Economic Modelling 60 (2017) 24–28

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/econmod

Time-varying leads and lags across frequencies using a continuous wavelet transform approach

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ARTICLE INFO

Article history:
Received 5 April 2016
Received in revised form
25 August 2016
Accepted 25 August 2016
Available online 28 September 2016

JEL classification:
C49

Keywords:
Time-varying leads and lags
Frequencies
Wavelet
Phase difference

ABSTRACT

A precise understanding of lead–lag structures in economic data is important for many economic agents such as policymakers, traders in financial markets, and producers in goods markets. To identify time-varying lead–lag relationships across various frequencies in economic time series, recent studies have used phase difference on the basis of a continuous wavelet transform. However, the extant literature includes several conflicting interpretations of phase difference. In this study, we extensively discuss wavelet phase difference, determine its most plausible interpretation, and thus attempt to address gaps in the existing literature. Consequently, this study suggests that some lead–lag results of previous works have been driven by incorrect interpretations of wavelet phase difference.

1. Introduction

It is well recognized that lead–lag relationships exist in economic data, hence understanding them is important for policymakers and other economic agents. For practical purposes, in particular, it is essential for many economic agents to identify the leading, coincident, and lagging indicators of business cycles in order to predict their duration (see, e.g., Nefti, 1979).

In fact, a substantial number of papers have hitherto examined lead–lag relationships between key macroeconomic and financial variables. For example, Dekle et al. (2001) examine the relationship between exchange rates and interest rates using high-frequency data from Korea, and Alsakka and ap Gwilym (2010) investigate lead–lag relationships in sovereign ratings.

Recently, many authors have started utilizing wavelet methods to capture the time-varying leads and lags across frequencies (see, e.g., Aguiar-Conraria and Soares, 2014).[1] To be precise, in the growing body of wavelet literature, previous researchers have used phase difference as a tool to obtain information about changing lead–lag dynamics at specific frequencies, such as those in business cycles.

This paper contributes to the literature in the following respects. First, we identify previous works that use wavelet phase difference to analyze lead–lag relationships and demonstrate that wavelet phase difference has been subjected to multiple interpretations. Second, and most important, we investigate the most plausible interpretation and thus attempt to address the gaps in the existing literature. Consequently, this study suggests that some lead–lag results of previous works have arrived at an incorrect conclusion due to the incorrect interpretation of wavelet phase difference.

The remainder of the paper is structured as follows. In Section 2, after a brief explanation of wavelet phase difference, we indicate that different interpretations coexist in the literature. In Section 3, we deliberate on which interpretation should be considered plausible. Section 4 concludes the paper.

2. Different interpretations of wavelet phase difference

To begin with, we summarize the different interpretations of wavelet phase difference in the literature.

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[1] Recently, an increasing number of studies have used wavelet methods to conduct empirical analysis in the field of economics. See, for example, Aguiar-Conraria and Soares (2011a, 2011b, 2014), Aguiar-Conraria et al. (2012), Rua (2012, 2013), Chen et al. (2013), Trezzi (2013), Fidrmuc et al. (2014), Tiwari et al. (2014), Berdiev and Chang (2015), Cascio (2015), Dima et al. (2015), Jiang et al. (2015), Li et al. (2015), and Aloui et al. (2016).

http://dx.doi.org/10.1016/j.econmod.2016.08.024
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Given a time series $x(t)$, the continuous wavelet transform is given by

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x(t)\tilde{\psi}_{\tau,s}^{*}(t)dt, \tag{1}$$

where $\tilde{\psi}$ represents wavelet daughters, s is the scaling factor controlling wavelet length, τ is the translation parameter controlling wavelet location in time, and the asterisk denotes complex conjugation. Note that if the absolute value of s is less (more) than 1, the wavelet is compressed (stretched). Wavelet daughters $\tilde{\psi}$ are obtained by scaling and shifting the mother wavelet ψ:

$$\tilde{\psi}_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right), \quad s, \tau \in \mathbb{R}, \quad s \neq 0. \tag{2}$$

In line with many other previous studies, we consider the Morlet wavelet, one of the most widely used mother wavelets,

$$\psi_{\omega_0}(t) = \pi^{-1/4}\left(e^{i\omega_0 t} - e^{-\omega_0^2/2}\right)e^{-t^2/2}, \tag{3}$$

where i denotes an imaginary unit (i.e., $i = \sqrt{-1}$) and ω_0 controls the number of oscillations within the Gaussian envelope. Following earlier studies, we assume that $\omega_0 = 6$, because in this case, s is almost equal to the Fourier period.

From the above wavelet transform, one obtains the phase angle

$$\rho_x(\tau, s) = \tan^{-1}\left[\frac{\mathrm{Im}\{W_x(\tau, s)\}}{\mathrm{Re}\{W_x(\tau, s)\}}\right], \tag{4}$$

where $\mathrm{Re}(W_x)$ and $\mathrm{Im}(W_x)$ are the real and imaginary parts of the wavelet transform W_x, respectively. The phase angle indicates the oscillation position of the time series $x(t)$ at a specified time and frequency.

For the bivariate case, we consider two time series of interest, $x(t)$ and $y(t)$. For each wavelet transform, the cross-wavelet transform is given by

$$W_{xy}(\tau, s) = W_x(\tau, s)W_y^{*}(\tau, s). \tag{5}$$

In order to evaluate the relationship between the two series, we utilize the following phase difference from the phase angle of the cross-wavelet transform:

$$\rho_{xy}(\tau, s) = \rho_x(\tau, s) - \rho_y(\tau, s) = \tan^{-1}\left[\frac{\mathrm{Im}\{W_{xy}(\tau, s)\}}{\mathrm{Re}\{W_{xy}(\tau, s)\}}\right], \tag{6}$$

with $\rho_{xy} \in [-\pi, \pi]$.

As regards the sign of the correlation between $x(t)$ and $y(t)$, to the best of our knowledge, all previous studies without exception interpret the phase difference ρ_{xy} as follows: When $\rho_{xy} \in (-\pi/2, \pi/2)$, $x(t)$ and $y(t)$ move in phase (positive correlation), whereas when $\rho_{xy} \in (\pi/2, \pi) \cup (-\pi, -\pi/2)$, $x(t)$ and $y(t)$ move out of phase (negative correlation). In particular, if $\rho_{xy} = \pi$ or $\rho_{xy} = -\pi$, they move in anti-phase.

However, as for lead–lag relationships, the literature presents completely different interpretations. First, most previous works in the wavelet literature adopt the following interpretation.[2]

Interpretation 1. *If $\rho_{xy} \in (0, \pi/2) \cup (-\pi, -\pi/2)$, then $x(t)$ leads $y(t)$. If $\rho_{xy} \in (-\pi/2, 0) \cup \rho_{xy} \in (\pi/2, \pi)$, then $y(t)$ leads $x(t)$.*

Second, some studies adopt an interpretation opposite to Interpretation 1.[3]

Interpretation 2. *If $\rho_{xy} \in (0, \pi/2) \cup (-\pi, -\pi/2)$, then $y(t)$ leads $x(t)$. If $\rho_{xy} \in (-\pi/2, 0) \cup \rho_{xy} \in (\pi/2, \pi)$, then $x(t)$ leads $y(t)$.*

Finally, to the best of our knowledge, two studies, that is, Marczak and Gómez (2015) and Marczak and Beissinger (2016), present the following interpretation.

Interpretation 3. *If $\rho_{xy} \in (0, \pi)$, then $x(t)$ leads $y(t)$. If $\rho_{xy} \in (-\pi, 0)$, then $y(t)$ leads $x(t)$.*

However, since the above interpretations are provided without any clear explanation, one does not understand why the previous studies present different interpretations.

3. Discussion and illustrations

In this section, we deliberate on which interpretation can be considered plausible and attempt to explain the difference between the three interpretations. The process of our deliberation is as follows. First, as regards the discrepancy in the interpretations when $\rho_{xy} \in (-\pi/2, 0) \cup (0, \pi/2)$, a comparison of Interpretations 1 and 3 with Interpretation 2 shows Interpretation 2 to be inappropriate. Second, as regards the discrepancy when $\rho_{xy} \in (-\pi, -\pi/2) \cup (\pi/2, \pi)$, a comparison of Interpretation 1 with 3 shows that only Interpretation 1 is plausible.

Further, we also discuss the indicators of composite index (CI) in Japan. One reason for choosing Japan is that all the data of the leading, coincident, and lagging indicators are available for roughly the last half century.[4]

3.1. Interpretations 1 and 3 versus Interpretation 2

When $\rho_{xy} \in (-\pi/2, 0) \cup (0, \pi/2)$, we find that Interpretations 1 and 3 differ from Interpretation 2. In view of the difference, one can readily disprove Interpretation 2. Now, consider a simple example of data generated:

$$x_t = \begin{cases} \cos\left(\frac{2\pi}{12}t + \frac{\pi}{3}\right) + \varepsilon_t, & (t \le 36) \\ \cos\left(\frac{2\pi}{12}t - \frac{\pi}{3}\right) + \varepsilon_t, & (t > 36) \end{cases} \tag{7}$$

and

$$y_t = \cos\frac{2\pi}{12}t + \varepsilon_t, \tag{8}$$

where ε_t is i.i.d. $N(0, 1)$. We give our observations in Panel A of Fig. 1; x leads y by $\pi/3$ for $t \le 36$ at a 12 cycle, whereas y leads x for $t > 36$. The phase difference ρ_{xy} calculated for 11–13 cycles is displayed in Panel B of Fig. 1.[5] For $t \le 36$, the phase difference is between 0 and $\pi/2$ (in the vicinity of $\pi/3$). On the other hand, for $t > 36$, the phase difference lies between $-\pi/2$ and 0 (in the vicinity of $-\pi/3$). This simple exercise supports Interpretations 1 and 3.

[2] For Interpretation 1, see Aguiar-Conraria et al. (2012, 2013), Caraiani (2012a), Trezzi (2013), Aguiar-Conraria and Soares (2014), Sousa et al. (2014), Cascio (2015), Funashima (2015, 2016a, 2016b), Ko and Lee (2015), Li et al. (2015), Lin et al. (2016), Dewandaru et al. (2015, 2016), Fousekis and Grigoriadis (2016), and Su et al. (2016). A recent study by Funashima (2016a, Fig. 2) provides a graphic explanation supporting Interpretation 1.

[3] For Interpretation 2, see Aguiar-Conraria et al. (2008), Aguiar-Conraria and Soares (2011b), Caraiani (2012b), Tiwari (2013), Andrieş et al. (2014), Tiwari et al. (2015a, 2015b), and Klarl (2016).

[4] Data are obtained from the website of the Cabinet Office for the Government of Japan. We use the ASToolbox provided by Luis Aguiar-Conraria and Maria Joana Soares to compute the phase difference. The ASToolbox can be downloaded at http://sites.google.com/site/aguiarconraria/joanasoares-wavelets.

[5] Note that the values are median over scales for 11–13 cycles.

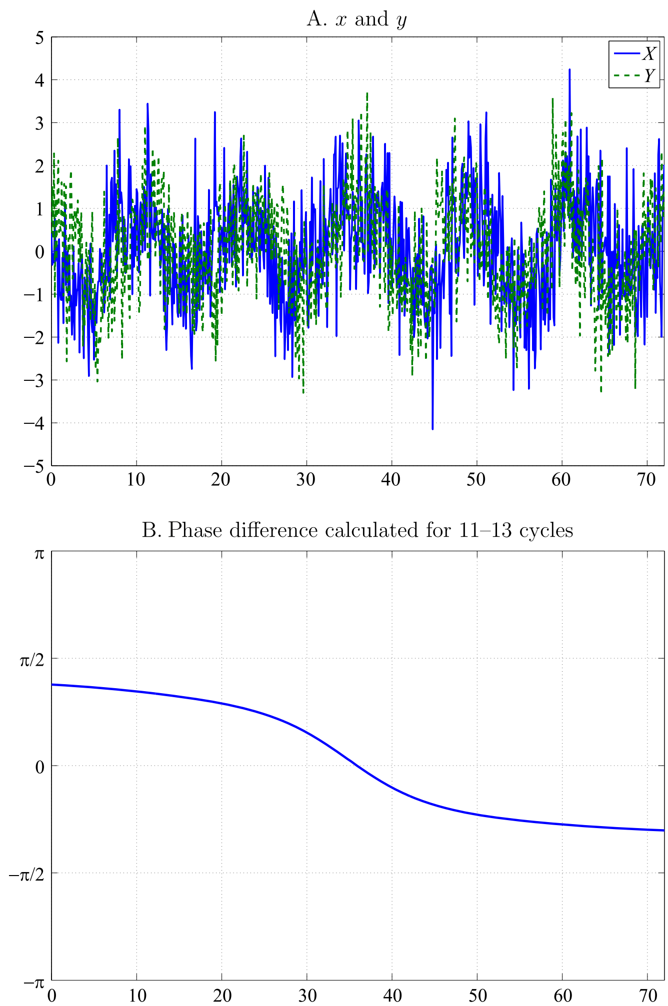

Fig. 1. x and y generated by (7) and (8) and the phase difference.

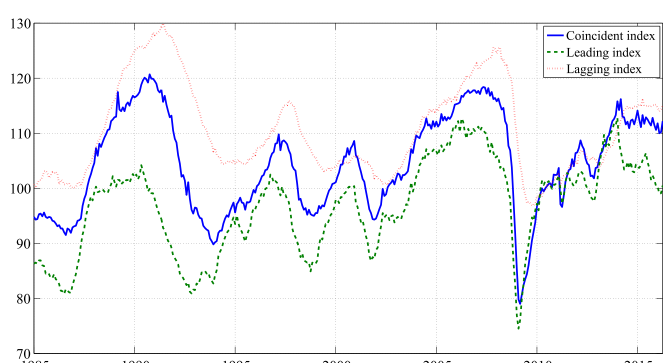

Fig. 2. Japanese CIs (2010 = 100).

Next, we validate Interpretations 1 and 3 using real data. Fig. 2 plots the leading, coincident, and lagging CIs in Japan. Thus, without any further analysis of their lead–lag relationships, we can show that the leading CI leads the coincident CI and the latter CI leads the lagging CI. Fig. 3 presents the results of their phase difference ρ_{xy}.[6] First, for the case where x is the coincident CI and y is the leading CI, we depict the phase difference as a solid line in Fig. 3; this is between $-\pi/2$ and 0. From Interpretations 1 and 3, we confirm that the leading CI leads the coincident CI. On the other hand, Interpretation 2 reaches the unacceptable conclusion that the coincident CI leads the leading CI.

Further, for the case where x is the coincident CI and y is the lagging CI, we depict the phase difference as a dashed line in Fig. 3; this is between 0 and $\pi/2$. In contrast to Interpretations 1 and 3, Interpretation 2 once again provides the inconsistent result that the lagging CI leads the coincident CI. These examples suggest that the results based on Interpretation 2 could be erroneous.

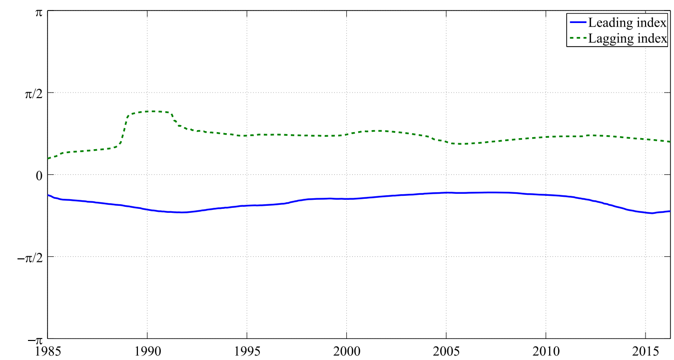

Fig. 3. Phase difference between coincident and leading CIs and between coincident and lagging CIs in Japan.

3.2. Interpretation 1 versus Interpretation 3

Next, we attempt to determine whether Interpretation 1 or Interpretation 3 is more plausible. Thus, besides x and y, we now consider the inverted series of y, defined as $\hat{y} \equiv -y$. Noting that $\hat{y} = e^{i\pi}y$ or $\hat{y} = e^{-i\pi}y$, we give its continuous wavelet transform as

$$W_{\hat{y}}(\tau, s) = e^{i\pi}W_y(\tau, s), \tag{9}$$

or

$$W_{\hat{y}}(\tau, s) = e^{-i\pi}W_y(\tau, s). \tag{10}$$

Accordingly, the phase angle of $\hat{y}$ is

$$\rho_{\hat{y}}(\tau, s) = \rho_y(\tau, s) \pm \pi, \tag{11}$$

and we obtain the phase difference between x and $\hat{y}$ as follows:

$$\rho_{x\hat{y}}(\tau, s) = \rho_x(\tau, s) - \rho_{\hat{y}}(\tau, s) = \rho_x(\tau, s) - \rho_y(\tau, s) \pm \pi = \rho_{xy}(\tau, s) \pm \pi. \tag{12}$$

Although y is inverted, as shown above, it holds when we consider the case of the inverted series of x, defined as $\hat{x} \equiv -x$. The following proposition formally states these results.[7]

Proposition 1. *Suppose the inverted series $\hat{x}$ and $\hat{y}$. Then, $\rho_{x\hat{y}}(\tau, s) = \rho_{xy}(\tau, s) \pm \pi$ and $\rho_{\hat{x}y}(\tau, s) = \rho_{xy}(\tau, s) \pm \pi$ are satisfied.*

Since a test of lead–lag relationship should be robust even when x or y is inverted, Proposition 1 provides us with information useful to discussing the critical difference between Interpretations 1 and 3. From Proposition 1, when x or y is inverted, Interpretation 1 indicates that the lead–lag relationship remains unchanged whereas Interpretation 3 indicates that the lead–lag relationship is reversed. This lead–lag difference for the inverted series in Interpretation 3 indicates an inconsistency in Interpretation 3.

For a relevant example, consider the relationship between the

[6] Note that the values are median over scales corresponding to the business cycle periodicities between 1.5 and 8 years, as in Baxter and King (1999).

[7] Incidentally, in addition to phase difference, many previous studies use wavelet coherency to examine the extent of interdependence between two time series of interest. Since wavelet coherency depends not on the phase angle of the cross-wavelet transform but on the amplitude, it is unaffected by the inverted shift.

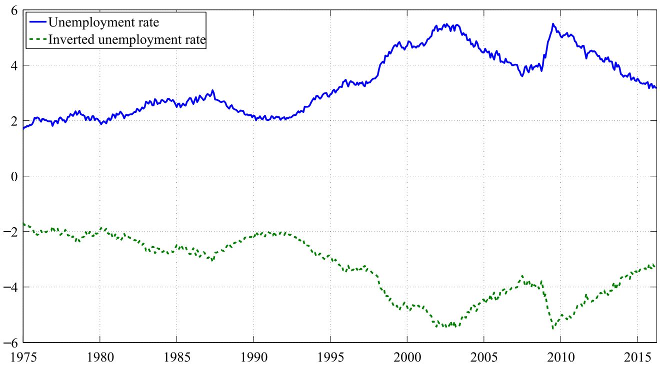

Fig. 4. Japanese unemployment rate and its inverted series.

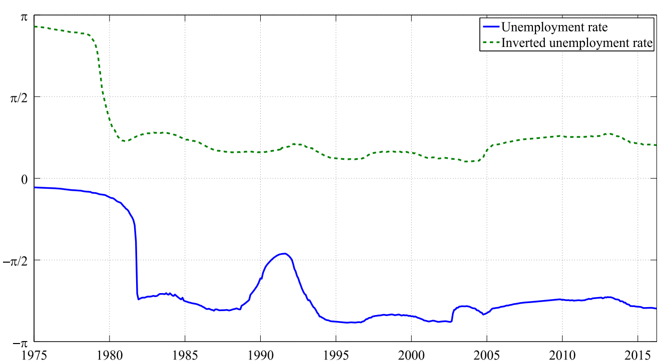

Fig. 5. Phase difference between industrial production and (inverted) unemployment rate in Japan.

business cycle and unemployment rate. As is well known, the unemployment rate lags behind the business cycle. To investigate this lead–lag relationship, one often compares output with the unemployment rate by inverting the latter. An important point to note here is that we must obtain the same results for the relationship between output and unemployment regardless of whether the unemployment rate is inverted or not. However, Interpretation 3 changes the lead–lag results due to the inverted operation.

For an example of real data, we examine the relationship between the industrial production and unemployment rate in Japan and conduct some exercises. In fact, as regards the Japanese CIs, the former series is a coincident indicator and the latter is a lagging indicator. As shown in Fig. 4, compared to the original series, the phase angle of the inverted unemployment rate is shifted by π or $-\pi$. Fig. 5 shows the results of the phase difference, ρ_{xy} (solid line) and $\rho_{x\hat{y}}$ (dashed line), where x is the industrial production, y is the unemployment rate, and $\hat{y}$ is the inverted series of the unemployment rate.[8] When we disregard the results around the beginning and end of the sample periods, the outcomes indicate that, on the whole, the phase difference ρ_{xy} lies between $-\pi$ and $-\pi/2$.[9] According to Proposition 1, the phase difference $\rho_{x\hat{y}}$ is inevitably shifted by π or $-\pi$, and hence it lies between 0 and $\pi/2$ on the whole. Both results suggest that the output and the original (inverted) unemployment rate are negatively (positively) correlated.

According to Interpretation 1, regardless of whether the unemployment rate is inverted or not, the same interpretation holds, and hence we can conclude that the unemployment rate lags behind the business cycle. On the other hand, according to Interpretation 3, the original result indicates that the unemployment rate is leading whereas the inverted result indicates that industrial production is leading. In other words, although substantively we conduct the same analysis with the original and inverted series of unemployment rate, Interpretation 3 gives contradictory results.

4. Conclusion

In addition to researchers in different fields of science, such as engineering and physics, wavelet methods are increasingly attractive to researchers in the fields of economics and finance. However, as this study indicates, there is no consensus in previous works on the interpretation of phase difference, which is one of the most widely used wavelet tools in economic analysis. As all the interpretations in these works have been provided without any clear explanation, the reason for these differences is uncertain. Thus, results of leads and lags on phase difference are ambiguous and unreliable.

In this paper, we have deliberated on the most plausible interpretation of phase difference and this has, to some extent, addressed the gaps in the newly growing body of wavelet literature. While our analysis is conducted by presenting several examples, the conclusion can arguably be applied to other cases, almost without exception. To summarize, only Interpretation 1 should be considered as plausible, and the phase difference results based on Interpretations 2 and 3 should be approached with caution.

Acknowledgments

The author is very grateful to three anonymous referees, Sushanta Mallick (the editor), and Yoshihiro Ohtsuka for their useful comments.

References

Aguiar-Conraria, L., Azevedo, N., Soares, M.J., 2008. Using wavelets to decompose the time–frequency effects of monetary policy. Physica A 387, 2863–2878.
Aguiar-Conraria, L., Soares, M.J., 2011a. Business cycle synchronization and the Euro: a wavelet analysis. J. Macroecon. 33, 477–489.
Aguiar-Conraria, L., Soares, M.J., 2011b. Oil and the macroeconomy: using wavelets to analyze old issues. Empir. Econ. 40, 645–655.
Aguiar-Conraria, L., Martins, M., Soares, M.J., 2012. The yield curve and the macro-economy across time and frequencies. J. Econ. Dyn. Control 36, 1950–1970.
Aguiar-Conraria, L., Magalhães, P., Soares, M.J., 2013. The nationalization of electoral cycles in the United States: a wavelet analysis. Public Choice 156, 387–408.
Aguiar-Conraria, L., Soares, M.J., 2014. The continuous wavelet transform: moving beyond uni- and bivariate analysis. J. Econ. Surv. 28, 344–375.
Aloui, C., Hkiri, B., Nguyen, D.K., 2016. Real growth co-movements and business cycle synchronization in the GCC countries: evidence from time–frequency analysis. Econ. Model. 52, 322–331.
Alsakka, R., ap Gwilym, O., 2010. Leads and lags in sovereign credit ratings. J. Bank. Financ. 34, 2614–2626.
Andrieş, A.M., Ihnatov, I., Tiwari, A.K., 2014. Analyzing time–frequency relationship between interest rate, stock price and exchange rate through continuous wavelet. Econ. Model. 41, 227–238.
Baxter, M., King, R.G., 1999. Measuring business cycles: approximate band-pass filters for economic time series. Rev. Econ. Stat. 81, 575–593.
Berdiev, A.N., Chang, C.P., 2015. Business cycle synchronization in Asia-Pacific: new evidence from wavelet analysis. J. Asian Econ. 37, 20–33.
Caraiani, P., 2012a. Stylized facts of business cycles in a transition economy in time and frequency. Econ. Model. 29, 2163–2173.
Caraiani, P., 2012b. Money and output: new evidence based on wavelet coherence. Econ. Lett. 116, 547–550.
Cascio, I.L., 2015. A wavelet analysis of US fiscal sustainability. Econ. Model. 51, 33–37.
Chen, S.L., Chou, C.C., Chen, N.J., 2013. A wavelet transform analysis of the

[8] As earlier, the values are median over scales, corresponding to the business cycle periodicities.
[9] When running the wavelet transform as well as other types of transforms, the problem of border distortions arises at the beginning and end of the sample periods because of the finite length of the time series. Consequently, the edge results are unreliable and should be disregarded. See Aguiar-Conraria and Soares (2014) for more details.

relationship between unexpected macroeconomic news and foreign exchange rates. Appl. Econ. Lett. 20, 292–296.
Dekle, R., Hsiao, C., Wang, S., 2001. Do high interest rates appreciate exchange rates during crisis? The Korean evidence. Oxf. Bull. Econ. Stat. 63, 359–380.
Dewandaru, G., Masih, R., Masih, A.M.M., 2015. Why is no financial crisis a dress rehearsal for the next? Exploring contagious heterogeneities across major Asian stock markets. Physica A 419, 241–259.
Dewandaru, G., Masih, R., Masih, A.M.M., 2016. What can wavelets unveil about the vulnerabilities of monetary integration? A tale of Eurozone stock markets. Econ. Model. 52, 981–996.
Dima, B., Dima, Ş.M., Barna, F., 2015. A wavelet analysis of capital markets' integration in Latin America. Appl. Econ. 47, 1019–1036.
Fidrmuc, J., Korhonen, I., Poměnková, J., 2014. Wavelet spectrum analysis of business cycles of China and G7 countries. Appl. Econ. Lett. 21, 1309–1313.
Fousekis, P., Grigoriadis, V., 2016. Price co-movement in the principal skim milk powder producing regions: a wavelet analysis. Econ. Bull. 36, 477–492.
Funashima, Y., 2015. Automatic stabilizers in the Japanese tax system. J. Asian Econ. 39, 86–93.
Funashima, Y., 2016a. The Fed-induced political business cycle: empirical evidence from a time–frequency view. Econ. Model. 54, 402–411.
Funashima, Y., 2016b. Wagner's law versus displacement effect. Appl. Econ. . http://dx.doi.org/10.1080/00036846.2016.1203063
Jiang, C., Chang, T., Li, X.L., 2015. Money growth and inflation in China: new evidence from a wavelet analysis. Int. Rev. Econ. Financ. 35, 249–261.
Klarl, T., 2016. The nexus between housing and GDP re-visited: a wavelet coherence view on housing and GDP for the U.S. Econ. Bull. 36, 704–720.
Ko, J.H., Lee, C.M., 2015. International economic policy uncertainty and stock prices: wavelet approach. Econ. Lett. 134, 118–122.
Li, X.L., Chang, T., Miller, S.M., Balcilar, M., Gupta, R., 2015. The co-movement and causality between the U.S. housing and stock markets in the time and frequency domains. Int. Rev. Econ. Financ. 38, 220–233.
Lin, F.L., Chen, Y.F., Yang, S.Y., 2016. Does the value of US dollar matter with the price of oil and gold? A dynamic analysis from time–frequency space. Int. Rev. Econ. Financ. 43, 59–71.
Marczak, M., Gómez, V., 2015. Cyclicality of real wages in the USA and Germany: new insights from wavelet analysis. Econ. Model. 47, 40–52.
Marczak, M., Beissinger, T., 2016. Bidirectional relationship between investor sentiment and excess returns: new evidence from wavelet perspective. Appl. Econ. Lett. http://dx.doi.org/10.1080/13504851.2016.1153782.
Nefti, S.N., 1979. Lead–lag relations, exogeneity and prediction of economic time series. Econometrica 47, 101–113.
Rua, A., 2012. Money growth and inflation in the Euro area: a time–frequency view. Oxf. Bull. Econ. Stat. 74, 875–885.
Rua, A., 2013. Worldwide synchronization since the nineteenth century: a wavelet based view. Appl. Econ. Lett. 20, 773–776.
Sousa, R., Aguiar-Conraria, L., Soares, M.J., 2014. Carbon financial markets: a time–frequency analysis of CO_2 prices. Physica A 414, 118–127.
Su, C.W., Yao, Z.L., Chang, H.L., 2016. The relationship between output and asset prices: a time- and frequency-varying approach. Theor. Appl. Econ. XXIII, 57–76.
Tiwari, A.K., 2013. Oil prices and the macroeconomy reconsideration for Germany: using continuous wavelet. Econ. Model. 30, 636–642.
Tiwari, A.K., Oros, C., Albulescu, C.T., 2014. Revisiting the inflation–output gap relationship for France using a wavelet transform approach. Econ. Model. 37, 464–475.
Tiwari, A.K., Bhanja, N., Dar, A.B., Islam, F., 2015a. Time–frequency relationship between share prices and exchange rates in India: evidence from continuous wavelets. Empir. Econ. 48, 699–714.
Tiwari, A.K., Dar, A.B., Bhanja, N., Arouri, M., Teulon, F., 2015b. Stock returns and inflation in Pakistan. Econ. Model. 47, 23–31.
Trezzi, R., 2013. A wavelet analysis of international risk-sharing. Econ. Lett. 118, 330–333.