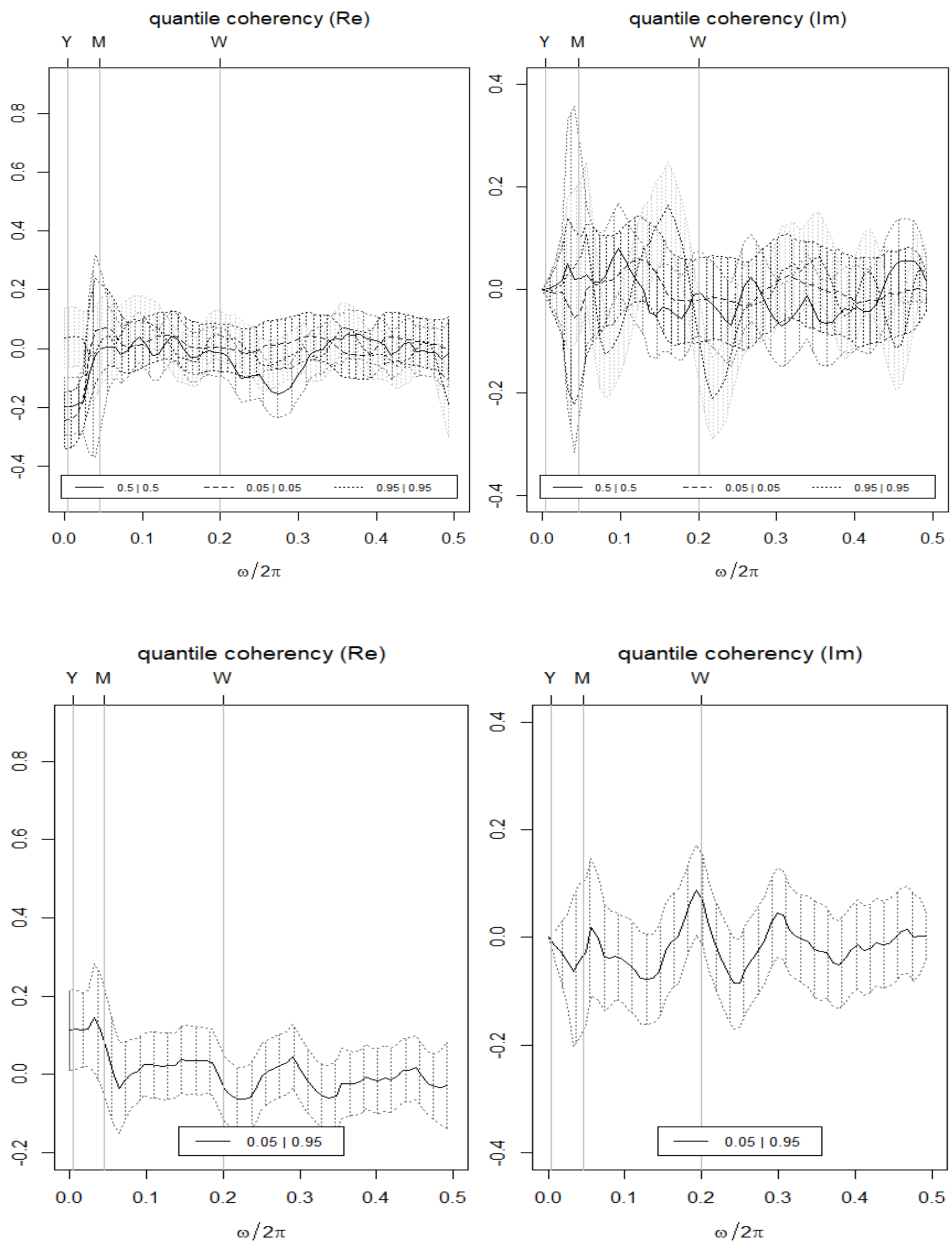

Figure A5. Quantile Coherency between Uncertainty Index and Interest Rate in Japan

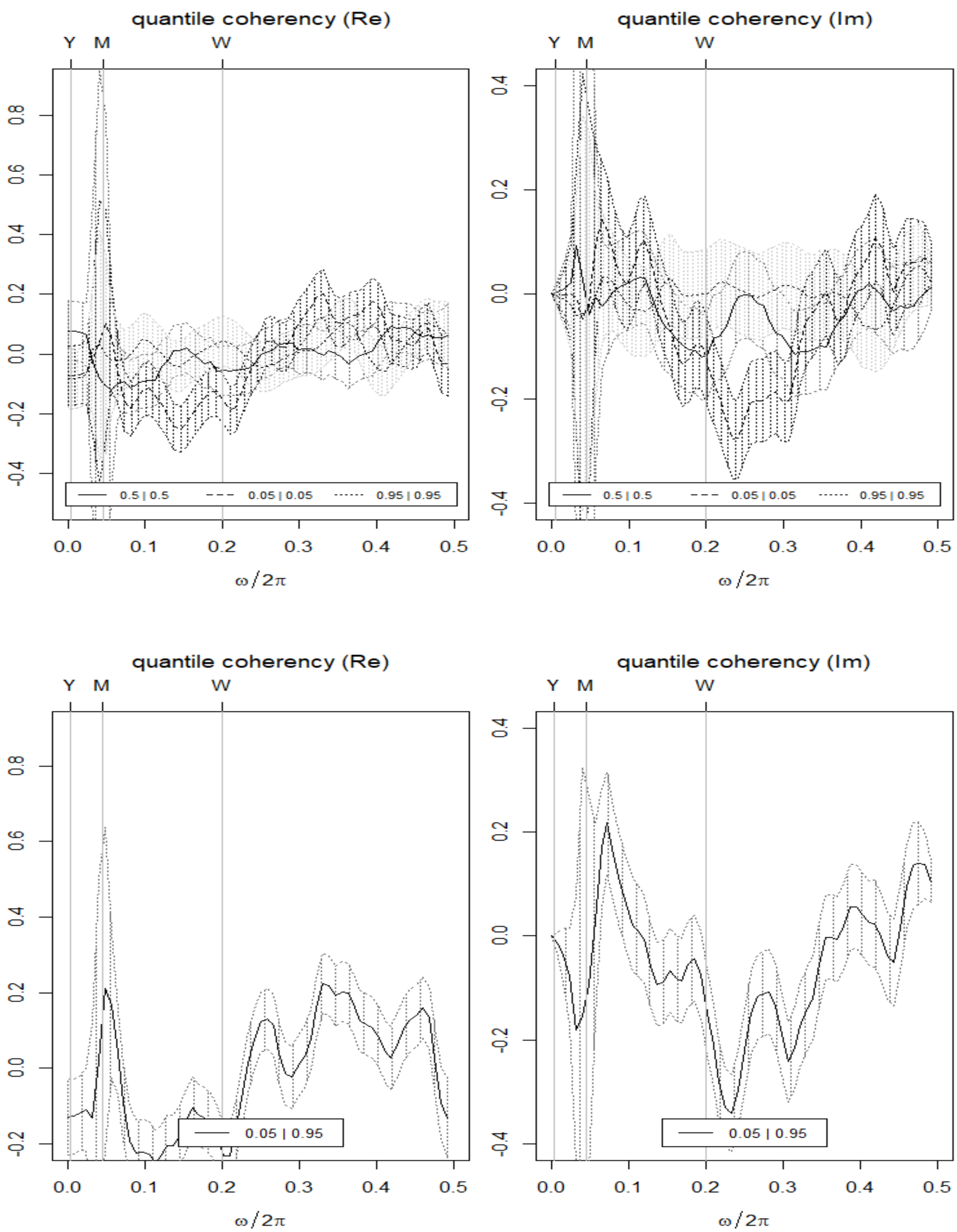

Figure A6. News-Based Uncertainty Index and Interest Rate of the US

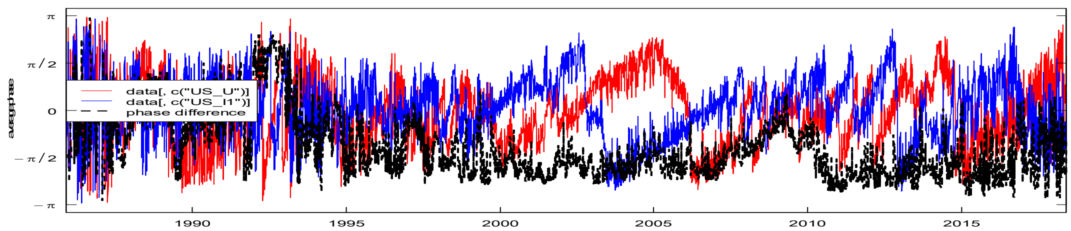

Figure A7. News-Based Uncertainty Index and Effective Monetary Stimulus of the US

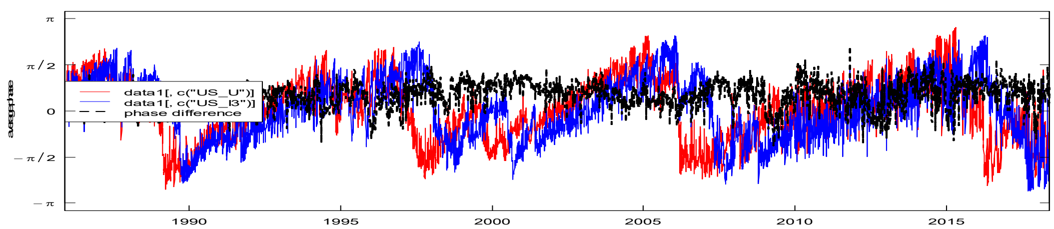

Figure A8. News-Based Uncertainty Index and Interest Rate of the UK