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The Impact of Regulatory Quality on the Nexus between Life Insurance Development and Economic Growth: Evidence from European Developing Countries

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Abstract

The purpose of this study is to explore whether the regulatory quality influences the relation between life insurance development and economic growth by applying a nonlinear panel smooth transition regression (PSTR) model. Using the data from Worldwide Governance Indicators (WGI) to assess the soundness of regulatory quality, this paper finds that the relationship between life insurance development and economic growth is significantly positive in the countries with relatively better regulatory quality. Our findings not only indicate that sound regulatory quality could encourage the growth effect of life insurance sectors but also have far-reaching practical implications for other economies to realize regulatory quality should matter for the development of the economic growth.

JEL classification numbers: E44, G22, O11, O47, P34

Keywords: Regulatory quality, Life insurance development, Economic growth, Nonlinear panel smooth transition regression (PSTR) model.

1 Introduction

It is widely believed that regulatory quality constitutes a potentially important mechanism for supporting a country's economic and financial development. However, only a few amounts of literature have been devoted to understanding the impact of regulatory quality on insurance market activities and economic growth. The main purpose of this study is to examine how regulatory quality affects the relation between life insurance development and economic growth by applying an innovative panel smooth transition regression (PSTR) model.

Prior literature shows that the impact of regulatory quality on economic growth is divergent. Some studies indicate that regulatory quality-related variables have a positive impact on economic growth (Clague et al., 1996; Minier, 1998; Persson, 2005), while a negative influence is documented as well (Blanchard and Shleifer, 2000; Persson and Tabellini, 1992; Tavares and Wacziarg, 2001). Additionally, the existing empirical findings on the effect of regulatory quality in life insurance market activities mainly investigate their direct impact on insurance. It is interesting to explore whether regulatory quality shapes the relationship between life insurance development and economic growth.

In this study, we utilize the data from Worldwide Governance Indicators (WGI) to assess the soundness of regulatory quality. The WGI is a long-standing research project to develop cross-country

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indicators of governance. Most importantly, these indicators are based on several hundred variables obtained from 31 different data sources, capturing governance perceptions as reported by survey respondents, non-governmental organizations, commercial business information providers, and public sector organizations worldwide. Regulatory quality in WGI is defined as capturing perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. The full sample dataset comprises a balanced panel of 11 European developing countries with a sample period from 2002 through 2017.

This study proceeds with two steps to examine the effects of regulatory quality on the relationship between life insurance development and economic growth. First, we apply a threshold technique with the instrumental variables to endogenously divide countries into groups with different levels of regulatory quality. Second, we investigate whether the effect of regulatory quality on life insurance development varies under different levels of economic development. If exceptions do exist, then it may not be possible to form a consensus applicable to all countries. This would mean that certain conditions must be modified and that other pre-conditions be met before a country conforms to anyone's universal consensus. Our main results demonstrate that the relationship between life insurance development and economic growth is significantly positive in the countries with relatively better regulatory quality.

Our empirical findings make several contributions to the literature. First, comparing to prior studies that separately investigate the effect of regulatory quality on insurance development (Ward and Zurbruegg, 2002; Beck and Webb, 2003; Lee et al., 2013) and the effect of insurance on economic growth (Han et al., 2010; Chen et al., 2012; Lee et al., 2013; Chang et al., 2014), we examine how regulatory quality shape the impact of insurance development on economic growth by a novel dynamic panel threshold model. Second, our findings further proof that a better regulatory quality indeed plays an important role in the relationship between life insurance market activities and economic growth.

The rest of this paper is as follows. Section 2 explains both the Moon and Perron unit root test and the primary structure of the PSTR model we apply in this research. Section 3 describes the data and variable selection. Section 4 presents our main empirical results of the PSTR model. Section 5 presents conclusions and further discussions.

2 Data and Methodology

2.1 Data

This paper adopts the quantitative methods to examine how regulatory quality affect the relation between life insurance development and economic growth by applying an innovative panel smooth transition regression (PSTR) model. We investigate the data-set of 11 European developing countries from 2000 to 2017. The real GDP (RGDP) per capita indicates the country's level of economic growth and the life insurance density (LID) per capita as proxy variable of development of insurance. Previous literature also uses life insurance density as insurance development indicators (Kjosevski, 2011, Cristea, 2014, Zouhaier 2014 & Dhiab et al., 2015), while other researches, such as Webb et al. (2002), Phutkaradze (2014) and Dhiab et al. (2015) use annual real GDP per capita as a proxy for economic growth. The data related to life insurance are collected from the base of Sigma SwissR data. The data of real GDP per capita is taken from the Organization for Economic Co-operation and Development and the World Bank Group.

To strengthen the reliability of evidence in this study, we add useful macroeconomic variables as control variables. Share price indices (INDEX) are calculated from the prices of common shares of companies traded on national or foreign stock exchanges, computed from the prices of selected stocks (typically a weighted average). The indicator is set as 100 in 2015. Exchange rates (EXRATE) are defined as the price of one country's currency to another. The indicator is measured in terms of US dollar per national currency. Gross fixed capital formations (CAPITAL) comprise the inhabitant investments of producer and deducting disposals in fixed assets during a given period. Trade (TRADE) is defined as import plus export. Exports of goods and services are the value of exporting goods and services at current prices, and Imports of goods and services are the value of importing goods and services in current prices.

Unemployment (UNEMP) is defined as the percentage of unemployed workers in the total labor force, and the unemployment rate is the number of unemployed divided by the number of the labor force in percentage. Inflation (INFLATION) is measured by the annual growth rate of the GDP implicit deflator displays the ratio of price varies within the economy as a whole. Long-term interest rates (LTINT) refer to government bonds maturing in ten years and to bonds whose capital repayment is guaranteed by governments. These macroeconomic variables are also taken from the Organization for Economic Co-operation and Development and the World Bank Group.

In this study, we utilize regulatory quality (RQ) as a transition variable in our PSTR model. Regulatory quality in WGI is defined as capturing perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. Table 1 outlines the longitudinal statistics for each variable in our study.

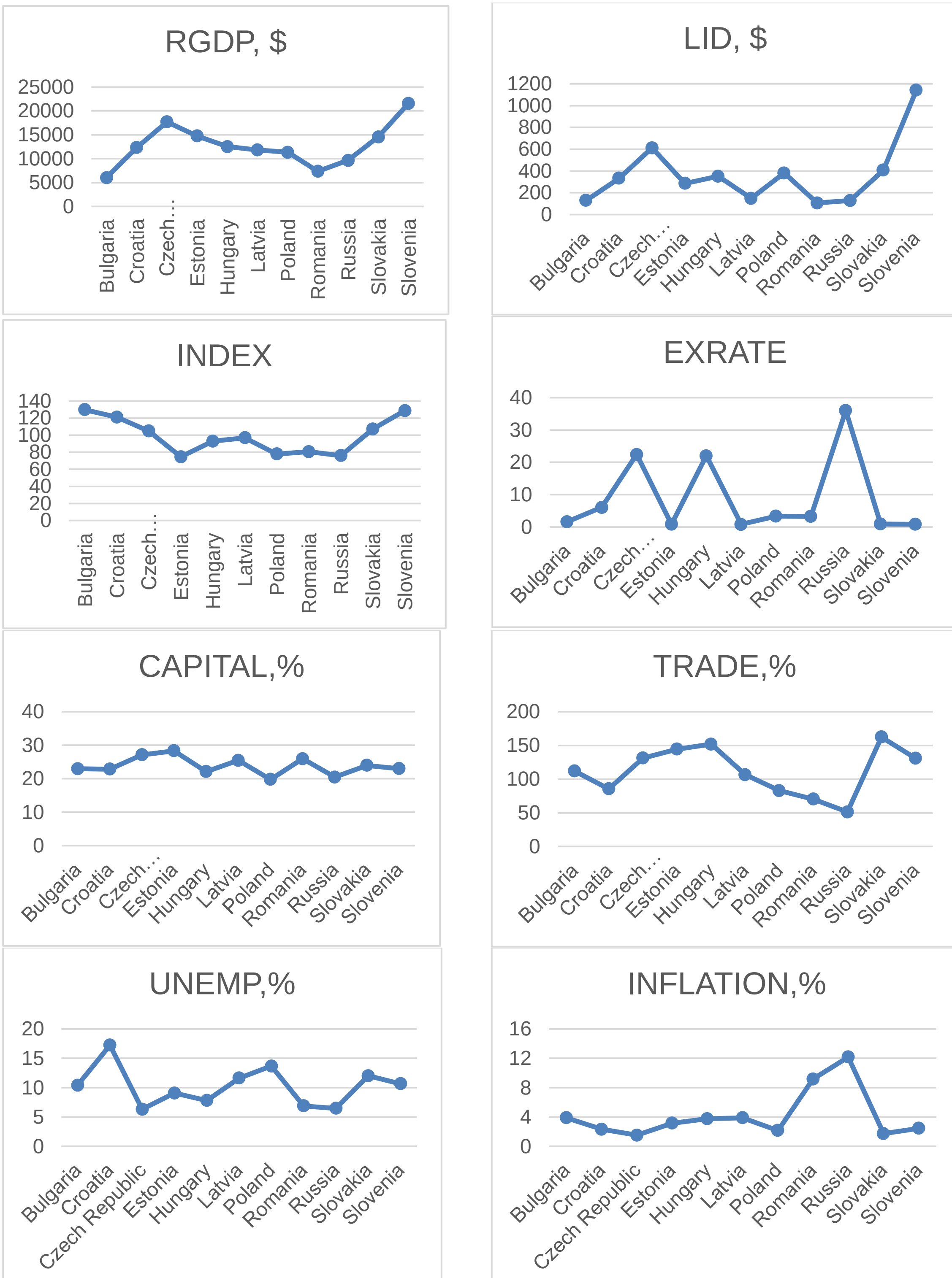
Table 1 shows that the average, minimum and maximum real GDP (RGDP) per capita of the overall sample countries in our study are $12,703, $2,078 and $27,448 respectively. Also, the average, minimum and maximum life insurance densities (LID) of the overall sample countries in this study respectively are $124, $2 and $465.respectively are $124, $2 and $465. Moreover, Table 1 also indicates that the skewness and Kurtosis of these variables utilizing in this study. The skewness of regulatory quality (RQ) is negative which means that the tail is on the left side of the distribution. The kurtosis of RGDP is less than 3 implying that the distribution produces fewer and less extreme outliers than does the normal distribution

Figure 1 indicates the cross-sectional variables descriptive statistics of 11 European developing countries, where mean value only. From this

figure, we observe that Slovenia has a higher average RGDP and LID than other countries. Most interestingly, the most higher average of RQ in our sample is Estonia.

Table 1: Variable Descriptive Statistics for European Developing Countries from Years 2002 to 2017

Variables	Mean	Max	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
RGDP, $	12703	27448	2078	5602	0.25	2.48	3.83	0.15
LID, $	124	465	2	118	0.95	2.92	26.35	0.00
INDEX	99.19	370.12	17.83	47.98	2.13	11.37	647.02	0.00
EXRATE	27.23	281.52	0.68	64.12	2.82	9.54	546.46	0.00
CAPITAL, %	111.76	189.18	46.19	37.66	0.05	2.00	7.45	0.02
TRADE, %	23.82	37.36	17.58	4.29	0.93	3.64	28.36	0.00
UNEMP, %	10.20	22.29	2.89	4.10	0.78	2.93	18.04	0.00
INFLATION	4.20	24.81	-1.71	4.88	2.06	7.45	270.03	0.00
LTINT, %	5.10	15.82	0.43	2.44	0.67	4.56	31.07	0.00
RQ	73.77	93.27	32.21	0.47	-0.90	3.78	28.28	0.00


RGDP, $
25000
20000
15000
10000
5000
0
Bulgaria Croatia Czech… Estonia Hungary Latvia Poland Romania Russia Slovakia Slovenia
LID, $
1200
1000
800
600
400
200
0
Bulgaria Croatia Czech… Estonia Hungary Latvia Poland Romania Russia Slovakia Slovenia
INDEX
140
120
100
80
60
40
20
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Bulgaria Croatia Czech… Estonia Hungary Latvia Poland Romania Russia Slovakia Slovenia
EXRATE
40
30
20
10
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Bulgaria Croatia Czech… Estonia Hungary Latvia Poland Romania Russia Slovakia Slovenia
CAPITAL,%
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TRADE,%
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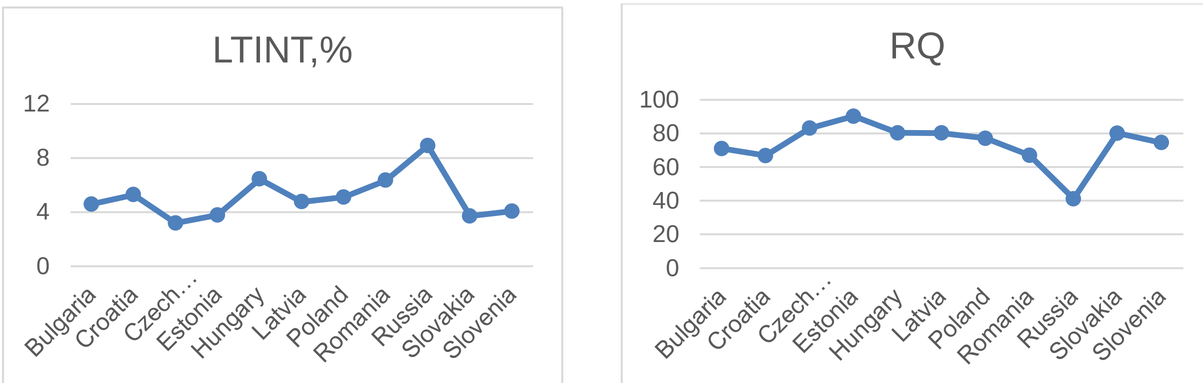
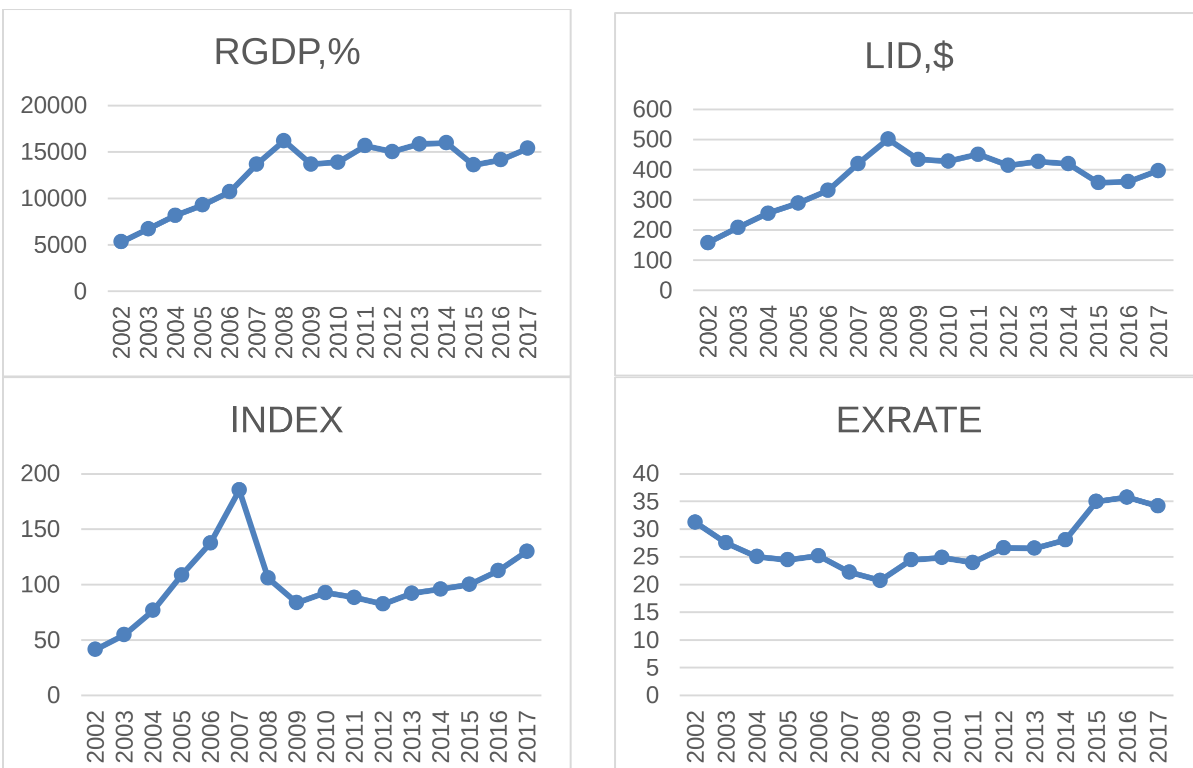


Figure 1: Cross-Sectional Variables Descriptive Statistics of 11 European Developing Countries

Figure 2 indicates the time-series variables descriptive statistics of 11 European developing countries from 2000 to 2017, where mean value only. According to this figure, we find that the highest RGDP and LID are in 2008. Additionally, these figures imply that the relationship between life insurance development and economic growth is positive.



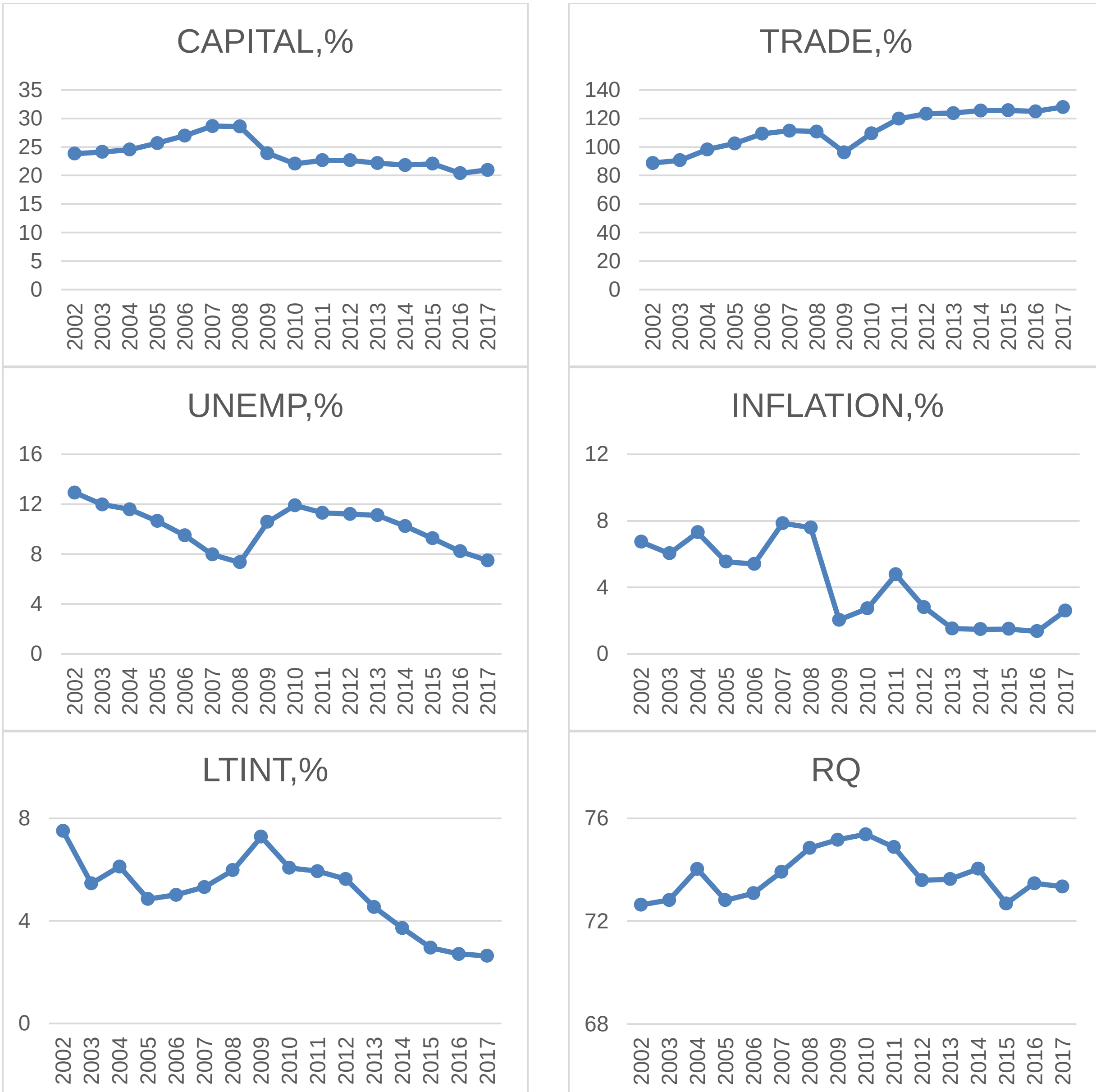


Figure 2: Time-Series Variables Descriptive Statistics of 11 European Developing Countries

2.2 Moon and Perron unit root test

In order to make sure all variables in the panel of this study are stationary before exercising the PSTR model, we initially execute Moon and Perron unit root test that was developed by Moon and Perron (2004). Among the panel unit root tests, Bai and Ng (2004) supplied an intact program to examine the degree of integration of series, and permit to tests for unit roots in the common factors and characteristic factors. Moon and Perron (2004) used a factor structure to simulate cross-sectional dependence, and used normal autoregressive procedure with fixed effects, that residuals follow a factor model. They stated that their intention for these de-factored data is similar, but still account for multiple common factors, in which the model is slightly different from Bai and Ng's (2004). Moon and Perron (2004) considered that the error terms are produced with r common factors and idiosyncratic shocks, with the same symbol as before, since the model can be written:

$$y_{it} = \alpha_i + y_{it}^0 \tag{1}$$

$$y_{it}^0 = \rho_i y_{i,t-1}^0 + \mu_{it} \tag{2}$$

$$\mu_{it} = \lambda_i' F_t + e_{it} \tag{3}$$

Where the null hypothesis corresponds to the unit root hypothesis H_0: $\rho_i = 1$, $\forall_i = 1,\ldots, N$, λ_i is a vector of factor loadings, F_t is a r × 1 vector of common factors and the idiosyncratic component e_{it} is assumed to be i.i.d., across i and over t. Whereas under the alternative the variable y_{it} is stationary for at least one cross-sectional unit. These examination processes include two steps, the first step, the data are decomposed, and the next step, the panel unit root test statistics depend on decomposed data and common factors are then raised. We want to know whether the factor structure permits for clear-cut conclusions about the stability of macroeconomic variables.

Moon and Perron (2004) want to remove the common factors, thus, the panel data must be projected onto the space orthogonal to the factor loadings, the de-factored residual and the de-factored data no more possess cross-sectional dependencies. They process the factors as nuisance parameters and suggest pooling de-factored data to construct a unit root test. It is probable to define standard pooled t-statistics, like in IPS, and to display their asymptotic normality. Since let $\hat{p}_{pool}^{+}$ be the modified pooled OLS estimator applying the de-factored panel data. There are two modified t-statistics which have a standard normal distribution under the null hypothesis following:

$$t_a = \frac{T\sqrt{N}(\hat{p}_{pool}^{+} - 1)}{\sqrt{2\gamma_e^4/\omega_e^4}} \xrightarrow[N,T\to\infty]{d} N(0,1) \tag{4}$$

$$t_b = T\sqrt{N}\left(\hat{p}_{pool}^{+} - 1\right)\sqrt{\frac{1}{NT^2} trace(Z_{-1}Q_A Z_{-1}')\frac{\omega_e^2}{\gamma_e^4}} \xrightarrow[N,T\to\infty]{d} N(0,1) \tag{5}$$

Where$\omega_e^2$is the cross-sectional average of the long-run variances$\omega_{ei}^2$of residual e_{it}, γ_e^4 is the cross-sectional average of ω_{ei}^4. And they raise feasible statistics t_a^* and t_b^* based on the estimator of the projection matrix and estimators of long-run variancesω_{ei}^2.

2.3 Panel smooth transaction regression model

The PSTR model proposed by González et al. (2005) is to be considered as the most recent extension STR model on panel data with heterogeneity among the panel members and throughout time. The underlying PSTR model consists of a single transition function and two extreme regimes that can be described as follow:

$$y_{it} = \mu_i + \beta_0' X_{it} + \beta_1' X_{it} g(q_{it}; \gamma, C) + \varepsilon_{it} \tag{6}$$

where i =1,⋯,N, t= 1,⋯, T. Specifically, N and T present the cross-section and time dimensions of the panel, respectively. The dependent variable y_{it} is a scalar; μ_i means the fixed individual effect; X_{it} is a k-dimensional vector of time-varying exogenous variables; and ε_{it} is the residual term. The transition function $g(q_{it}; \gamma, C)$, a continuous function of the observable variable q_{it}, is normalized to be bounded between 0 and 1; these extreme values are associated with regression coefficients β_0' and $\beta_0' + \beta_1'$. The vale of q_{it} determine the values of $g(q_{it}; \gamma, C)$, and thus the effective regression coefficient are $\beta_0' + \beta_1' g(q_{it}; \gamma, C)$ for individual i at time t. Following the method proposed by Granger and Terӓsvirta (1993), Terässvirta (1994), and Jansen and Terässvirta (1996), we expressed the transition function as follows:

$$g(q_{it};\gamma,C)=\left(1+exp\left(-\gamma\prod_{j=1}^{m}(q_{it}-c_j)\right)\right)^{-1}\ with\ \gamma>0\ and\ C_1\le C_2\le\cdots\le C_m \quad (7)$$

where $C=(C_1,\cdots,C_m)'$ is an m-dimension vector of location parameters and the slope parameter γ determines the smoothness of the transaction. In general, considering m=1 or m=2 is sufficient, because these values allow for typically encountered variations in the parameters. In the case of m=1, the model identifies that the two extreme regimes are associated with low and high values of q_{it} and that a single monotonic transition of the coefficients exists from β_0' to $\beta_0'+\beta_1'$ as q_{it} increases, such that the change is centered near C_1. In the case of m=2, the minimum of the transition function is at $(C_1+C_2)/2$ and achieves the value one at the low and high values of q_{it}. When γ approaches infinity, the PSTR model reduces to a three-regime panel threshold regression PTR model the outer regimes of which are identical to each other but different from the middle regime.

The multi-level PSTR model is a generalized PSTR model that allows for more than two different regimes; it can be expressed as follows:

$$y_{it}=\mu_i+\beta_0'X_{it}+\sum_{j=1}^{r}\beta_1'X_{it}g_j\left(q_{it}^{j};\gamma_j,c_j\right)+\varepsilon_{it} \quad (8)$$

where the transition function $g_j\left(q_{it}^{j};\gamma_j,c_j\right)$, j=1,⋯,r depend in the slope parameters γ_j and on the location parameters c_j. If r = 1, $q_{it}^{j}=q_{it}$, and $\gamma_j\rightarrow\infty$ for all j=1,⋯,r, the transition function becomes an indicator function , in which I$[A]$ = 1 when event A occurs, and I$[A]$ = 0 otherwise; the model in Eq. (4) becomes a PTR model with r + 1 regimes. Consequently, the multilevel PSTR model is a generalization of the multiple regimes PTR denoted by Hansen (1999).

2.4 Building the panel smooth transition regression model

Building the panel smooth transition regression model requires three stages, such as specification, estimation, and evaluation. The specification stage includes testing for homogeneity and choosing the transition variable q_{it}. If the testing fails to exhibit homogeneity, specification covers determining the appropriate form of the transition function; this form is described by the value of m in Eq. (3). A nonlinear least square method is used to estimate parameters. On the estimation stage, the estimated model is restricted to misspecification tests to determine whether adequate data description is provided. The null hypotheses tested in this stage contain parameter constancy, absence of remaining heterogeneity, and absence of autocorrelation among the errors. On the last stage, the number of regimes in the panel must be specified, implying that value has to be assigned to r in Eq. (4).

3 Estimation Results and Interpretations

The number of common factors r is estimated for each variable in table 4. Unlink Bai and Ng (2004), Moon and Perron (2004) used $\hat{y}$ as residuals and the information criteria are calculated from demeaned first differences. Similarly, we calculate two statistics t_a^* and t_b^* with Bartlett and Quadratic Spectral kernel after assessing the sensitivity of our results to the choice of the kernel function used to estimate ω_{ei}^2,. In this case, bandwidth parameters are optimally chosen according to the procedure of Newey and West (1994). And the results for a model with time trends are replied. We employ the same criteria to appraise the number of common factors as if this model only has individual effects. During a model within individual effects, the null is extremely rejected for all variables.

When international cross-correlations are taken into account, the results rely on the specification of these cross-sectional dependencies. The series tests are built on a dynamic factor model by Moon and Perron and opposition to these specifications is dependent on a common factor or time effects. It appears that the consequents are globally and intelligibly better in favor of the unit root assumption for most leading macroeconomic and financial indicators.

Table 5 presents the threshold as well as parameter estimates using regulatory quality (RQ) as the transition variable. The effect of life insurance density (LID) on economic growth differs across different regimes of regulatory quality level. Life insurance has a significantly negative impact on economic growth if the soundness of regulatory quality is weak. In contrast, this negative effect of insurance development on economic growth becomes significantly positive after a country's regulatory quality exceeds a certain level of threshold. Regarding the effects of other control variables on economic growth, the results are generally consistent with the findings in the growth literature. In sum, the evidence of table 5 reveals that regulatory quality plays an important role in the growth effect of life insurance.

Table 4: Moon and Perron Panel Unit Root Test for All Sample

Variables	$\hat{\gamma}$	t_a^*	t_b^*	$\hat{p}_{pool}^*$	t_a^{*B}	t_b^{*B}	$\hat{p}_{pool}^{*B}$
RGDP	5	-11.589	-5.889	0.591	-11.750	-5.957	0.590
		0.000	0.000		0.000	0.000	
LID	5	-6.949	-4.333	0.696	-8.183	-4.776	0.671
		0.000	0.000		0.000	0.000	
INDEX	5	-12.641	-7.022	0.484	-13.701	-7.324	0.467
		0.000	0.000		0.000	0.000	
EXRATE	5	-4.675	-3.647	0.811	-6.297	-3.447	0.699
		0.000	0.000		0.000	0.000	
CAPITAL	5	-7.048	-4.947	0.742	-6.889	-5.070	0.755
		0.000	0.000		0.000	0.000	
TRADE	4	-8.767	-5.855	0.691	-9.216	-6.150	0.691
		0.000	0.000		0.000	0.000	
UNEMP	5	-7.865	-6.521	0.639	-8.029	-6.937	0.647
		0.000	0.000		0.000	0.000	
INFLATION	5	-16.615	-8.874	0.383	-18.281	-9.373	0.363
		0.000	0.000		0.000	0.000	
LTINT	5	-12.799	-9.222	0.538	-14.388	-9.182	0.502
		0.000	0.000		0.000	0.000	
RQ	3	-10.519	-7.376	0.635	-11.638	-7.390	0.605
		0.000	0.000		0.000	0.000	

Table 5: Linearity Test and Parameter Estimation for All Sample

Specification		**PSTR**
Transition variable		**RQ**
Fisher Test with the null of linearity		27.724*** (0.000)
Fisher Test with the null of r=1		1.632 (0.122)
VARIABLES	**Parameter $\widehat{\beta_0}$**	**Parameter $\widehat{\beta_0}$+$\widehat{\beta_1}$**
LID	-0.0994***	0.4272***
LINDEX	0.1774*	0.0168
EXRATE	-0.0104***	-0.0010*
CAPITAL	0.0572**	-0.0168*
TRADE	-0.0582***	0.0065***
UNEMP	-0.1421***	-0.0322
INFLATION	0.0114***	-0.0003
LTINT	-0.0298***	0.0369***
Location parameter	C1= 58.9647	
Smooth parameter	γ1= 0.8685	
Residual sum of squares	RSS= 1.8652	

Note: *, **, and *** stand for 10%, 5%, and 1% significant level.

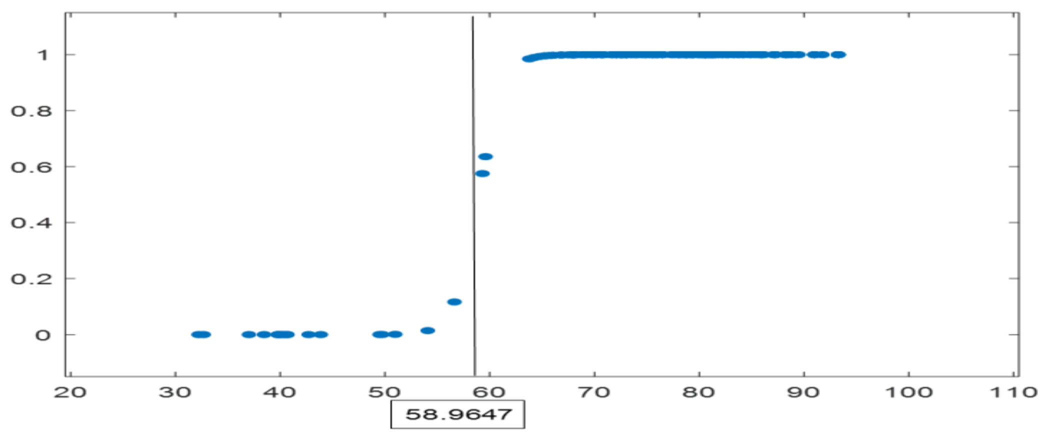


Figure 3: The Transition Function Value for all Sample

Also, Figure 3 depicts the scattered charts showing the changes in the transition function value for all samples in our study. We can obviously tell that the coefficients changed smoothly from weak regulatory quality to strong regimes. From Figure 4, we can see the threshold of regulatory quality is 58.9647 for these European developing countries. Specifically, most of these countries in our sample had reached this level, except Russia. Again, our results imply that life insurance development could be harmful because of the problem of adverse selection and moral hazard when lacking a sound regulatory quality environment. On the contrary, when it has achieved a certain level or threshold of regulatory quality, this significantly negative effect becomes positive and significant.

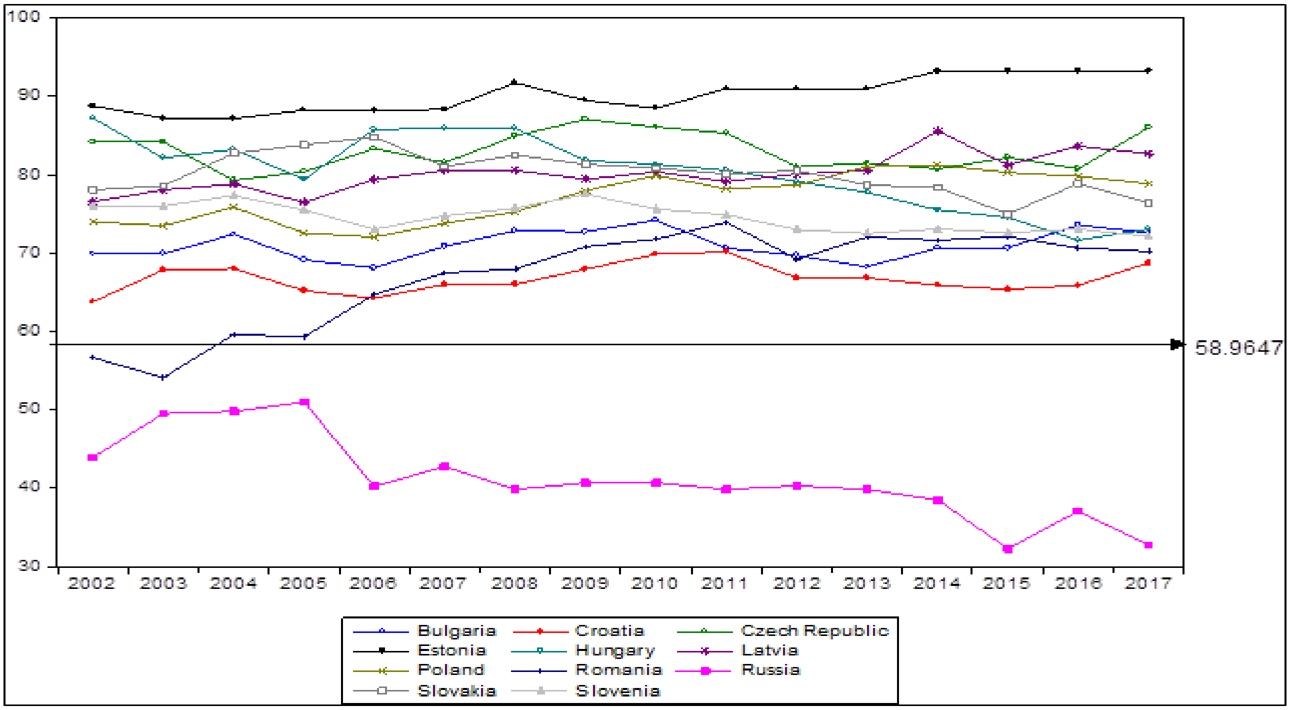


Figure 4: Regulatory Quality for 11 European Developing Countries from Years 2002 to 2017

4 Conclusion

The main purpose of this study is to examine whether regulatory quality affects the relationship between life insurance development and economic growth by applying an innovative panel smooth transition regression (PSTR) model. We investigate the data-set of 11 European developing countries from 2000 to 2017.

The empirical results show that the effect of life insurance density on economic growth differs across different regimes of regulatory quality level. Life insurance has a significantly negative impact on economic growth if the soundness of regulatory quality is weak. In contrast, this negative effect of insurance development on economic growth becomes significantly positive after a country's regulatory quality exceeds a certain level of threshold.

Our empirical findings demonstrate that unhealthy circumstances of regulatory quality could deter the growth effect of life insurance sectors. It implies that policymakers and authorities should pay particular attention to consider taking some specific measures in order to improve regulatory quality. For example, control of corruption is crucial for improving regulatory quality. As we know, corruption leads to an inefficient allocation of resources, leading to high investment cost and low profits of government as well foreign investors. These interesting results and suggestions may provide rich implications for non-European economies.

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