Economic Research-Ekonomska Istraživanja

ISSN: 1331-677X (Print) 1848-9664 (Online) Journal homepage: http://www.tandfonline.com/loi/rero20

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To cite this article: Kuan-Min Wang & Yuan-Ming Lee (2018) The impacts of life insurance asymmetrically on health expenditure and economic growth: dynamic panel threshold approach, Economic Research-Ekonomska Istraživanja, 31:1, 440-460, DOI: 10.1080/1331677X.2018.1429943

To link to this article: https://doi.org/10.1080/1331677X.2018.1429943

Published online: 20 Feb 2018.

ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA, 2018
VOL. 31, NO. 1, 440–460
https://doi.org/10.1080/1331677X.2018.1429943

The impacts of life insurance asymmetrically on health expenditure and economic growth: dynamic panel threshold approach

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ABSTRACT
This study examines the impacts of life insurance asymmetrically on health expenditure and economic growth. Using the dynamic panel threshold model, we find that life insurance growth has a regime switch factor that may change the relationship between health expenditure growth and economic growth. Our results show that the asymmetrical information of life insurance growth affects the causal relationship between health expenditure growth and economic growth. In a low life insurance growth regime, the negative growth of life insurance can stimulate health expenditure and economic growth, which can have a positive feedback effect. However, in the interval of high life insurance growth, the growth does not affect health expenditure or economic growth; there is an adverse feedback effect between economic growth and health expenditure growth, whereby economic growth stimulates health expenditure growth, but health expenditure growth reduces economic growth.

ARTICLE HISTORY
Received 7 September 2016
Accepted 6 December 2017

KEYWORDS
Life insurance; asymmetrical effect; health expenditure; economic growth; dynamic panel threshold model

JEL CLASSIFICATIONS
C12; C23; G15; I15

1. Introduction

Research on the global medical economy has concentrated on the economic development and health expenditures of Organisation for Economic Development and Co-operation (O.E.C.D.) countries to explore the impact of economic development on health expenditure. The findings demonstrate that health expenditures vary greatly in countries with similar levels of economic development. All O.E.C.D. countries apparently face continuing growth in health expenditures. According to *OECD Health Data* (2012), however, real health expenditure growth among O.E.C.D. countries has tended to slow or decline rather than stay on a long-term upward trend. As shown in Figure 1, public health expenditure growth in 2010 stopped and then fell by about 0.5%. Since the 2007–09 subprime mortgage crisis in the United States, O.E.C.D. countries have faced fiscal deficits. Public health expenditures

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‡We thank the Ministry of Science and Technology Of Taiwan (MOST 102-2410-H-240-001–) for financial support.

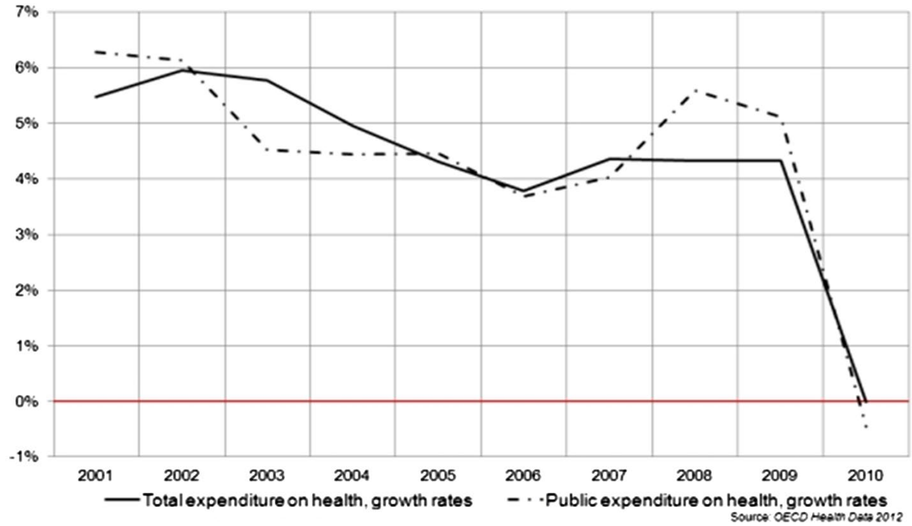

Figure 1. Average O.E.C.D. health expenditure growth rates in real terms, 2000 to 2010, public and total. Source: Authors.

tended to remain constant before the subprime mortgage crisis, although reducing health expenditures and other financial burdens were considered. Real health expenditure cuts began in 2010, when the European debt crisis took hold.

In addition to issues of national revenue and expenditure, some of the literature suggests that reductions in health expenditures are related to national insurance systems or insurance consumption. Some studies indicate that a country's health insurance system affects its health expenditure (e.g., Gertler and Sturm, 1997; Cardon and Hendel, 2001; Joglekar, 2008). However, the impact of private insurance has rarely been discussed, and there are no studies on macroeconomic issues. The early studies concentrated on microeconomics-based cases. Cardon and Hendel (2001) argued that adverse selection is the main cause of insurance market failure. They established a structured adverse selection model to test the impacts of the insurance consumption of consumers with different risk preferences by using individual countries' data and found no asymmetric information. Joglekar (2008) found that increased private insurance reduced out-of-pocket public health expenditure in Jamaica. Gertler and Sturm (1997) indicated that increased private insurance could reduce a government's public health expenditures. Using Jamaican data, they found that increased private insurance could reduce the public health expenditures of the rich and improve private healthcare quality. They thus suggested that total governmental health expenditure should be reduced to focus on public healthcare provision to the poor.

This study discusses how the development of the life insurance affects the relationship between health expenditure growth and economic growth from the macroeconomic perspective and tests whether the asymmetry impact from life insurance growth affects the relationship between health expenditure growth and economic growth.

Our results show that the asymmetrical information of life insurance growth affects the causal relationship between health expenditure growth and economic growth. In a low life insurance growth regime, the negative growth of life insurance can stimulate health expenditure and economic growth, and health expenditure and economic growth have a positive feedback effect. However, in the interval of high life insurance growth, the growth does not affect health expenditure or economic growth; there is an adverse feedback effect between economic growth and health expenditure growth, whereby economic growth stimulates health expenditure growth, but health expenditure growth reduces economic growth.

The remainder of this paper is organised as follows. Section 2 provides a literature review. Section 3 introduces the study's model and methodology. Section 4 presents the empirical results. Section 5 discusses the implications of the results, and Section 6 concludes the study.

2. Literature review

Based on the architecture of the Solow economic growth model, Newhouse (1992) argued that technological change is the most important factor driving health expenditure growth in several countries. Fuchs (1996) found that 85% of health economics scholars in the United States agreed with Newhouse's proposal that technological change was the most important factor driving the rapid growth of health expenditure from the 1960s onward; he argued that the impact of insurance on the relationship between health expenditure and economic growth should be analysed with technological change in mind. Finkelstein (2007) empirically tested the overall impact of the implementation of Medicare in 1965 on hospitals in the United States and found that hospital expenditures grew by 37%. This estimated result is six times higher than Newhouse's (1977) estimated result from a health insurance experimental study in the 1970s. This difference occurred because Finkelstein adopted an overall equilibrium analysis method and considered the impact of health insurance on market supply (hospital behaviour) and demand (consumer behaviour), while Newhouse used a partial equilibrium analysis method and considered consumer behaviour responses but not the impact on hospital behaviour. A comparison of the differences in the two analysis methods isolates the major factor driving health expenditure growth – the implementation of health insurance and associated technological innovation.

According to Finkelstein's (2007) overall equilibrium analysis method, the implementation of health insurance changes not only the relative prices of medical services but also the nature and size of the medical service market, thus further changing the incentives for hospitals to enter the market and adopt new technologies. This particular analysis method allows Finkelstein to conclude that the implementation of health insurance can explain half of the health expenditure growth from 1965 to 1970. According to Newhouse (1977), health insurance implementation can explain one-eighth to one-tenth of health expenditure growth, at most. These differences in the estimations of the impact of health insurance implementation on health expenditure growth occurred because Newhouse regarded technological change as exogenous without analysing the impact of health insurance on technological change, while Finkelstein regarded technological change as endogenous and health insurance as an important factor driving hospitals to adopt new technologies.

From the theoretical perspective, Hall and Jones (2007) analysed the continuous rise in the proportion of health expenditure against the rise in gross domestic product (G.D.P.) and found that it is a reasonable reaction to economic growth. The theoretical basis of this finding is the assumption that the marginal decreasing rate of consumption is greater than the marginal decreasing rate of medical service productivity returns. They argued that the assumption is not impractical. An individual with an increased income may increase purchases of various commodities to increase utility levels according to preferences. Finkelstein

(2007) and Hall and Jones (2007) conclude that technological change is endogenous and that the major driving factor of technological change is income growth and the implementation of health insurance. This theoretical perspective's policy implication is that the suppression of the growth of medical costs (total sum payment) via regulation will result in decreased health expenditure by the public sector, but overall health expenditure growth will not decrease. The impact does not affect people with high incomes but has an adverse effect on the access to medical services of people with low incomes.

In the past, health expenditure was regarded as a luxury. Baltagi and Moscone (2010) empirically found that health expenditure is, instead, a necessity in relation to national income.[1] However, Wang (2011) argued that different economic growth rates or health expenditure growth rates may result in different relationships between economic growth and health expenditure growth – not necessarily relationships that are positive and significant. The elasticity of health expenditure against national income will change according to the given economic or health expenditure growth rates. Importantly, Wang (2011) introduces the exogenous variable of insurance market growth to examine the relationships between the two.

The role of insurance mostly involves the impact of public/out-of-pocket insurance. However, the relationship between financial market development and economic growth has been a subject of concern. The importance of the development of the private health insurance market on economic growth was gradually yet increasingly noted in the 1990s. Similar to the development of the banking industry and capital market, the development of the insurance industry occurred in response to the commercial and household demands on financial intermediaries. The value of insurance is in enabling various public and private actors to take risks in stabilising the economy. If this function works as it is supposed to, insurance companies can use their reserves to boost capital markets and stimulate the economy.[2]

Previous studies have assessed the major issues in the relationship between insurance consumption and economic growth by focusing on a few countries and short sample periods (Catalan et al., 2000; Ward and Zurbruegg, 2000) or special sectors (Beenstock et al., 1988; Browne and Kim, 1993). Das et al. (2003) empirically found that, from the perspective of the ripple effect, the impact of insurance on economic growth is negative. Blum et al. (2002) argued that the relationships between the insurance market and the real economic sector can be roughly divided into (1) having no relationship; (2) economic growth increases the demand for insurance (demand-following); (3) insurance growth results in economic growth (supply-leading); (4) insurance growth results in negative economic growth due to moral hazard behaviour; and (5) the two are mutual causes and effects (i.e., interdependent).

Haiss and Sümegi (2008) applied panel data to examine the relationship between insurance and economic growth based on an endogenous growth model for the whole E.U., the E.U.-15+(including Switzerland, Norway, and Iceland), and the emerging C.E.E. countries (new EU Member States from Central and Eastern Europe). They found an insignificant effect of life insurance on economic growth for the whole E.U. and E.U.-15+countries.

Han et al. (2010) also employed the generalized method of moments (G.M.M.) approach to examine the relationship between insurance development and economic growth for a panel data-set of 77 countries. The model adopted G.M.M. with instrument variables to avoid the over-identifying problem. The results indicate that the model does not suffer the problem of over-identifying and validates the employed instrument variables. Their empirical results showed evidence of a positive impact of insurance development on economic growth.

Recently, Lee and Chiu (2012), Lee et al. (2015), and Lee et al. (2016) used the panel approach to find the significant impacts of globalisation on economic growth and insurance development. Chang et al. (2013) also found similar results with the bootstrap panel method. Hu and Yu (2014) thought that risk management in life insurance companies has significant economic impact. Additionally, Ihori et al. (2011), used the simulation analysis for data from Japan and found that Health insurance reform would affect economic growth.

This literature review is largely an analysis of the architecture of information symmetry. The method overlooks the possible asymmetrical impact of insurance growth on the relationship between health expenditure growth and economic growth. Hence, the use of asymmetric information, multinational data, and the the dynamic panel threshold model (D.P.T.M.) in this study is novel.

3. Model and methodology

We construct the long-run relationship among national income, health expenditure, and insurance consumption as follows:

$$GDP_{it} = A_i + B_i THE_{it} + C_i LSP_{it} + u_{it} \tag{1}$$

GDP_{it} denotes per capita income at time t for country i, THE_{it} is per capita health expenditure at time t for country i, and LSP_{it} is per capita life insurance consumption at time t for country i. Coefficient A_i is autonomous health expenditure, B_i is induced health expenditure as the income elastic of health expenditure, and C_i is induced life insurance consumption as the income elastic of life insurance consumption. If panel cointegration exists, the short-run error-correction model is as follows:

$$\Delta Z_{it} = \Gamma_{0i} + \sum_{j=1}^{k} \Gamma_{1i} Z_{it-j} + \Phi_i (GDP_{it-1} - A_i - B_i THE_{it-1} - C_i LSP_{it}) + \varepsilon_{it} \tag{2}$$

$\Delta Z_{it} = \{\Delta GDP_{it}, \Delta THE_{it}, \Delta LSP_{it}\}'$ and Φ_i are the adjustment speeds of the error-correction model for country i. The error-correction term is $ECM_{it-1} = GDP_{it-1} - A_i - B_i THE_{it-1} - C_i LSP_{it}$, which implies that short-run disequilibrium could return to long-run equilibrium through error-correction adjustment. When the threshold effect occurs, we set up a short-run D.P.T.M. as follows:

$$\Delta Z_{it} = \begin{cases} \Gamma_{10i} + \sum_{j=1}^{k} \Gamma_{11i} \Delta Z_{it-j} + \Phi_{1i}(GDP_{it-1} - A_i - B_i THE_{it-1} - C_i LSP_{it}) + \varepsilon_{1it}, \ \Delta LSP_{it-d} < \gamma \\ \Gamma_{20i} + \sum_{j=1}^{k} \Gamma_{21i} \Delta Z_{it-j} + \Phi_{2i}(GDP_{it-1} - A_i - B_i THE_{it-1} - C_i LSP_{it}) + \varepsilon_{2it}, \ \Delta LSP_{it-d} \geq \gamma \end{cases} \tag{3}$$

In Equation (3), $\Delta LSP_{it-d} < \gamma$ implies that the life insurance growth rate is smaller than the threshold value, as in regime 1, while $\Delta LSP_{it-d} \geq \gamma$ implies that the life insurance growth rate is no smaller than the threshold value, as in regime 2. To test the causality between THE_{it} and GDP_{it}, the critical values are obtained by the bootstrap method.

This study analyses how life insurance growth affects health expenditure growth and economic growth by expanding Hansen's (1999) threshold model to allow the existence of the explanatory variables of the lag terms – that is, by using the D.P.T.M. in the empirical tests. The small sample bias refers to Appendix of Chen and Lin (2010). In empirical tests, bias correction is important. After using insurance growth as the threshold variable, the intervals create unbalanced panel data. Using the threshold model in the estimation, when $t = 11$ (years), observations at each interval may decrease in number. Thus, least squares dummy variable (L.S.D.V.) bias may be ignored in the D.P.T.M. Finally, the regression model includes exogenous variables (lag-term of variables) that can make the bias more complicated and close to the L.S.D.V. estimator equation (see Appendix A).[3]

4. Empirical results

The 24 sample countries used in this study comprise Australia, Austria, Belgium, Canada, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Italy, Japan, South Korea, Luxembourg, Mexico, the Netherlands, Norway, Poland, Portugal, Spain, Switzerland, the United Kingdom, and the United States. The sample period covers 1999 to 2012. The data are taken from the OECD.Stat statistics database (http://stats.oecd.org/). The variables used include per capita G.D.P., per capita total health expenditure, and per capita life insurance premium. All variables are defined in Table 1. Natural logarithms of these variables are analysed in the empirical tests.

First, this study analyses trends in the time series data of individual countries. Figure 2 illustrates G.D.P. trends in the 24 sample countries. All countries showed upward trends over time. In 2008, G.D.P. declined, possibly because of the impact of the subprime mortgage crisis. Figure 3 shows the total health expenditure trends, most of which are upward. Figure 4 illustrates the life insurance trends, which indicate that G.D.P. and total health expenditure have more significant volatility.

To verify the presence of a nonlinear relationship, this study analyses the relationship between life insurance growth and economic growth, as well as the growth of health expenditure. The kernel probability density function is applied in adapting the three insurance variables, using the rates of life insurance growth, economic growth, and health expenditure growth. Figure 5 shows the kernel density adaption line graphs depicting the relationship among life insurance growth rate (L.S.P.), economic growth rate (G.D.P.), and health expenditure growth rate (T.H.E.). The horizontal axis illustrates the kernel density distribution of L.S.P., while the vertical axis illustrates the kernel density distribution of G.D.P. and T.H.E. The L.S.P. is skewed to the right, and G.D.P. and T.H.E. are skewed to the left. The adaption

Table 1. Variables definition.

Variable name	Per capita gross domestic product	Per capita total health expenditure	Per capita life insurance
Code	G.D.P.	T.H.E.	L.S.P.
Variable description	Gross domestic product/ per capita (expenditure approach)	International total expenditure on health/per capita	Total gross premiums-Life/ per capita
Frequency	Annual	Annual	Annual
Currency	US dollar	US dollar	US dollar

Source: OECD. Stat database (http://stats.oecd.org/).

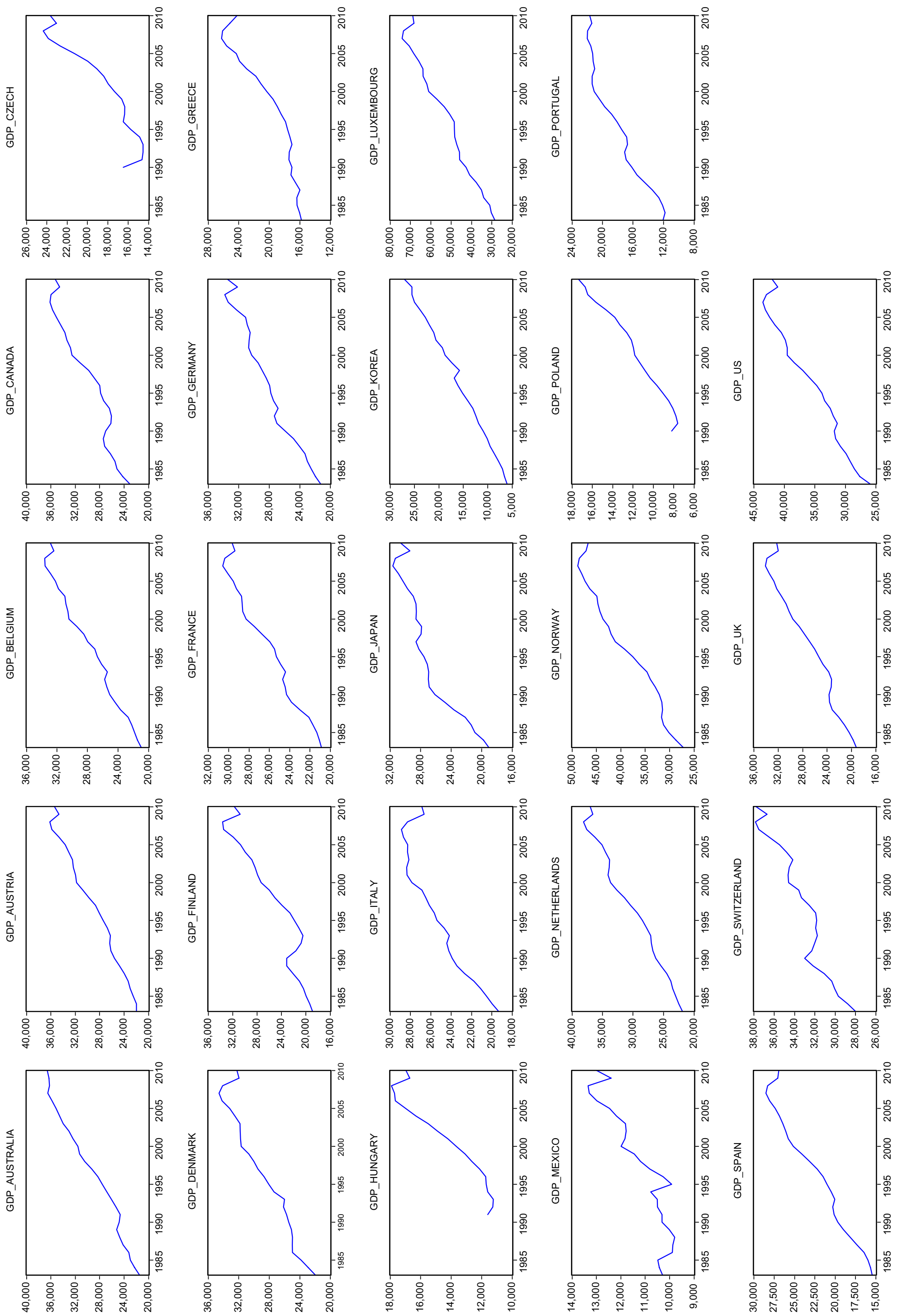

Figure 2. The time trends of G.D.P. in 24 countries. Source: Authors.

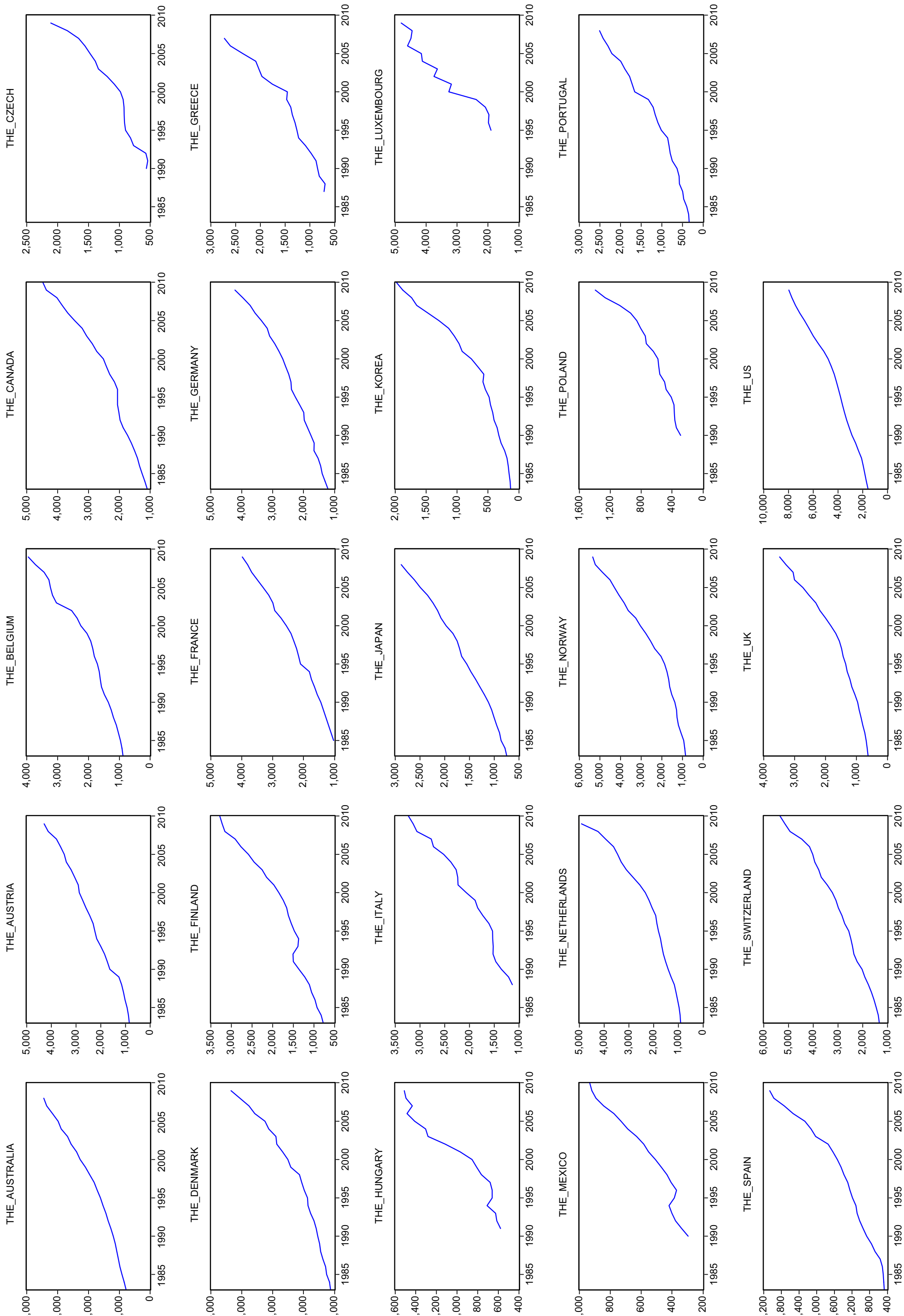

Figure 3. The time trends of health expenditure in 24 countries. Source: Authors.

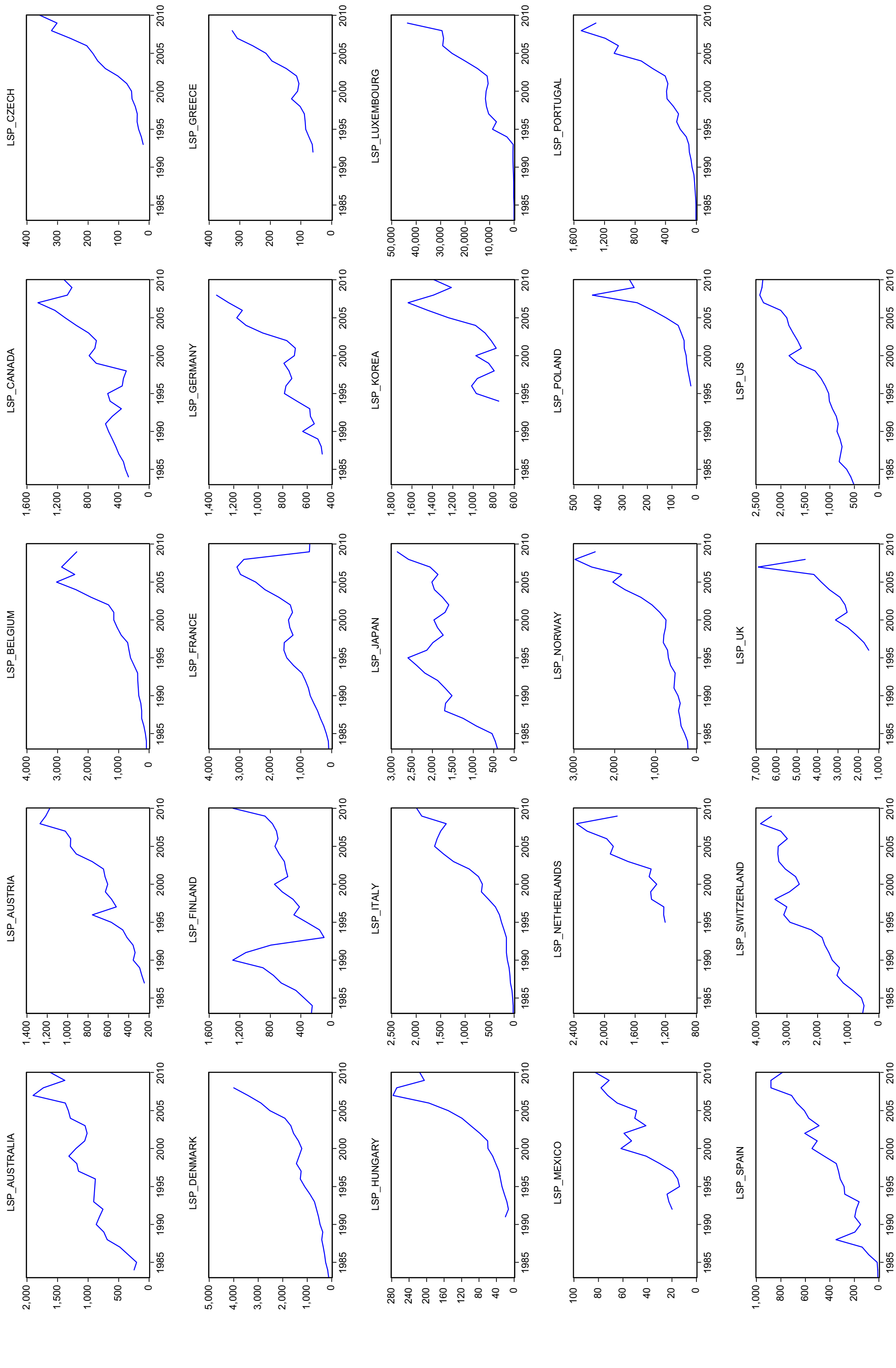

Figure 4. The time trends of life insurance premium in 24 countries. Source: Authors.

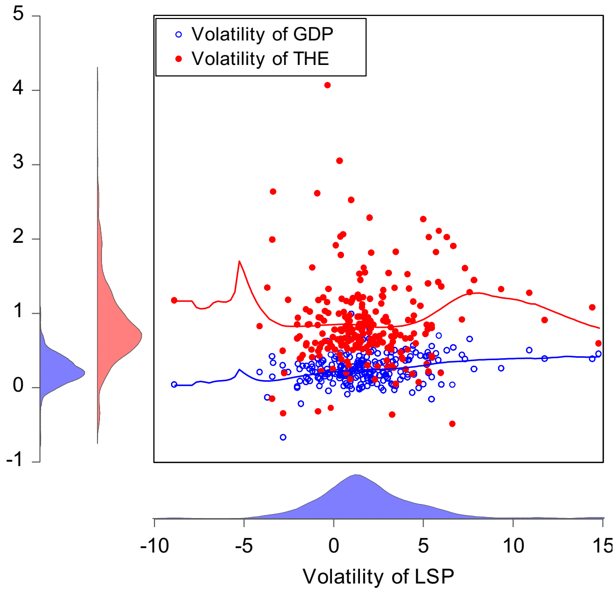

Figure 5. The kernel density adaption line graphs depicting the relationship between life insurance growth rate, economic growth rate and health expenditure growth rate. Source: Authors.

lines of the L.S.P., G.D.P., and T.H.E. kernels have a nonlinear relationship. In addition, when the L.S.P. standard deviation is −5, the kernel adaption lines of L.S.P. and T.H.E. jump upward, slowly changing the relationship from a positive correlation to a negative one. L.S.P. and G.D.P. are roughly positively correlated.

This study determines whether the variables are consistent with the stationary characteristics using a panel unit root test. Table 2 shows the test results. Five testing methods are used: the t* testing method proposed by Levin et al. (2002), *t*-testing method proposed by Breitung (2000), W testing method proposed by Im et al. (2003), ADF-Fisher Chi-square testing method proposed by Maddala and Wu (1999), and PP-Fisher Chi-square testing method. The results suggest that the level items of the three variables have unit roots. After the first-order differentiation, the three variables are given stationary characteristics.[4]

To confirm the long-run cointegration relationship among the variables, this study applies the Kao residual cointegration testing method and Johansen Fisher panel testing method. As shown in Table 3, the model has a cointegration relationship. The long-run relationship is

$$GDP_{it} = 1.343 + 1.418THE_{it} + 0.295\,LSP_{it} \tag{4}$$

The estimation result suggests that health expenditure has a positive impact on national income and that life insurance consumption has positive impacts on national income.

In the case of cointegration, the dynamic panel threshold error-correction model (E.C.M.) is estimated. In the estimation of the short-run model, the error-correction terms are established according to Equation (4):

$$ECM_{it-1} = GDP_{it-1} - 1.343 - 1.418THE_{it-1} - 0.295\,LSP_{it-1}$$

As Figure 5 shows, a change in life insurance consumption leads to an asymmetric relationship among insurance growth, health expenditure growth, and national income growth. An

Table 2. Panel unit root test.

Methods	Y	G	L.S.P.
Levels			
Levin, Lin & Chu t* test	8.641	−3.850***	−2.903***
	(1.000)	(0.000)	(0.002)
Breitung t-stat test	12.445	0.933	4.220
	(1.000)	(0.825)	(1.000)
Im, Pesaran and Shin W-stat test	6.696	−0.307	0.064
	(1.000)	(0.379)	(0.525)
ADF-Fisher Chi-square test	40.847	71.402	59.732
	(0.972)	(0.149)	(0.413)
PP-Fisher Chi-square test	8.378	67.068	50.406
	(1.000)	(0.258)	(0.750)
Difference	ΔY	ΔG	ΔLSP
Levin, Lin & Chu t* test	−7.593***	−13.102***	−9.891***
	(0.000)	(0.000)	(0.000)
Breitung t-stat test	0.473	−3.380***	−0.119
	(0.682)	(0.000)	(0.453)
Im, Pesaran and Shin W-stat test	−4.462***	−8.212***	−3.572***
	(0.000)	(0.000)	(0.000)
ADF-Fisher Chi-square test	121.950***	172.461***	115.852***
	(0.000)	(0.000)	(0.000)
PP-Fisher Chi-square test	141.423***	225.746***	147.343***
	(0.000)	(0.000)	(0.000)

Note: We specified lags at 4 by minimum A.I.C. Exogenous variables: individual effects, individual linear trends. The notation '***' implied statistical significance at the 1% level. Fisher tests are computed using an asymptotic Chi-square distribution. Within the parentheses (.) as the *p*-value. All other tests assume asymptotic normality. When carrying out the test as well as the estimation, all variables are formed in natural logarithms.
Source: Authors.

Table 3. Panel cointegration tests.

Testing methods	Statistics (*p*-value)
Kao Residual Cointegration Test	
ADF	−4.863***
	(0.000)
Johansen Fisher Panel Cointegration Test	
Trace test	
None	116.20***
	(0.000)
At most 1	22.440**
	(0.013)
At most 2	12.970
	(0.225)
Max-eigen test	
None	108.70***
	(0.000)
At most 1	20.600**
	(0.024)

Note: In Johansen Fisher Panel Cointegration Test, trace and max-eigenvalue test are according to the *p*-value of MacKinnon et al. (1999). Within the parentheses (.) as the *p*-value. We specified lags at 1 by minimum A.I.C. The notation '***' and '**' implied the rejection of the null of no cointegration at the 1% and 5% levels, respectively.
Source: Authors.

asymmetry test is conducted to confirm the asymmetrical adjustment mechanism. *LSP* is used as the threshold indicator variable.

This study adopts Hansen's (1999) testing method to test the thresholds. Following the Akaike information criterion (A.I.C.), a lag term of 1 and threshold variables with the lag period $d = 1$ of Equation (3) are used. Table 4 shows the test results. In the bootstrap likelihood ratio test (see

Table 4. The linearity test for the threshold model (threshold variables lag-period $d = 1$).

Threshold variable	ΔLSP_{it-1}
Test for single threshold	
Threshold value [γ_1]	**−0.165**
F1 (L.R. Test)	32.781***
Bootstrap *p*-value	**(0.000)**
10%, 5%, 1% critical values	20.892, 23.749, 32.348
Test for double threshold	
Threshold value [γ_1, γ_2]	−0.165, 0.406
F2 (L.R. Test)	**16.179**
Bootstrap *p*-value	(0.160)
10%, 5%, 1% critical values	18.500, 21.452, 24.262
Test for triple threshold	
Threshold value [γ_1, γ_2, γ_3]	−0.165, 0.241, 0.406
F3 (L.R. Test)	15.645
Bootstrap *p*-value	**(0.120)**
10%, 5%, 1% critical values	17.431, 18.341, 20.803

Note: The critical values (C.V.) are obtained by the bootstrap method. Prior to estimating the equation, within the parentheses (.) as the *p*-value. We need to determine the correct number of regimes to describe the underlying dynamics of economic growth. The likelihood ratio (L.R.) test with the values from the bootstrap method is reported in Table 5.
Source: Authors.

Table 5. The bootstrapping results.

Upper bound 97.5%	Upper bound 95%	Coefficients	QUANT-value	Lower bound 5%	Lower bound 2.5%
0.034	0.033	−1.056	0.000	0.020	0.018
−0.068	−0.149	0.537	1.000	−0.879	−0.992
0.264	0.180	−0.027	0.646	−0.314	−0.355
0.085	0.075	−0.204	0.000	−0.041	−0.059
0.069	0.057	0.666	1.000	−0.095	−0.107
0.215	0.185	−0.116	0.018	−0.088	−0.106
0.079	0.061	−0.029	0.330	−0.082	−0.096
0.041	0.037	0.004	0.069	0.002	0.000

Note: The threshold variable is ΔLSP_{it-1} and the threshold value is −0.165.
Source: Authors.

Table 5), when using ΔLSP_{it-1} as the threshold variable, the model has a threshold of −0.165. Hence, the lag period of the threshold variable at 1 is used as parameter *d* for the empirical model. For the threshold estimation, this study uses the maximum likelihood functions of $LR_1(\gamma)$, $LR_2^r(\gamma)$, $LR_1^r(\gamma)$, as shown in Figure 6, reflected in the first step $\hat{\gamma}_1$ estimation and the re-estimation results of $\hat{\gamma}_2^r$ and $\hat{\gamma}_1^r$. The graph results are shown in Figure 6(a)–(c). The 1 and 2 threshold confidence intervals are used, and there is one threshold point.[5]

After confirming the existence of the threshold effect, a threshold model estimation is conducted. Table 6 shows the estimation results of the dynamic panel threshold E.C.M. model. Panel A uses ΔGDP_{it} as the explained variable estimation results, while panel B uses ΔTHE_{it}. As the results in panel A indicate, when in the interval of low life insurance consumption growth (regime 1) $\Delta LSP_{it-1} < -0.165$, health expenditure growth promotes economic growth. However, life insurance consumption growth reduces economic growth. When in the interval of high insurance growth (regime 2) $\Delta LSP_{it-1} \geq -0.165$, health expenditure growth reduces economic growth. In regime 1 of panel B, economic growth promotes health expenditure growth. However, life insurance consumption growth reduces health expenditure growth.

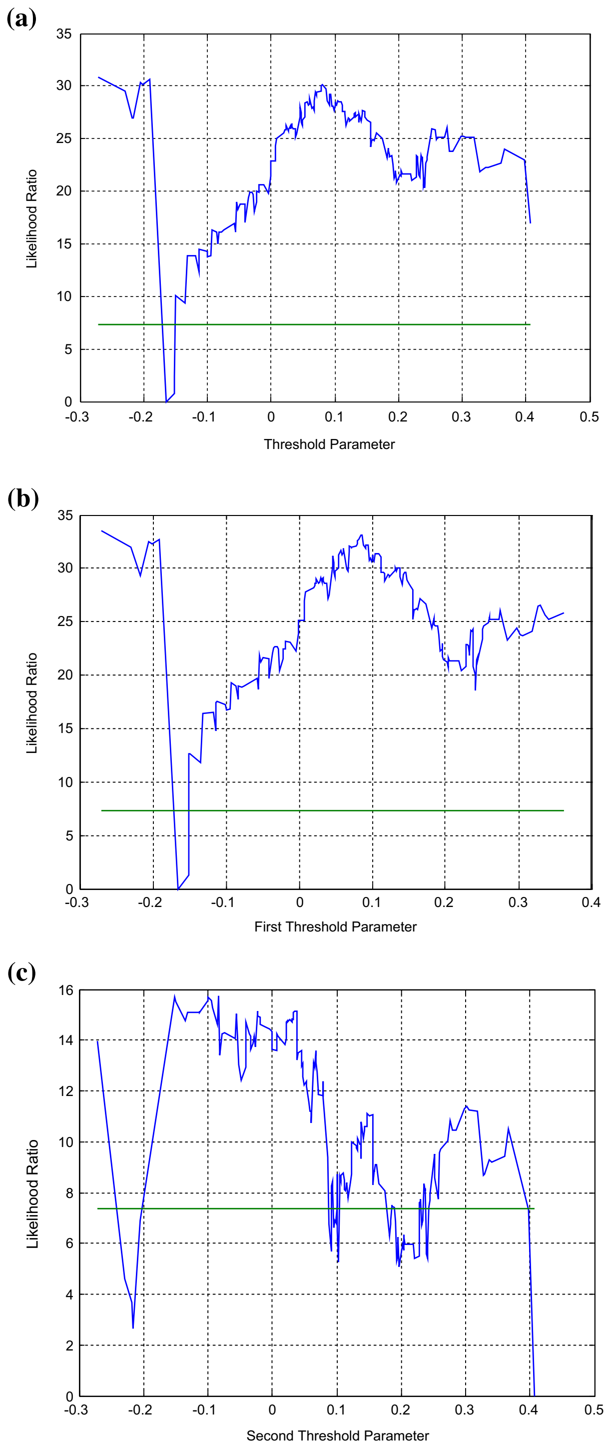

Figure 6. The first threshold parameter confidence interval of (a) the single-threshold model and (b) the double-threshold model. (c) The second threshold parameter confidence interval of the double-threshold model. Source: Authors.

Table 6. The estimation results of dynamic panel threshold E.C.M. model; Panel A model as:

$$\Delta GDP_{it} = \begin{cases} \Gamma_{10i}+\Gamma_{11i}\Delta GDP_{it-1}+\Gamma_{12i}\Delta THE_{it-1}+\Gamma_{13}\Delta LSP_{it-1}+\Phi_{1i}ECT_{it}+\varepsilon_{1it}, \ \Delta LSP_{it-1}<-0.165 \\ \Gamma_{20i}+\Gamma_{21i}\Delta GDP_{it-1}+\Gamma_{22i}\Delta THE_{it-1}+\Gamma_{23}\Delta LSP_{it-1}+\Phi_{2i}ECT_{it}+\varepsilon_{2it}, \ \Delta LSP_{it-1}\geq-0.165 \end{cases}$$

Panel B model as:

$$\Delta THE_{it} = \begin{cases} \Gamma_{20i} + \Gamma_{21i}\Delta THE_{it-1} + \Gamma_{22i}\Delta GDP_{it-1} + \Gamma_{23}\Delta LSP_{it-1} + \Phi_{2i}ECT_{it} + \varepsilon_{2it}, \ \Delta LSP_{it-1} \geq -0.165 \\ \Gamma_{10i} + \Gamma_{11i}\Delta THE_{it-1} + \Gamma_{12i}\Delta GDP_{it-1} + \Gamma_{13}\Delta LSP_{it-1} + \Phi_{1i}ECT_{it} + \varepsilon_{1it}, \ \Delta LSP_{it-1} < -0.165 \end{cases}$$

Variables	Coefficients	Upper bound 97.5%	Upper bound 95%	Lower bound 5%	Lower bound 2.5%
Panel A	Dependent variable: ΔGDP_{it-1}				
Regime 1	$\Delta LSP_{it-1} < -0.165$				
	−1.056(0.000)	0.034	0.033	0.020	0.018
	0.537(0.000)	−0.068	−0.149	−0.879	−0.992
	−0.204(0.000)	0.085	0.075	−0.041	−0.059
	−0.027(0.708)	0.264	0.180	−0.314	−0.355
Regime 2	$\Delta LSP_{it-1} > -0.165$				
	0.666(0.000)	0.069	0.057	−0.095	−0.107
	−0.116(0.036)	0.215	0.185	−0.088	−0.106
	0.004(0.138)	0.041	0.037	0.002	0.000
	−0.029(0.340)	0.079	0.061	−0.082	−0.096
Panel B	Dependent variable: ΔTHE_{it-1}				
Regime 1	$\Delta LSP_{it-1} < -0.165$				
	2.648(0.000)	1.262	0.961	−0.622	−0.796
	−1.517(0.000)	0.085	0.083	0.055	0.053
	−0.154(0.098)	0.212	0.184	−0.190	−0.241
	−0.622(0.039)	0.825	0.516	−2.664	−2.972
Regime 2	$\Delta LSP_{it-1} \geq -0.165$				
	0.517(0.000)	0.093	0.046	−0.260	−0.289
	−0.237(0.037)	0.191	0.157	−0.222	−0.264
	−0.007(0.489)	0.039	0.032	−0.048	−0.054
	0.116(0.343)	0.432	0.394	−0.325	−0.392

Note: The dynamic panel threshold E.C.M. model includes fixed-effect, the estimated coefficients have been corrected, and the critical values are obtained by the bootstrap method. Within the parentheses (.) as the *p*-value.
Source: Authors.

Table 7. The causal relationships in two intervals.

Regimes	Regime 1 ($\Delta LSP_{it-1} < -0.165$)	Regime 2 ($\Delta LSP_{it-1} \geq -0.165$)
Causality direction	$\Delta GDP \underset{+}{\overset{+}{\rightleftarrows}} \Delta THE$	$\Delta GDP \underset{-}{\overset{+}{\rightleftarrows}} \Delta THE$
	$\Delta GDP \overset{-}{\leftarrow} \Delta LSP$	$\Delta GDP \overset{x}{\leftarrow} \Delta LSP$
	$\Delta THE \overset{-}{\leftarrow} \Delta LSP$	$\Delta THE \overset{x}{\leftarrow} \Delta LSP$

Note: The notation "$\xrightarrow{+}$" and "$\underset{+}{\longleftarrow}$" implied the positive causality effect, "$\overset{-}{\longleftarrow}$" implied the negative causality effect, and "$\overset{x}{\longleftarrow}$" implied the causality effect is insignificant.
Source: Authors.

In addition, the short-run imbalance is adjusted to long-run equilibrium by the error-correction mechanism. The result of regime 1 in panel B suggests that economic growth promotes health expenditure growth from the short-run disequilibrium adjustment. As shown in Table 7, in countries with low life insurance growth, health expenditure growth and economic growth have a positive feedback effect because life insurance growth is harmful to both economic and health expenditure growth. In countries with high life insurance growth, life insurance growth does not affect health expenditure or economic growth, while health expenditure growth does not increase economic growth but has an adverse impact on it. However, economic growth can promote health expenditure growth.

5. Discussion and implications

Table 7 clearly shows how the asymmetry effect of life insurance growth affects the causal relationship between health expenditure and economic growth. Philipson and Zanjani (2014) suggested that health impacts can result in asymmetric information. Several explanations for this result are possible. First, in low (or negative) life insurance growth, there may be a substitution effect between life insurance and health spending but a negative wealth effect on economic growth. Thus, in the absence of insurance protection, economic growth must then be accompanied by increased health spending to maintain living standards. This phenomenon is similar to the findings of Joglekar (2008) and Gertler and Sturm (1997); moreover, Das et al. (2003) argue that insurance growth results in negative economic growth due to moral hazard behaviour. Second, amid high life insurance growth, the substitution effect between life insurance and health spending and the wealth effects of life insurance on economic growth may disappear. The government may then reduce health expenditures to avoid crowding out other government spending. This effect is consistent with the findings of Haiss and Sümegi (2008); it differs from Ward and Zurbruegg (2000) and Han et al. (2010), but they might be neglecting the asymmetric information of insurance market growth and failing to consider the relationship between health expenditures and economic growth.

6. Conclusion

This study discussed the impact of insurance factors while exploring whether insurance market growth can affect the causal relationship and direction between health expenditure growth and economic growth. Our results prove that the asymmetrical information of life insurance growth affects the causal relationship between health expenditure growth and economic growth. This study offers several main contributions to research. First, it conducts a cross-national empirical analysis of how life insurance growth asymmetry impacts the relationship between health expenditure growth and economic growth in O.E.C.D. countries. The asymmetry impact triggered by life insurance growth can change the relationship between health expenditure growth and economic growth. The unique aspect of our research is that the asymmetric information in multi-nation insurance markets could produce different substitution and income (wealth) effects, deduct the different causalities of variables, and affect the fiscal expenditures of countries to health expenditures. These results are absent from previous research. Secondly, this study uses the D.P.T.M. to test the relationship between health expenditure growth and economic growth. By adding the impact of life insurance growth on economic growth, this study analyses the possible impact of life insurance growth rates (i.e., low and high insurance growth) on economic growth rates at various intervals. This indicates that different developments in international insurance markets influence the economic growth and fiscal policy of health expenditures in each country, these findings provide a reference that governments can use during their evaluation and development of health expenditure policies as well as to assess possible changes caused by life insurance growth or the impact of health expenditure growth on economic growth. Finally, this paper does not consider the intra-relationship effects of variables, an issue for future research.

Notes

1. Similar to previous findings in Parkin et al. (1987).
2. Wagstaff and Lindelow (2008) suggest that, during the 1990s, China's government and labour insurance schemes increased financial risk associated with household healthcare spending but that the rural cooperative medical scheme significantly reduced financial risk in some areas while increasing it in others (though not significantly). From their results, it appears that China's new health insurance schemes (i.e., private schemes, including coverage for schoolchildren) have also increased the risk of high levels of out-of-pocket health spending.
3. We using the bootstrap method to address heterogeneity or serial correlation.
4. In a panel setting, McCoskey and Selden (1998) rejected the null of nonstationarity for health care expenditures and G.D.P., implying that the former ordinary least squares result could be reinforced, but they did not account for a time trend in their tests.
5. The likelihood ratio testing for a threshold is based on the statistic F1 (test for single threshold). The asymptotic distribution of F1 is nonstandard and strictly dominates the Chi-square distribution. If F1 rejects the null of no threshold (Equation (A9)), further testing to discriminate between one and two thresholds is required. Thus, an approximate likelihood ratio test of one versus two thresholds based on the statistic F2 (test for double threshold) is executed. If F2 rejects the null of one threshold, then the statistic F3 (test for triple threshold) – an approximate likelihood ratio test of two versus three thresholds – is required (see Hansen, 1999). More information can be obtained about the threshold estimates from plots of the concentrated likelihood ratio function, as in Figure 6(a)–(c) (corresponding to the first-stage estimate $\hat{\gamma}_1$ and the refinement estimators $\hat{\gamma}_1^{\gamma}$and $\hat{\gamma}_2^{\gamma}$). The point estimates are the value of γ at which the likelihood ratio hits the zero axis, which is on the far left of the graph. The 95% confidence intervals for $\gamma_2$and$\gamma_1$can be found from $LR_2^r(\gamma)$ and $LR_1^r(\gamma)$ by the values of γ for which the likelihood ratio lies beneath the blue line.
6. Efron and Tibshirani (1993) stated that the bootstrapping method can be applied to simulate the distribution of critical values for test statistics if the standard distribution of test statistics is unavailable under common test circumstances. However, Hansen and King (1996) stated that the asymptotic distribution of F_1 test statistics can be obtained through the bootstrapping method. Hence, using the bootstrapping method to construct the p-value of F_1 test statistics within asymptotic distribution is acceptable
7. The Hansen (1999) P.T.M. does not include dynamic setting so the model could deduce the asymptotic distribution. This article employed the D.P.T.M. model to deal with the requirements of the endogeneity in a dynamic setting in the Panel model and the threshold setting, nonlinearity problems. It is very difficult to deduct the asymptotic distribution from this D.P.T.M. At the present time, we still cannot find any previous research that could deduct the asymptotic distribution. Therefore, the bootstrapping method is the best way to correct the error bias problem in D.P.T.M. The results in this paper validate this issue.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by Ministry of Science and Technology, Taiwan [grant number MOST 102-2410-H-240-001–].

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Appendix A. Dynamic Panel Threshold Model

Developing further from the panel threshold model (P.T.M.) of Hansen (1999), we introduce these models with explanatory variables for lag length (delay). D.P.T.M.s are used to examine the tests, where small sample biases can be made by referencing the Appendix of Chen and Lin (2010). It is important to correct biases when performing research tests. In this study, exchange rate fluctuation is used as a threshold variable, and then each interval is found to become an unbalanced set of panel data. In addition, when estimations are made using the P.T.M., the observed values of each interval are reduced. Under such circumstances, least squares dummy variable (L.S.D.V.) bias might be overlooked by D.P.T.M.s.

The panel threshold regressive model uses values of observable variables, and segments the data into multiple intervals rather than simply using cut-off points to divide them. Hansen (1999) stated that estimations using the least squares (L.S.) method reflected the asymptotic distribution theory. This study first applied the bootstrapping approach to correct biases of dynamic panel data, and then set the exchange rate fluctuations as the threshold variable. Threshold values are picked to divide the model into various regimes. Assuming that the model has two regimes, the regression model can be set out as follows:

$$y_{it} = \alpha_i + \left(\beta_1 y_{it-1} + x_{it}\eta_1\right) I\left(q_{it} \le \gamma\right) + \left(\beta_2 y_{it-1} + x_{it}\eta_2\right) I\left(q_{it} > \gamma\right) + e_{it} \tag{A1}$$

where country $i = 1,\ldots,N$; time $t = 1,\ldots,T$; y_{it} is the response variable; x_{it} is the explanatory variable for the vector m; q_{it} is the observed threshold variable; $\gamma \in \Gamma$ is the threshold estimator parameter; Γ is the potential threshold estimated value; β_1 and β_2 are the slopes for the two different intervals; and e_{it} is the error term. $I(q_{it} \le \gamma)$ denotes the indicator variable: when $q_{it} \le \gamma$, the value is 1; otherwise, the value is 0. $I(q_{it} > \gamma)$ denotes the opposite variable. The estimation steps are as follows: (i) when $\gamma \in \Gamma$ is given, first use the L.S. method to estimate the sum of squared residuals (S.S.R.); (ii) use the minimum S.S.R. to estimate the optimal threshold estimation value $\hat{\gamma}$; (iii) use the threshold value to divide the model into two regimes; and (iv) finally estimate each regime using the L.S. method.

This study used bootstrapping to correct the biases from the D.P.T.M. For a given $\gamma \in \Gamma$, first obtain $\hat{\beta}_1(\gamma)$ and $\hat{\beta}_2(\gamma)$ under fixed effects, then compute $\hat{\alpha}_i(\gamma)$ and $\hat{e}_{it}(\gamma)$ for all i and t. For each individual i, $e_i^*(\gamma) = (e_{i,-49}^*(\gamma), e_{i,-48}^*(\gamma), \ldots, e_{iT}^*(\gamma))$ was obtained from the repetitive substitution of $\hat{e}_i(\gamma) = (\hat{e}_{i,-49}(\gamma), \hat{e}_{i,-48}(\gamma), \ldots, \hat{e}_{iT}(\gamma))$. For all i and t, bootstrapping sample can be collected from $y_{it}^* = \hat{\alpha}_i + \hat{\beta}_1 y_{it-1}^* I(q_{it} \le \gamma) + \hat{\beta}_2 y_{it-1}^* I(q_{it} > \gamma) + e_{it}^*(\gamma)$. During the estimation process, data for the first I (number of countries) would be omitted. The remaining observed values are used to estimate $\beta_{1,b}^*(\gamma)$ and $\beta_{2,b}^*(\gamma)$. Under a given γ, the corrected β_1 and β_2 can be defined as

$$\hat{\beta}_{1,B}(\gamma) = 2\hat{\beta}_1(\gamma) - \tfrac{1}{B}\sum_{b=1}^{B} \beta_{1,b}^*(\gamma),$$

$$\hat{\beta}_{2,B}(\gamma) = 2\hat{\beta}_2(\gamma) - \tfrac{1}{B}\sum_{b=1}^{B} \beta_{2,b}^*(\gamma),$$

After correction, the transposed parameter is defined as $\hat{\gamma}_B = arg \min_{\gamma \in \Gamma} \hat{S}' NT(\gamma)$, where $\hat{S}' NT(\gamma) = \sum_{i=1}^{N}\sum_{t=1}^{T} \left[\hat{y}_{it} - \hat{\beta}_{1,B}(\gamma)\hat{y}_{i,t-1} I(q_{it} \le \gamma) - \hat{\beta}_{2,B}(\gamma)\hat{y}_{i,t-1} I(q_{it} > \gamma)\right]$ and $\left(\hat{\beta}_{1,B}, \hat{\beta}_{2,B}\right) = (\hat{\beta}_{1,B}(\hat{\gamma}_B), \hat{\beta}_{2,B}(\hat{\gamma}_B))$.

We further considered the existence of external variable Equation (A1) in the dynamic panel model. For a given $\gamma \in \Gamma$, we obtained the fixed effects of $\hat{\beta}_1(\gamma), \hat{\beta}_2(\gamma), \hat{\eta}_1(\gamma), \hat{\eta}_2(\gamma)$, and further computed $\hat{\alpha}_i(\gamma)$ and residual error $\hat{e}_{it}(\gamma)$. For individual i, the bootstrapping external variable and error $(x_i^*, e_i^*(\gamma))$ could be obtained by substitution (i.e., $\left(x_{is}^*, e_{is}^*\right) = (x_{i\tau}, e_{i\tau})$; $s = 1,\ldots,T$; and τ randomly substitutes $\{1,\ldots,T\}$). When the bootstrapped sample is obtained, the transposed parameter after corrected bias can be easily estimated.

After estimating the optimal panel threshold value $\hat{\gamma}$, the panel threshold effect test is conducted to examine whether the panel threshold effect is significant. The null hypothesis of the test is

$$\mathrm{H}_0 : \alpha_1 = \alpha_1 \text{ and } \beta_1 = \beta_1 \tag{A2}$$

Under the null hypothesis of Equation (A2), the threshold of this model disappears and becomes the model of Arellano and Bond (1991), which has no threshold:

$$y_{i,t} = \mu_i + \alpha_1' y_{i,t-1} + \beta_1' x_{i,t} + e_{i,t} \tag{A3}$$

Following estimation, the omission of μ_i leads to

$$y_{i,t}^* = \alpha_1' y_{i,t-1}^*(\gamma) + \beta_1' x_{i,t}^* + e_{i,t} \tag{A4}$$

The regression parameter β_1 is estimated by ordinary least squares, yielding estimate $\tilde{\beta}_1$, the residual error of $\hat{e}_{i,t}^*$ and the sum of squared errors $\tilde{S}_0$ are $\hat{e}^{*'}\hat{e}^*$. Therefore, under the null hypothesis of Equation (A2), its test statistic is as follows:

$$F_1 = \frac{\hat{S}_0 - S_1^*(\hat{\gamma})}{\hat{\sigma}^2} \tag{A5}$$

Since the n.ull hypothesis of the model was defined as without a threshold effect (its threshold value γ was not identified), the commonly used standard test statistics such as L.M. and Wald statistics cannot be used. Since the D.P.T.M. model is an extended P.T.M. of Hansen

(1999), we followed the suggestion of Hansen and King (1996) and used the bootstrapping method to simulate the critical value of F_1 test statistics during the testing process.[6] As soon as we discover the threshold effect, we can further test for the value of γ to determine the magnitude of the threshold effect. According to Hansen (1999), the null hypothesis test would then be H_0: $\gamma = \gamma_0$ and its proximity ratio

$$LR_1(\gamma_0) = \frac{S_1^*(\gamma_0) - S_1^*(\hat{\gamma})}{\hat{\sigma}^2} \tag{A6}$$

The above-mentioned asymptotic distribution of the LR_1 test statistic was not a standard Chi-square distribution. Hence, we can use the standard approach to find the critical value of the test. Since the asymptotic distribution in this D.P.T.M. is unclear, we temporarily apply the methodology derived from Hansen (1999) to conduct the test. However, we are unable to determine whether it is completely consistent with the current settings of our model. This issue will be taken up in a future study.[7] Here, we apply the formula suggested by Hansen (1999) to calculate the critical value of the significant level α:

$$c(\alpha) = -1\log(1 - \sqrt{1-\alpha}) \tag{A7}$$

When $LR_1(\gamma_0)$ exceeded the critical value $c(\alpha)$, the null hypothesis is rejected, meaning that the effects from the application of D.P.T.M. are significant. For the next step, we take the previously estimated threshold value as given for our search of the second threshold, where $\hat{\lambda}_2^{\gamma}$ is the estimation for the second threshold value such that Equation (A7) is valid:

$$\hat{\gamma}_2^{\gamma} = arg \min_{\gamma^2} S_2^*(\gamma_2) \tag{A8}$$

$$S_2^{\gamma^*}(\gamma_2) = \begin{cases} S^*(\hat{\gamma}_1, \gamma_2), \ if \ \hat{\gamma}_1 < \gamma_2 \\ S^*(\gamma_2, \hat{\gamma}_1), \ if \ \gamma_2 < \hat{\gamma}_1 \end{cases}$$

The corresponding variance of the residual errors for the estimated second threshold value is $\hat{\sigma}_2^2 = \frac{1}{N(T-1)} S_2^{\gamma^*}(\hat{\gamma}_2^{\gamma})$. After obtaining this variance, we conducted a test for the second threshold effect, for which the null and alternative hypotheses are respectively stated below:

H_0: Only one threshold value.

H_1: Two threshold values exist.

The F_2 statistic of the corresponding test is given as

$$F_2 = \frac{S_1^*(\hat{\gamma}_1) - S_2^{\gamma^*}(\hat{\gamma}_2^{\gamma})}{\hat{\sigma}^2} \tag{A9}$$

The LR proximity ratios for $LR_1^{\gamma}(\gamma)$ and $LR_2^{\gamma}(\gamma)$ are as follows:

$$LR_1^{\gamma}(\gamma) = \frac{S_1^{\gamma^*}(\gamma) - S_1^{\gamma^*}(\hat{\gamma}_1^{\gamma})}{\hat{\sigma}^2} \tag{A10}$$

$$LR_2^{\gamma}(\gamma) = \frac{S_2^{\gamma^*}(\gamma) - S_2^{\gamma^*}(\hat{\gamma}_2^{\gamma})}{\hat{\sigma}^2} \tag{A11}$$

Following Bai (1997), who stated that the estimation process of a double threshold regression model should hold the same asymptotic distribution as that of a single threshold regression model, we take the same approach of a single threshold regression model to construct the critical values for the test statistics in Equations (A9), (A10) and (A11). An approach similar to that suggested by Hansen and King (1996) was taken: the bootstrapping method was applied to obtain the asymptotic distribution and simulate critical values for the F_2 test statistic. For $LR_1^{\gamma}(\gamma)$ and $LR_2^{\gamma}(\gamma)$, we used Equation (A7) to calculate the critical value of the significant level α, as suggested by Hansen (1999). If two panel threshold effects existed after the test, we have to accept that as an assumption and re-estimate the data to further obtain the double panel threshold estimates with the minimum sum of squared errors.