3. Co-Movement of Healthcare Financing in OECD Countries: Evidence from Discrete Wavelet Analyses[1]

Wen-Yi CHEN[2]

Yu-Hui LIN[3]

Abstract

This study applied the recently developed discrete wavelet analyses to investigate the co-movement and spill-over relationship of healthcare financing across nine OECD countries during the period of 1960-2012 for the first time. Healthcare financing data used for this study were retrieved from the 2014 version of OECD Health Statistics database. Our results suggest that the public share of total healthcare financing in nine OECD countries has exhibited signs of co-movement over the period of 1960-2012 in the short, medium, and long-runs. The public-private mix of healthcare financing in National Health Service (NHS) systems led those in the Social Health Insurance (SHI) and Private Health Insurance (PHI) systems in the short and medium-runs, while the public-private mix of healthcare financing in the PHI health care system lagged behind that of the SHI and NHS systems over the period of 1960-2012. Policy diffusion for any change in the public-private mix of healthcare financing should run from public financing healthcare systems (such as the SHI and NHS systems) to the private financing healthcare system (PHI system).

Keywords: Co-movement; Healthcare Financing; Discrete Wavelet Analyses; Wavelet Multiple Correlation; Wavelet Multiple Cross correlation.

JEL Classification: C3, I1,J6.

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2 Department of Senior Citizen Service Management, National Taichung University of Science and Technology, Taichung, Taiwan. E-mail: chenwen@nutc.edu.tw

3 Corresponding Author: Yu-Hui LIN, Department of Business Administration, Nan Kai University of Technology, Nan-Tou, Taiwan. E-mail: lin2138@nkut.edu.tw

I. Introduction

Economists have long been concerned with the co-movement of asset prices across different markets, because it provides information that helps investors in making investment decisions such as asset allocation, portfolio diversification and risk management. Over the past decades, many studies have examined the co-movement relationship among various economic variables across different markets. For example, Rua and Nunes (2009) proposed using the continuous wavelet analysis to assess the co-movement of stock prices among international stock markets. The continuous wavelet analysis is a promising technique to analyze the co-movement of stock prices across different countries because this technique can illustrate the magnitude of correlation of stock prices between two different markets in a time-frequency space. It follows that the trend of the co-movement of stock returns can be separated into short, medium, and long-run horizons that serve as an important reference for investors to make investment decisions in the short, medium, and long-run, respectively. Following Rua and Nunes's methodology, the co-movement of various economic variables have been studied in many applications such as the co-movement of returns across different stock markets (Bogdanova, 2015; Alou, Hkiri, 2014; Graham et al., 2013; Loh, 2013; Madaleno, Pinho, 2012; Graham, Kiviaho, Nikkinen, 2012; Graham, Nikkinen, 2011), the co-movement of returns across different energy markets (Vacha, Barunik, 2012); the co-movement relationship between oil price and exchange rate (Tiwari, Mutascu, Albulescu, 2013), the co-movement relationship between oil price and stock price (Akoum et al., 2012), and the co-movement relationship among various macroeconomic variables (Tiwari, Oros, Albulescu, 2014; Rua, 2010).

It is worth noting that there exists another strand of literature using the so-called discrete wavelet analysis to identify the co-movement relationships among various economic variables across different countries. The discrete wavelet analysis was first proposed by Ramsey and Lampart (1998a,b) to study the relationship between income and other macroeconomic variables (such as consumption expenditure and money supply). This technique became very popular in the field of applied economics after Gencay, Selcuk, Whitcher (2001) and Pervical and Walden (2000) provided the details of the discrete wavelet method for time series analyses (Chen, 2016; Gallegati and Semmler 2014). Following Ramsey and Lampart's methodology, the co-movement relationships among various economic variables have also been explored in different applications such as the co-movement of long term interest rates among European countries (Dar, Shah, 2014), the co-movement of returns across different stock markets (Dajcman, Kavkler, 2014; Dajcman, 2013; Tiwari et al., 2013; Dajcman, Festic, Kavkler, 2012; Fernández-Macho, 2012), the co-movement of real estate securities returns across different countries (Zhou, 2012; Zhou, 2010), and the co-movement relationships among various macroeconomic variables (Dar et al., 2013).

Although the empirical investigation of the co-movement relationships among various economic variables and its practical implications have been receiving attention in the fields of financial and macroeconomic analyses, economists have not paid much attention to potential co-movement relationships in other areas. Therefore, the purpose of this study is to investigate the co-movement of healthcare financing within the Organization for Economic Cooperation and Development (OECD, hereafter) countries.

We specifically concentrate on an important element of healthcare financing, namely, the public share of total healthcare financing (measured as public expenditure on health as a % of the total expenditure on health). Our focus on the public share of total healthcare financing in OECD countries has a fourfold significance: First, our focus on the public share of total healthcare financing is inspired by the facts that most OECD countries finance their healthcare services through public financing systems such as the Social Health Insurance system (SHI, hereafter), which is primarily funded by social insurance contributions, and the National Health Service system (NHS, hereafter), which is primarily funded through central taxation, and that an increase (decrease) in public-private mix in healthcare financing over a period of time is mostly likely to reflect the phenomenon of convergence in healthcare financing towards a more public-like (or private-like) financing system (Chen, 2013). Second, healthcare financing structure may have a significant effect on equity of financing, healthcare utilization, and health status (Leiter, Theurl, 2012). Third, many health policies focus on healthcare financing from different perspectives such as revenue collection (the way money is raised to pay health system costs), pooling risk (spreading the financial risk associated with the need to use health services), and purchasing (the process of paying for health services) (World Health Organization, 2010). Fourth, the co-movement of healthcare financing across different countries may reflect the convergence of healthcare systems, diffusion of health policies, globalization and market integration. Understanding the trend of co-movement of healthcare financing within OECD countries will provide a more complete picture of the evolution of different healthcare systems which will better allow the prediction of future healthcare system behavior.

As we mentioned in the previous paragraph, there is no research available which specifically investigates the co-movement of healthcare financing within OECD countries. Since the convergence of healthcare financing across OECD countries implies the co-movement of healthcare financing within OECD countries, we made use of the literature investigating the convergence of healthcare systems for our literature review. There are two types of studies focusing on the convergence of healthcare systems (Chen, 2013). The first type focuses on the convergence of a single-dimensional indicator of convergence in the healthcare system such as healthcare expenditure (Aslan 2009; Chou and Wang 2009; Wang 2009) and the public share of total healthcare financing (Chen, 2013; Leiter and Theurl 2012). The other type investigates multi-dimensional indicators of convergence in the healthcare system such as the mix of several financing sources (Götze, and Schmid, 2012; Glied, 2009; Barros, 2007) and a mix of three components (i.e., healthcare financing, service provision, and regulation) of healthcare systems (Rothgang et al. 2010; Schmid et al.,2010; Cacace et al.,2008; Rothang et al. 2008).

It is important to address the fact that there are two major challenges in the study of the convergence hypothesis. First, the study of convergence hypothesis based on two convergence hypotheses (namely, σ convergence hypothesis characterized by as decreasing in variation, and β convergence hypothesis interpreted as catching up with the benchmark level of the target variable) is restricted in the time domain. This restriction ignores the possibility that the strength and/or direction of the convergence of healthcare financing is most likely to vary over different frequencies (such as short, medium, and long-runs). Second, the spill-over relationship in terms of a lead-lag relationship of different public-private mixes of healthcare financing among different healthcare systems plays an essential role in interpreting the direction of convergence within a set of healthcare financing systems. Nevertheless, the analytical frameworks of the σ or β convergence hypotheses are incapable of providing the means for evaluating this relationship important to the convergence of healthcare financing.

In response to these two shortcomings of the convergence hypothesis, we have focused our analyses on the co-movement of healthcare financing in OECD counties. There are two advantages of our emphasis on the co-movement rather than the convergence of healthcare financing. First, the co-movement of healthcare financing is a necessary condition for the convergence of healthcare financing, and the co-movement of healthcare financing also reflects the evolution of healthcare systems, as it reflects the convergence of policies due to the diffusion of innovation, globalization, and market integration. Second, recent studies on the co-movement relationship among various economic variables have proposed the time-frequency approach to decompose the causal relationship between two time series variables from time and frequency domains (Aguiar-Conraria and Soares, 2014). Therefore, the magnitude of the co-movement of healthcare financing and the spill-over relationship in terms of a lead-lag relationship of different public-private mixes of healthcare financing among different healthcare systems can be generated from time and frequency domains.

In choosing the econometric methodology, we decided not to apply the continuous wavelet analysis proposed by Rua and Nunes (2009) for our analyses because this type of wavelet analysis utilizes a simple pairwise correlation to investigate the co-movement relationship between two time series, creating several disadvantages such as comparison of a large number of wavelet correlation and cross-correlation graphs, spurious correlation within the multivariate set of variables, and amplification of type-I error due to experiment-wise error (Chen, 2016; Dar and Shah, 2014; Tiwari et al., 2013; Fernández-Macho, 2012). Instead, we adopted the discrete wavelet analysis proposed by Fernández-Macho (2012) to investigate the co-movement of healthcare financing across nine OECD countries (Namely, Austria, Finland, Iceland, Ireland, Japan, Norway, Spain, United Kingdom, and United States) over the period from 1960 to 2012. According to Fernández-Macho's (2012) discrete wavelet analysis, the wavelet multiple correlation and cross correlation were calculated to measure the co-movement and spill-over relationship of healthcare financing across these nine OECD countries. These two correlation measures have several appealing features. First, compared to the continuous wavelet analysis using n(n-1)/2 (n meaning the number of target variables or countries used for our analyses) wavelet correlation graphs (there are 36 graphs in our case) and $J \times n(n-1)/2$ (J is the number of scales) phrase-differences graphs (there are 144 graphs in our case) to illustrate the overall and cross correlations, the wavelet multiple correlation and cross correlation introduced by Fernández-Macho (2012) only needs two graphs to demonstrate the overall and cross correlations based on a multivariate set of healthcare financing variables on a scale-by-scale basis over a period of time. Second, owing to this concise presentation of the overall and cross correlations, we can avoid a possible spurious correlation and inflation of type-I error (approximately $84.22\%=1-(1-\alpha)^{36}$ in our case at 5% significance level) generated from the pairwise correlations within a multivariate set of healthcare financing systems (Chen, 2016; Dar and Shah, 2014; Tiwari et al., 2013; Fernández-Macho, 2012). Therefore, the empirical results generated by the present study will provide more reliable evidence of the co-movement and spill-over relationship of healthcare financing across the nine OECD countries over the period from 1960 to 2012.

II. Empirical Model and Data

II.1 Data and Variables

Data used for this study were retrieved from the 2014 version of OECD Health Statistics database (Organization for Economic Cooperation and Development, 2014). Our healthcare financing variable is the public share of total healthcare financing (measured as public expenditure on health as percentage of total expenditure on health). This variable refers to the public-private mix of healthcare financing. The annual data used in this study covered the period from 1960 to 2012 for nine OECD countries, which are Austria, Finland, Iceland, Ireland, Japan, Norway, Spain, the United Kingdom, and the United States. These nine countries were selected because they provide the longest time-span (53 years) of healthcare financing data (Organization for Economic Cooperation and Development, 2014).

In general, there are three types of financing of healthcare systems based on three sources. The first type of healthcare system is the NHS system, and this type of healthcare system features public healthcare financing based on general taxation, with the delivery of healthcare provision mainly dependent on public providers, and with the dominant regulation mechanisms carried out through compressive planning and tight control by the government (Chen, 2013). By this definition, Finland, Iceland, Ireland, Norway, Spain, and the United Kingdom were assigned to this group. The second type of system is the SHI system. This type of healthcare system is characterized by public healthcare financing based on social health insurance, with the delivery of healthcare provision relying on both public and private providers, and with regulation mechanisms based on negotiations between fund holders and providers with some control by the government (Chen, 2013). By this definition of the SHI, Austria and Japan were classified in this group. The third type of healthcare system belongs to the Private Health Insurance system (PHI, hereafter). This type of healthcare system is characterized by private healthcare insurance based on premiums and direct financing by private households such as out-of-pocket payments and different types of cost-sharing (Chen, 2013). The United States is the only country which can be classified as a PHI system.

II.2 Discrete Wavelet Analysis

In this study, we utilized the wavelet multiple correlation and cross correlation proposed by Fernández-Macho (2012) to investigate the co-movement and spill-over relationship of healthcare financing across nine OECD countries. To derive the wavelet multiple correlation and cross correlation, we first performed the discrete wavelet transformation (DWT, hereafter) for our time series data. It is important to note that the conventional DWT suffers from several shortcomings such as the 2^J restriction (namely, the total observations are restricted by 2^J, J is a decomposition level of time scales) observations in the discrete wavelet analysis) and sensitivity of the decomposition of the variance and covariance (correlation) of time series due to the selection of wavelet function and starting point (Chen, 2016; Sevensson, Krüger 2012). In this study, the maximum overlap discrete wavelet transformation (MODWT, hereafter) method was adopted for our analyses because this method overcomes several previously mentioned drawbacks of the DWT. Additionally, the MODWT wavelet variance estimator is asymptotically more efficient than the DWT wavelet variance estimator (Pervical, Walden 2000). The MODWT decomposes a time series into the following relationship:

[1] $$\sum_t r_t^2 = \sum_{jt} w_{jt}^2 + \sum_t v_t^2$$

where, r_t is the value of the public share of total healthcare financing at time *t*. *j* denotes the time scale. w_{jt} is the wavelet coefficient at time *t* and j^{th} scale (*j=1,2,…,J)*, and v_t presents the scaling coefficient over different time scales. As indicated by Sevensson and Krüger (2012), the unbiased estimator of the wavelet variance is given by equation [2] below

[2] $$\sigma_{\lambda_j}^2 = \frac{1}{T}\sum_{t=1}^{T} w_{jt}^2$$

where, $\sigma_{\lambda_j}^2$ is the variance of the original time series at time scale λ_j, and T is the time-span observed in our study. Equation [2] implies that the variance of the original time series is the sum of variances over different time scales, and it follows that we can perform the analysis of variance across different time scales, and further define the wavelet correlation and wavelet cross correlation for two time series on a scale by scale basis. Based on the property imposed in equation [2] and the same notations and description of discrete wavelet multiple (cross) correlation used in Chen (2016) and many others, the wavelet multiple correlation is given by Equation [3] below:

[3] $$\varphi_{\mathbf{x}}(\lambda_j) = Corr(w_{ijt}, \hat{w}_{ijt}) = \frac{Cov(w_{ijt}, \hat{w}_{ijt})}{\sqrt{Var(w_{ijt})Var(\hat{w}_{ijt})}} \quad , j=1,2,\ldots,J$$

where, $\varphi_{\mathbf{x}}(\lambda_j)$ represents the wavelet multiple correlation at time scale λ_j, and $\varphi_{\mathbf{x}}(\lambda_j)$ depends on a set of countries ($\mathbf{x} = X_t = (x_{1t}, x_{2t},..., x_{nt})$) with different public shares of total healthcare financing and wavelet coefficients $W_t = (w_{1jt}, w_{2jt},..., w_{njt})$ which are derived from the MODWT with a Daubechies least asymmetric (*LA*) wavelet filter of length *L*=4 (commonly denoted as *LA*(4)) to each country's public share of total healthcare financing (x_{it}) at scale λ_j. Additionally, $w_{ij} = (w_{ij1}, w_{ij2},..., w_{ijT})$ is selected in order to maximize $\varphi_{\mathbf{x}}(\lambda_j)$, and $\hat{w}_{ij}$ denotes fitted values in the regression of w_{ij} on the rest of the wavelet coefficients at time scale λ_j. Based on equation [3], it is straightforward to define the wavelet multiple cross correlation as follows:

[4] $$\varphi_{\mathbf{x},\tau}(\lambda_j) = Corr(w_{ijt}, \hat{w}_{ijt+\tau}) = \frac{Cov(w_{ijt}, \hat{w}_{ijt+\tau})}{\sqrt{Var(w_{ijt})Var(\hat{w}_{ijt+\tau})}} \quad , j=1,2,\ldots,J$$

where, $\varphi_{\mathbf{x},\tau}(\lambda_j)$ represents the wavelet multiple cross correlation at time scale λ_j, and τ denotes a lag between observed and fitted public share of total healthcare financing of the country chosen as the criterion country at scale λ_j. The notations of $\mathbf{x}$, w_{ij}, and $\hat{w}_{ij}$ are the same as for equation [3]. The lead-lag relationship between one country whose public share of total healthcare financing maximizes the wavelet multiple correlation and a linear combination of the public shares of total healthcare financing from the other countries can be decided by the symmetry of the graph of the wavelet multiple cross correlation. If the curve is significant on the right (left) side of the graph of the wavelet multiple cross correlation, the country whose public share of total healthcare financing maximizes the wavelet multiple correlation is leading (lagging) the other countries (Chen, 2016; Fernández-Macho 2012). The consistent estimators for the wavelet multiple correlation (denoted by $\tilde{\varphi}_{\mathbf{x}}(\lambda_j)$) and wavelet multiple cross correlation (denoted by $\tilde{\varphi}_{\mathbf{x},\tau}(\lambda_j)$) have been established by Fernández-Macho (2012), and the 1-α confidence intervals for the wavelet multiple correlation is constructed as follows:

[5] $$CI_{1-\alpha}(\varphi_{\mathbf{x}}(\lambda_j)) = \tanh\left(\tilde{z}_j - c_2\Big/\sqrt{T/2^j-3}\ ,\tilde{z}_j + c_1\Big/\sqrt{T/2^j-3}\right),\ j=1,2,\ldots,J$$

where, $\tilde{z}_j = \operatorname{arctanh}(\tilde{\varphi}_{\mathbf{x}}(\lambda_j))$, and $\tilde{\varphi}_{\mathbf{x}}(\lambda_j)$ is the consistent wavelet multiple correlation estimator. T is the time span. Note that $\tilde{z}_j$ follows the folded normal distribution with mean $z_j = \operatorname{arctanh}(\varphi_{\mathbf{x}}(\lambda_j))$ and variance $(T/2^j-3)^{-1}$ (or $\tilde{z}_j \sim FN(z_j,\ (T/2^j-3)^{-1})$). c_1 and c_2 denote the folded normal critical values. The 1-α confidence intervals for the wavelet multiple cross correlation can be constructed in the same way by substituting $\varphi_{\mathbf{x}}(\lambda_j)$ and $\tilde{\varphi}_{\mathbf{x}}(\lambda_j)$ for $\varphi_{\mathbf{x},\tau}(\lambda_j)$ and $\tilde{\varphi}_{\mathbf{x},\tau}(\lambda_j)$ (the consistent wavelet multiple cross correlation estimator) in the equation [5].

III. Results and Discussions

III.1 Descriptive statistics

Table 1 presents the descriptive statistics for the public shares of total healthcare financing across nine OECD countries over the period from 1960 to 2012. There are three clusters of countries which were roughly differentiated as three different types of healthcare systems, these being the SHI, NHS, and PHI healthcare systems. As indicated in Table 1, all countries classified as the NHS type of healthcare system (such as Finland, Iceland, Ireland, Norway, Spain, and the United Kingdom) generated the highest public share of total healthcare financing (approximately 78.53% on average) during the period of 1960-2012. The United States healthcare system, representing the PHI system displayed the lowest public share of total healthcare financing (below 40%). The public share of total healthcare financing from two countries with the SHI type of healthcare system (Austria and Japan) was in-between (approximately 72.85% on average) that of the NHS and PHI type of healthcare systems. These results reflect the different funding sources and managerial strategies of healthcare systems. As indicated in Chen (2013), the financing of the NHS system depends on general taxation, and this type of system emphasizes the role of the government in regulating the delivery of healthcare services from public healthcare providers. The financing of the SHI system depends on social insurance (contributed by both public and private sectors), and this type of system is dependent on negotiations between fund holders and both public and private healthcare providers with some control by the government. The financing of the PHI system depends on private health insurance premiums and direct financing by private households and this type of system relies on the mechanism of free market.

Table 1

Descriptive Statistics for Public Share of Total Health Care Financing (%) †

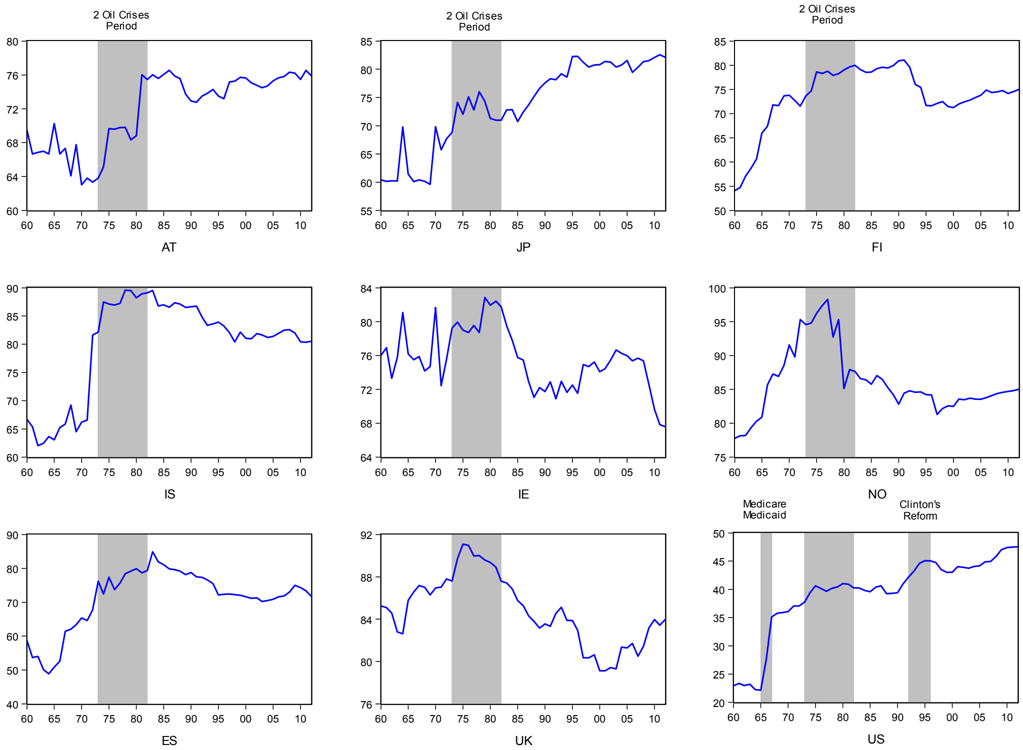
Types	Countries	Codes	Mean	Std. Dev.	Min	Max
Social Health Insurance (SHI)	Austria	AT	71.901	4.323	63.010	76.546
	Japan	JP	73.793	7.568	59.613	82.597
	Average	SHI	72.847	5.545	62.112	79.570
	Finland	FI	73.538	6.417	54.090	81.070
	Iceland	IS	80.093	8.691	62.035	89.583
National Health	Ireland	IE	75.550	3.595	67.573	82.858
Service (NHS)	Norway	NO	86.016	4.895	77.768	98.286
	Spain	ES	71.183	8.867	48.863	84.914
	United Kingdom	UK	84.771	3.258	79.122	91.079
	Average	NHS	78.525	4.588	68.189	85.788
Private Health Insurance (PHI)	United States Average	US PHI	39.260 39.260	6.967 6.967	22.130 22.130	47.567 47.567

† The whole sample period starts from 1960 to 2012, resulting in a total of 53 annual observations in level.

In order to better present our data for the co-movement of healthcare financing across these nine OECD countries, we present individual trends of the public share of total healthcare financing for these nine OECD countries from 1960-2012 in Figure 1. As indicated in Figure 1, most of these nine OECD countries reached their peak public share of total healthcare financing around the period of the two oil crises. Subsequent to the two oil crises, trends differ between countries with differing healthcare system types. We found that the public share of total healthcare financing decreased in those countries (Finland, Iceland, Ireland, Norway, Spain, and the United Kingdom) with the NHS type of healthcare system after the period of two oil crises. In contrast with the decreasing trend seen for the public share of total healthcare financing in those countries with the NHS type of healthcare system, Austria and Japan (characterized by the SHI type of healthcare system) increased their public share of total healthcare financing after the period of the two oil crises. In addition, we found a dramatic increase in the US public share of total healthcare financing after 1965, when the US government implemented two social health insurance programs for the elderly (Medicare program) and indigent people (Medicaid program). Another dramatic increase in the US public share of total healthcare financing was found for the 1992-1996 period, when the Clinton administrative proposed a reform of the US healthcare system shifting it from the private-like financing system towards the public-like system. Since then, the upward trend of the US public share of total healthcare financing has continued and reached its peak in 2012 due to an expectation of insurance coverage expansions stemming from the passing of the Affordable Care Act (Chen. Liang, and Lin, 2016).

Figure 1

Trends of Public Share of Total Health Care Financing (%)



III.2 Discrete Wavelet Analyses

Based on our analyses shown in Table 1 and Figure 1, it is worth addressing that the co-movement of healthcare financing was identified within the NHS and SHI type of healthcare systems. In addition, the public shares of total healthcare financing in these nine OCED countries are most likely to have the unit root property (those unit roots tests are available upon request to the authors), and several structural breaks of the public share of total healthcare financing were observed during the period of 1960-2012. Therefore, the co-movement of healthcare financing within these nine OECD countries during our study period is not unambiguous, and call for deeper investigation. Since the wavelet analysis can simultaneously deal with some properties of time series data that may bias our estimates such as structural breaks and unit root property (Chen, 2016; Chen et al., 2016), we present our wavelet analyses as follows:

Table 2

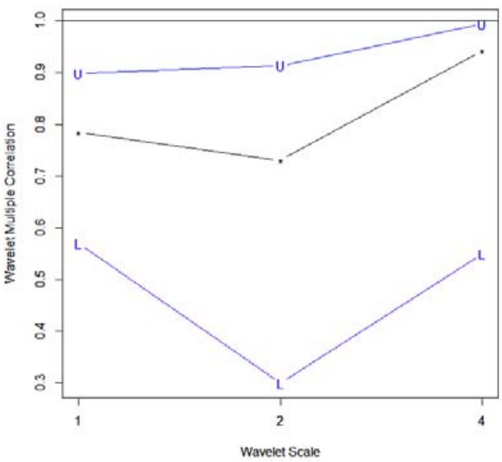
Wavelet Multiple Correlations and Multiple Cross Correlations†

	Scale	Level-1 (2-4 yrs)		Level-2 (4-8 yrs)		Level-3 (8-16 yrs)	
	Lags	Coef	95% CI	COR	95% CI	COR	95% CI
Multiple Cross Correlation	-12	0.547	[0.202, 0.771]	0.784	[0.409, 0.932]	0.986	[0.870, 0.999]
	-9	0.773	[0.550, 0.893]	0.765	[0.371, 0.926]	0.972	[0.757, 0.997]
	-6	0.498	[0.138, 0.742]	0.820	[0.491, 0.944]	0.955	[0.638, 0.995]
	-3	0.744	[0.500, 0.878]	0.758	[0.356, 0.923]	0.865	[0.178, 0.985]
Multiple Correlation	0	0.784	[0.569, 0.898]	0.730	[0.300, 0.914]	0.941	[0.550, 0.994]
Multiple Cross Correlation	3	0.594	[0.268, 0.798]	0.704	[0.251, 0.904]	0.938	[0.532, 0.993]
	6	0.767	[0.540, 0.890]	0.833	[0.521, 0.949]	0.970	[0.743, 0.997]
	9	0.387	[-0.001, 0.673]	0.856	[0.578, 0.956]	0.995	[0.954, 0.999]
	12	0.470	[0.101, 0.725]	0.612	[0.093, 0.870]	0.978	[0.807, 0.998]

† Bold fonts represent 5% significance level.

Figure 2

Wavelet Multiple Correlations †



†The wavelet scales "1", "2", and "4" represent three time frequencies that capture dynamics with three different periods in the range of 2-4 years, 4-8 year, and 8-16 years, respectively. The blue lines correspond to the upper and lower bounds of the 95% confidence interval.

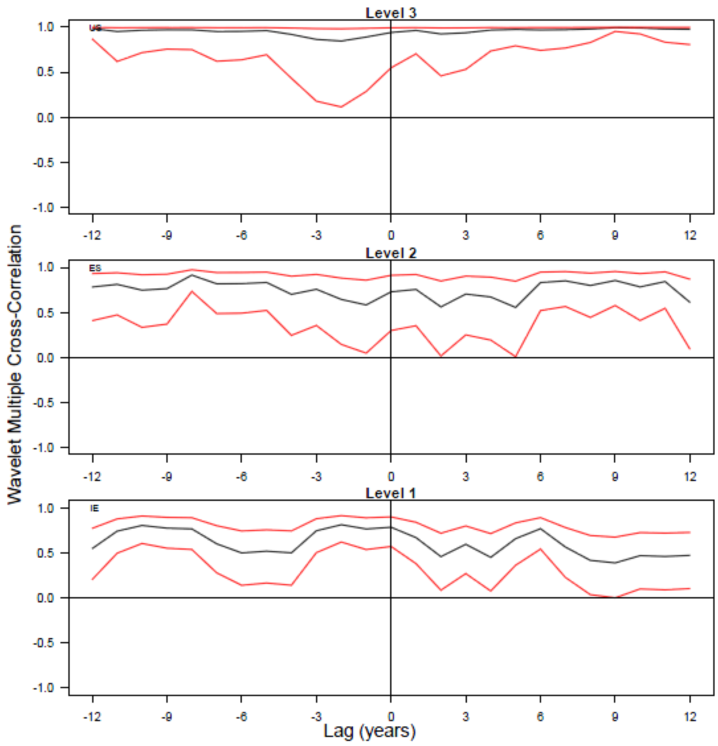
Table 2 presents the wavelet multiple correlations and cross correlations for different time scales with some specific leads and lags (for an interval within 12 years). The maximum time scale J is given by , where T denotes the time-span (Pervical and Walden 2000), which in our case, implies a maximum level of five that can be chosen. Due to the relatively short period of our time-span, we restricted our maximal time scale J to three. Namely, the wavelet scales "1", "2", and "4" display three time scales that describe dynamics with three different periods in the range of 2-4 years (short-run), 4-8 years (medium-run), and 8-16 years (long-run), respectively (Crowley, 2007). In order to better present our results, we plot wavelet multiple correlations for the public shares of total healthcare financing across nine OCED countries at different time scales in Figure 2. The blue lines in Figure 2 correspond to the upper and lower bounds of the 95% confidence intervals. It is clear from Figure 2 that the wavelet multiple correlations are significantly positive at three time scales, and we found that the values of the short-run, medium-run, and long-run correlations are 0.784, 0.730, and 0.941, respectively (see Table 2). These results demonstrate a medium and high correlation of healthcare financing across these nine OECD countries in the short-run, medium-run, and long-run over the period of 1960-2012. Thus, the co-movement of healthcare financing across these nine OECD countries during our study period is soundly justified. In particular, the wavelet multiple correlation in the long-run is higher than 90%, so discrepancies of healthcare financing across these nine OECD countries are mostly likely to be small and negligible in the long-run.

Figures 3-4 present the classical and the visualized plot of the wavelet multiple cross correlations for different time scales with some specific leads and lags (for an interval within 12 years) proposed by Fernández-Macho (2012), and Polance-Martínez and Fernández-Macho (2014), respectively. The classical plot is useful for identifying the symmetry of the graph of the wavelet multiple cross correlation, while the visualized plot illustrates well the strength of wavelet multiple cross correlations. The country whose public share of total healthcare financing maximizes the wavelet multiple correlation against the linear combination of public shares of total healthcare financing from other countries is shown in the left corner (middle) of Figure 3 (Figure 4). This specific country acts as a potential leader or follower of other eight OECD countries (Fernández-Macho 2012). As indicated in Figures 3-4, we find that most of the wavelet multiple cross correlations for different time scales with most leads and lags (for an interval within 12 years) are significantly positive at 5% significance level. The only insignificant wavelet multiple cross correlation appeared at the 2-4 years frequency with the lag of 9 years (see Figures 3-4, and Table 2). The countries shown in the upper left corner (middle) of Figure 3 (Figure 4) suggest that Ireland, Spain, and United States are the potential leaders or followers of the other eight OECD countries in terms of public share of total healthcare financing in the short-run (2-4 years), medium-run (4-8 years), and long-run (8-16 years), respectively.

In order to clarify the spill-over relationship between the selected country and the other eight OECD countries, we first located the strongest wavelet multiple cross correlation values from Figure 4. If these strongest wavelet multiple cross correlation values were not located at the origin point (namely, the zero-lag point), we checked the symmetry of the wavelet multiple cross correlation plot (Figure 3) at three different time scales. As indicated in Figure 4, in the frequency of the short-run (2-4 years) and medium-run (4-8 years) cycles, the maximal values of wavelet multiple cross correlations are located at the leads of 2 years and 8 years for Ireland and Spain, respectively. The maximal value of wavelet multiple cross correlation was located at the lag of 9 years for the United States in the frequency of the long-run (8-16 years) cycle. These maximal values of wavelet multiple cross correlations were not located at the origin point.

Figure 3

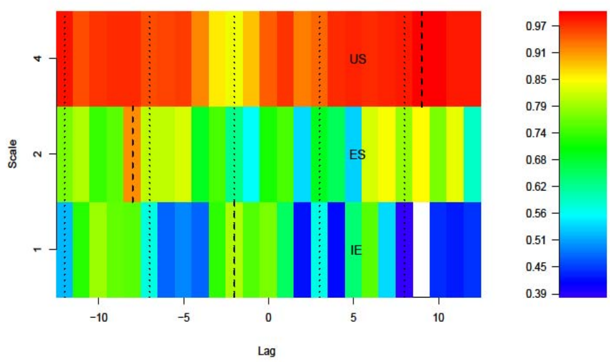
Wavelet Multiple Cross-Correlations (Classical Plot)†



†The upper-left corner signals the variable acting as a potential leader or follower. “Level 1”, “Level 2”, and “Level 4”, represent three different wavelet scales that capture dynamics with three different periods in the range of 2-4 years, 4-8 year, and 8-16 years, respectively. The red lines correspond to the upper and lower bounds of the 95% confidence interval.

Figure 4

Wavelet Multiple Cross-Correlations (Visualized Plot)†



†The wavelet coefficients are within 95% confidence interval for each wavelet correlation. The numbers of“1”, “2”, and “4” displayed in the y axis represent three different wavelet scales that capture dynamics with three different periods in the range of 2-4 years, 4-8 year, and 8-16 years, respectively. Zones in which the 95% interval spans zero are indicated in white color. The long-dashed vertical lines indicate where in time the strongest wavelet multiple correlation values are localized.

In addition, we find that the curves of the wavelet multiple cross correlation are significant on the left side of Figure 3 in the frequency of the short-run (2-4 years) and medium-run (4-8 years) cycles, while it is significant on the right side of Figure 3 in the frequency of the long-run (8-16 years) cycle. These findings suggest that the NHS style of healthcare systems (such as those healthcare systems in Ireland and Spain) has a leading effect in terms of the public-private mix of healthcare financing on the other two types of healthcare systems (SHI and PHI systems), while the PHI style of healthcare system used in the United States is mostly likely to lag behind the other two types (NHS and SHI) of public financing healthcare systems.

IV. Conclusions

Co-movement in healthcare financing mirrors the evolution of healthcare systems due to several social forces such as material force (demographic change, medical technological progress, and globalization), institutional force (Europeanization), and ideational force (individualization, prosperity in economics, and affluence (Chen, 2013; Cacace et al., 2008). Previous studies on this topic are limited (see the literature reviews in the Introduction section). Therefore, the main propose of this study is to investigate three important research questions: First, whether or not the public share of total healthcare financing across OECD countries co-move. Second, through identifying the lead-lag relationship of the public share of total healthcare financing within the OECD countries, we determined whether or not the spill-over relationship of healthcare financing exists and third, in what the direction this spill-over relationship goes. To this end, we calculated the wavelet multiple correlations and cross correlations proposed by Fernández-Macho (2012) to investigate the co-movement and spill-over relationship of healthcare financing, across nine OECD countries (Austria, Finland, Iceland, Ireland, Japan, Norway, Spain, the United Kingdom, and the United States) over the period of 1960-2013.

Several findings generated from our analyses merited further attention: First, our results obtained from Figure 1 shows most countries with public financing healthcare systems such as the NHI and SHI systems reached their peak public share of total healthcare financing around the period of the two oil crises. The financial difficulties of the NHS healthcare system during the economic recession of the two oil-crisis periods from the mid 1970s through early 1980s led to an end of welfare expansion of the postwar period in OECD countries (Chen, 2013). The public-private mix of healthcare financing in the United States is influenced by reform measures which shifted the healthcare system toward a more public-like healthcare financing system (such as the implementation of Medicare and Medicaid programs, the healthcare reform proposed by the Clinton administrative and the pass of the Affordable Care Act). Second, although a slight divergence trend of the public share of total healthcare financing between the NHI and SHI healthcare systems after the two oil-crisis periods was found, our results from wavelet multiple correlations in Table 2 and Figure 2 show highly significant co-movement trends of healthcare financing in these nine OECD countries in the short-run, medium-run, and long-run. This result reflects the fact that globalization forces governments in OECD countries to compete for international capital and labor by deregulating the labor market and reducing social provisions. This also reflects the

Europeanization process which obligated member states to decrease public deficits to a maximum of 3% of GDP, thus changing the public-private mix of healthcare financing and restricting the utilization of new medical technology (Chen, 2013). Third, we found that the public-private mix of healthcare financing in the NHS healthcare system leads those in the other type of healthcare systems (such as the SHI, and PHI systems) in the short-run and medium-run, while the public-private mix of healthcare financing in the PHI health care system used in the United States lags behind those in the other two types of public financing systems (the SHI, and NHS systems). It follows that diffusion of policy impacting changes in the public-private mix of healthcare financing should run from the public financing healthcare systems to the private financing healthcare systems.

This study makes several contributions in comparison to previous research on the study of co-movement of asset prices and macroeconomic variables in different markets or countries. First, we identified the existence of comovement of healthcare financing over the longest time span (53-year time span) across nine OECD countries for the first time, contributing to the literature on the evolution of healthcare systems and diffusion of cross-national health policies. Second, the wavelet analyses proposed by Fernández-Macho (2012) allowed us to describe the spill-over relationship in terms of lead-lag relationship of the public share of total healthcare financing within the OECD countries. Finally, the limitation of this study is inherent in is its single-dimensional indicator (i.e., the public share of total healthcare financing) used in our analyses. We are aware of that a complete picture of co-movement of healthcare systems should be revealed by analyzing other multi-dimensional indicators such as financing and delivery methods, regulation, and values, goals, and perception in healthcare (Chen, 2013). Nevertheless, these multi-dimensional indicators were scarce in the OECD health dataset, so we require more complete data to overcome the limitation of this study.

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