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The CCE model applied to the nexus of real GDP and the insurance market

- Allowing cross-sectional dependence in panel data estimations

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Abstract

Existing studies on the relationship between the insurance market and economic development tend to use empirical methods that rely on the unrealistic assumption of cross-sectional independence. This thesis aims to highlight the drawbacks of this assumption. The results are achieved by comparing the results of the Common Correlated Effects (CCE) model to the two-way fixed effects model as well as the fixed effects model. All three models confirm most previous research, stating that there is a positive cointegrated relationship between the insurance market and real GDP. However, the results show that the CCE model accounts for more unobserved heterogeneity than the competition. This is indicated by a higher degree of normally distributed residuals which are assigned a significantly lower degree of absolute average pairwise correlation. Therefore, the estimates produced by the CCE model are more reliable, making it more appropriate to use when investigating cross-sectionally dependent panel data.

Keywords: Insurance market, economic development, cross-sectional dependence, cointegration, CCE estimation.

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1. Introduction

The importance of the insurance market, as an *"essential characteristic of economic growth"* (UNCTAD, 1964. p. 55), was formally acknowledged at the very first United Nations Conference of Trade and development in 1964. Previous research often points out two main ways in which the market contributes. Firstly, by mobilizing capital and channel it into the corporate and public sector. Insurance companies are, together with investments and pension funds, the major institutional investor of funds into the financial markets. Along with deregulation and globalisation, their impact as financial intermediaries have increased substantially over recent decades (OECD, 2020). In fact, during the 1990s the total assets of insurance companies grew faster than the ones of banks (Outreville, 2013). Secondly, the insurance market creates financial stability by the transferring of risk to an entity that is better equipped to bear it. This encourages individuals and firms to specialize and potentially undertake projects that they would not have otherwise. It is also of importance for trade, commerce, and entrepreneurial activity in general since many of these sectors incorporate manufacturing, shipping, and other services that are considerably reliant on insurance (Das et al., 2003).

There are many types of insurances that protect the owner from different kinds of risks which affect economic activity in various ways. The most common way of generalising the sector is to divide the market into life and nonlife insurances. Life insurance mainly protects against risks concerning health, savings, pensions, or inability to work. Nonlife insurance, also called property-liability insurance, often refers to financial protection against any other risks that are not included in life insurance, for example: credit, mortgage, or auto insurance. The division has shown to be successful when evaluating differences in the importance of the market, not least when also taking countries' level of development into account. These studies most often conclude that life insurance is more important for advanced countries and that nonlife insurance has more influence in emerging countries, see Haiss & Sümegi (2008) and Arena (2008) for two notable examples.

A potential structural change in the insurance market in recent years lies in the internal relationship between life and nonlife insurance penetration (ratio of premiums to GDP) in advanced countries. Before the great financial crisis, life insurance was larger than nonlife insurance in terms of penetration. But changes during the last decade have reversed this relationship. This development cannot be seen in emerging countries where life and nonlife insurance penetration follow a similar trend and the relationship is relatively stable (Sigma no4, 2020).

It is well documented that most economic and financial variables evaluated across countries are likely to be affected by cross-sectional dependence (CD). However, there is a lack of studies considering CD when analysing the relationship between the insurance market and economic development. This may result in a misleading conception of the relationship since conventional panel data methods such as the pooled ordinary least squares and the generalised least squares as well as the fixed effects and random effects estimators are likely to produce inconsistent estimations under CD (Le et al., 2018).

The common correlated effects (CCE) estimator of Pesaran (2006) models CD via so-called common factors. This relatively new econometric approach has received considerable attention in panel data regressions, so much that it now constitutes a new branch in the literature (Reese, 2017, p. 11, 148). Additional findings by Westerlund et al. (2019) have made it possible to use the CCE model in panels with a small number of time periods (T).

The purpose of this thesis is to highlight the drawbacks of using conventional panel data models in the presence of CD while re-examining the relationship between the insurance market and real GDP. The results will be achieved by comparing the results of the CCE model to the fixed effects model as well as the two-way fixed effects model. To the best of my knowledge, this is the first time that the CCE estimator is applied to the analysis of the insurance market. The model allows for more unobserved heterogeneity which makes it possible to consider a larger and more heterogeneous set of countries. While many previous studies on the topic focus on a smaller set of countries, the 73 countries included in this thesis will allow for a wider analysis even though the period of 20 years is relatively short. Since most previous research relies on observations before 2010 [1], the 9 subsequent years included in this study makes it possible to explore potential changes in the market during recent years.

This thesis is organized into six chapters. The next chapter provides background and an overview of the previous literature on the relationship between the insurance market and economic development as well as an introduction to the literature on CD. Thereafter, we move on to the presentation and motivation of the econometric methodology in chapter three. The fourth chapter describes the dataset which is accompanied by descriptive statistics and tests.

[1] See Din et al., (2017) for a recent survey regarding studies on insurance and economic growth.

Chapter five provides test results and regression analysis. The sixth and final chapter is dedicated to concluding remarks and a discussion regarding limitations and future research.

2. Literature review

2.1. Insurance market and economic development

The relationship between the financial market and economic development has received considerable empirical attention. Most of these studies either use the credit market or the stock market as separate or simultaneous measures of financial development. The empirical evidence indicates that the banking sector and stock market have an independent, significant, and positive effect on economic growth. For example, the studies of King & Levine (1993) and Beck & Levine (2004) both use panel data estimations and come to similar conclusions, stating that the correlation is strong and robust.

Compared to the vast research focusing on the credit market and the stock market, relatively few studies have examined the relationship between economic development and the insurance market (Haiss & Sümegi, 2008). Most empirical studies that do, implicitly base their economic growth theory on a Solow-Swan neoclassical growth model. This model implies that growth in production is due to changes in labour, capital, and technology, where increasing insurance activities increase productivity which in turn drives the level of investment and output (Outreville, 2013).

The relationship was first explored by Ward & Zurbruegg (2000). The authors examined the short- and long-run dynamic relationship between annual real GDP and total real premiums from 1961 to 1996. Based on cointegration analysis and causality tests, the study concludes that the insurance industry granger causes economic growth in some countries but that the relationship is reversed in others [2]. Two of the countries where the relationship was found to be reversed are The United Kingdom and The USA (Ward & Zurbruegg, 2000).

Their results are, however, disputed. Kugler & Ofoghi (2005) points out that it is possible to find cointegration at an aggregate level and no cointegration at a disaggregated level and vice versa. The authors argue that the results of Ward and Zurbruegg (2000) were affected by the fact that they used aggregate data of total insurance, combining all insurance premiums, instead of a disaggregated level. While re-examining the relationship in The United Kingdom, Kugler

[2] Granger causality refers to lagged causality, if lagged values of x_{it} causes y_{it} or vice versa it is said to have granger causality (Enders, 2010 p. 318)

& Ofoghi (2005) divide insurance premiums into several different sectors for example motor, accident, and health insurance. Their results conclude that there is a long-run relationship between the insurance market and economic growth in The United Kingdom and that relationship is bilateral, contradicting the results of Ward and Zurbruegg (2000).

Furthermore, Webb et al. (2002) examine the relationship of 55 countries over the period 1980 – 1996 and divides the market into life and nonlife insurance premiums. The data was separately and together with traditional control variables believed to explain growth (human capital, export, and technology) subject to a three-stage-least square instrumental variables approach. Their findings suggest a highly significant correlation between the insurance market and economic growth.

As pointed out, there are some disagreements on the relation between the insurance market and economic development and how to properly address the issue. However, most empirical research concludes that the insurance market has a positive impact on economic development and that the cointegrating relationship is significant.

2.2. Literature on cross-sectional dependence

Increased globalization and economic integration between countries and their financial entities have made CD likely to be rule rather than exception when analysing macroeconomic data (Westerlund & Edgerton, 2008). The presence of CD may result in misleading inference and inconsistent estimators, it is therefore important to investigate. The issue affects most empirical research using cross-sectional data since the origin varies. Chudik and Pesaran (2015b) points out spatial dependence, omitted common effects and pairwise dependent residuals as common causes.

The impact of CD is determined by its size as well as the nature of the dependence. Chudik et al. (2011) suggests that the CD can be characterized as strong or weak. The former refers to global shocks that affect all countries simultaneously and the latter potential spill-over effects between a limited group of countries. While strong CD does not diminish, the effect of weak CD does as countries are located further away from the origin. An example of weak CD is trade where the surrounding countries are more correlated than the ones further away. Strong CD are often more general and arguably more realistic because of today’s economic integration. Common factors are one example of a strong CD. In the context of trade, a common factor can be illustrated by Chinas actions on the world market which affects all countries (Chudik et al., 2011).

This concept of strong and weak CD is important for the estimations of the fixed effects model. If the CD is strong, it is assumed to correlate with the regressors which makes the fixed effects estimators biased and inconsistent. Weak CD, on the other hand, is assumed to be uncorrelated with the regressors. In this case, the estimates of the fixed effect model will be consistent, although inefficient, and the standard errors will be biased (De Hoyos & Sarafidis, 2006; Eberhardt et al., 2013).

The estimates of the CCE model have proven to be consistent and asymptotically normal even though subject to strong and/or weak CD. The reason is that the model deals with the CD in a general way by the usage of cross-sectional averages (Chudik et al., 2011). This is a great advantage since it is not possible to test if the CD is strong or weak.

Previous literature has identified three main ways of addressing CD in an empirical specification. First, the dependence can be modelled if the drivers of the correlation are known. This approach is popular in spatial econometric models where the correlation is determined, for example, by location or distance of units. However, since neither location nor distance changes over time, the approach is often limited to cross-section data. A second way is to use a two-way fixed effects model which accounts for correlation that is both time-invariant and time-variant across units. A drawback of this approach is the assumption that the impact of CD is the same across units, thereby disregarding the possibility of common factors that affect countries differently. If this assumption of homogeneity is violated, it will lead to CD in the residuals and thus, the problem remains unsolved. The third way is to model CD to arise from unobserved common factors. This is utilized by the CCE estimator and will be further elaborated in the next chapter (Eberhardt & Teal, 2011).

An example of a study highlighting the drawbacks of not accounting for CD in a cross-country panel is the one by Fuleky et al. (2017). The authors use the CCE model in their analysis of international risk sharing while allowing for cross-sectional heterogeneity and compares the results to the fixed effects model. The conclusions, somewhat simplified, suggest that CD distorts the coefficients of fixed effects estimations. It is therefore argued that the fixed effects model is inappropriate to use, even when applied to a relatively homogenous set of countries, such as the OECD, since the estimations are misleading (Fuleky et al., 2017).

To the best of my knowledge, Petrova (2019) is the only study utilizing CD through the CCE model while evaluating the relationship between the insurance market and real GDP. However, the study investigates ways of testing for cointegration and is not concerned with the estimates of the cointegrating relationship. Also, while Petrova's panel covers a longer period (35 years), this thesis includes additional 24 countries.

3. Methodology

3.1 Model selection

The baseline model for this thesis is the ordinary least squares (OLS) estimator. Equation (1) represents the simplest case where only one factor is considered in the model.

$$y_{i,t} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{i,t} \tag{1}$$

Observed common factors, such as interest rates, are often straightforward and not hard to include in the model. However, there is a lack of good proxies for unobserved common factors. In the context of insurance premiums, an example of an unobservable common factor would be a financial crisis that affects both insurance premiums and GDP. Another example would be cultural factors that may influence individuals' attitudes towards risk. A popular approach when dealing with such factors is to assume that they are made up of individual and time-specific fixed effects. Transforming the dependent and explanatory variables into deviations from means makes it possible to isolate and terminate the part of the error term that is assumed to capture these specific fixed effects. See equation (2).

$$\varepsilon_{i,t} = \delta_i + \mu_t + \vartheta_{i,t} \tag{2}$$

In this two-way fixed effect model, the error term ($\varepsilon_{i,t}$) consist of three parts which are individual-specific (δ_i), time-specific (μ_t) and random ($\vartheta_{i,t}$). A common alternative is to assume that there are no time-specific effects ($\mu_t = 0$), making it a so-called fixed effects model. In most empirical scenarios, however, the approach of fixed effects only accommodates some unobserved factors and is not enough to deal with all. While it can account for shocks that have equal effect for all countries, it cannot deal with shocks that impact each country differently (Westerlund et al., 2019). It is therefore likely that the goal of achieving an exogenous error term, by using a fixed effects approach, is not sufficient since the remaining part ($\vartheta_{i,t}$) is not fully random but cross-sectionally correlated which will cause endogeneity. This is problematic since there is a risk of producing inconsistent estimators of the parameters of interest (Kapetanios et al., 2010). In addition, correlated error terms also indicate that there is information in the residuals which has not been used in the estimations.

In recent research, much focus has reached factor augmented regressions. A key assumption in these models is that CD can be represented by averages of common factors which could be included in the specification as additional regressors. The most common way of modelling these factors is by using either principal component factors, or the cross-sectional averages of the observables (Westerlund & Urbain, 2015).

Pesaran (2006) suggested a new estimator which assumes that there is a common factor representation within the CD. The model takes CD into account by approximating linear combinations of the unobserved common factors through cross-sectional averages of the explanatory and dependent variables (Chudik & Pesaran, 2015b). These averages are then included in a panel OLS regression, as illustrated by equation (3). This is the CCE estimator.

$$y_{i,t} = \alpha_i + \beta_i x_{i,t} + \gamma_i \bar{z}_t + \vartheta_{i,t} \tag{3}$$

The regression equation for the CCE model augments the baseline OLS estimator with $\bar{z}_t = (\bar{y}_{it}, \bar{x}_{it}{}')$, representing a vector of the cross-sectional averages.

The CCE approach is relatively simple to implement and produces consistent estimates under a variety of situations making it attractive to use in applied work, as further elaborated in Chudik & Pesaran (2015a). In addition, the approach has shown to be robust to alterations and extensions of the original data generating process considered by Pesaran (Westerlund et al., 2019). Monte Carlo experiments conducted by Kapetanios et al. (2010) have also shown that CCE estimators, in general, have better small sample properties than other similar panel data models, such as the principal component estimator.

A disadvantage of the CCE approach is that it rarely fulfils the assumption that both the number of time periods (T) and cross-sectional units (N) are large (Westerlund et al., (2019). As a reaction to this limitation, Westerlund et al. (2019) presented a new theory where they show that the consistent and asymptotically normal estimations from the CCE do not only hold when T is large but also when T is fixed. The performance of the fixed T CCE model was analysed in an extensive Monte Carlo simulation showing that the estimator also performs well in the fixed small T panel setup.

Allowing T to be fixed makes it possible to relax several requirements of the CCE model originally presented by Pesaran (2006). One important implication is that the conditions placed on the properties of the residuals and the common factors are more general than the ones previously considered. These results open for extended usage of the CCE approach for panels where only N is large (Westerlund et al., 2019).

The main restriction of the fixed T CCE approach is that the number of factors, *m*, needs to be smaller or equal to the number of observables, k +1. In other words, the number of factors cannot be larger than the number of cross-sectional averages that are used to estimate the factors (Westerlund et al., 2019).

Given the structure of the dataset used in this thesis, with large N and small T, and the high likelihood of CD, the fixed T CCE approach is arguably the most appropriate model for estimating the relationship between the insurance market and real GDP. Although previous studies and theoretic reasoning leans towards including time-specific effects in the fixed effects model, both the fixed effects model and the two-way fixed effects model will be used to allow for a more extensive analysis. In all regressions, the dependent variable ($y_{i,t}$) is logged values of real GDP and the three different proxies for insurance premiums (total, life, and nonlife) are used separately as explanatory variables ($x_{i,t}$). By using the explanatory variables separately, potential distortions due to multicollinearity are avoided.

3.2 Testing for cross-sectional dependence

To apply the most appropriate methods for this thesis, an initial CD test will be carried out to get further knowledge of the series in the dataset. The commonly used Breusch-Pagan Large Multiplier test has been shown to perform badly for panels with N > T and will therefore not be used. Instead, given the large N and small T composition of the dataset, the CD will be investigated using the Pesaran (2004) pre-estimation test. This test is based on a rescaled sum of the pairwise cross-sectional correlation coefficients and has shown to have good finite sample properties in heterogenous panels even when T is small (Pesaran 2004).

Although preferable as a pre-estimation test, Juodis & Reese (2021) showed that the CD test of Pesaran has limitations when tested on the residuals of the CCE model as well as the two-way fixed effects model if T is small. Specifically, the authors show that the test statistic tends to diverge as the number of time periods of the sample increases. In absence of a more suitable and available test, focus when evaluating the residuals for CD will be attributed to average pairwise correlations.

3.3 Panel unit root

The increased attention to CD has divided the panel unit root tests into a first-generation, which assumes cross-sectional independence, and a second-generation that allows for cross-sectional dependence. Two popular first-generation tests are the Levin, Lin and Chu test and the Im, Pesaran and Shin test. A drawback of these tests is the requirement that N should be small enough in relation to T [3]. Simulation studies have shown that the results suffer from size distortions when this requirement is not satisfied which limits the applicability of the tests. (Baltagi, 2013, p. 282). In addition, Breitung (1999) proves that these tests suffer from an extensive reduction of power when individual-specific trends are included. He therefore suggested a new approach which he, by Monte Carlo experiments, show to generate more reliable results, including when only small samples are considered (Breitung, 1999). The benefits of Breitung's unit root test are also supported by a later simulation study of Hlouskova & Wagner (2006) where they test the performance of several unit root tests. The null hypothesis of the test is that the panels contain unit roots, and the alternative is that they are stationary.

However, the assumption of cross-sectional independence is also present in Breitung's panel unit root test. Applying this test directly to cross-sectional dependent panels may therefore lead to misleading results. The cross-sectionally augmented Dickey-Fuller (CADF) test of Pesaran is a popular example of the second-generation panel unit root tests that allow for cross-sectional dependence. The test statistics are based on the augmented Dickey-Fuller test where lagged cross-sectional means and its first differences are included to incorporate the CD. The null hypothesis is that all panels are non-stationary, and the alternative is that at least some panels are stationary. The approach has shown to have satisfying power even for small values of N and T which makes the CADF test suitable for this thesis (Pesaran, 2006).

Lag length when testing for unit root will be set to 3 based on the value of $T^{1/3}$ [4]. This approach of choosing lags is standard in the panel data literature, see for example Fuleky et al. (2017).

3.4 Cointegration

In similarity to the panel unit root tests, there has been an increased interest in cointegration techniques to test for long-run relationships and there are now several different methods to choose from. An important feature of cointegration concerns the consistency of the estimated parameters. If the variables are cointegrated, the parameters give "super consistent" estimations

[3] Formally it requires that $N \rightarrow \infty$ in such a way that $N / T \rightarrow 0$.
[4] $20^{1/3} \approx 3$

that converge to the long-run equilibrium faster than estimations using stationary variables (Enders, 2010, p. 373).

Petrova (2019) points out that the majority of cointegration analysis in previous research relies on Pedroni's residual based panel cointegration test. This test requires that both N and T are large. Due to limitations in data availability, this is often not satisfied when investigating the insurance market. The study demonstrates that Pedroni's test tends to over-reject the null hypothesis of no cointegration when this requirement is not met. Petrova (2019) therefore argues that much of the evidence from previous studies where authors have found cointegration between the insurance market and economic development is likely to be due to the size of the panel (Petrova, 2019).

This thesis will apply the cointegration test of Westerlund (2005). A great advantage of this test is that it, in contrast to the popular tests of Kao and Pedroni, does not require modelling of heteroscedasticity nor the serial correlation properties of the data by the researcher. As argued by Westerlund (2005), the choices required in the modelling is problematic since it may have a great effect on the outcome of the test. Another advantage is that the approach allows for two separate alternative hypotheses, the first being that all panels are cointegrated and the second that a fraction of the panels are cointegrated. The null hypothesis in both cases is that there is no cointegration.

Unlike the panel unit root tests, the literature has not yet developed a clear consensus of how to model CD when testing for cointegration (Hlouskova & Wagner, 2009). One solution is to subtract cross-sectional means and thereby assume that the dependence can be approximated by averages of common time effects. Although this approach has its limitations, Westerlund (2005) argues that it is effective to general forms of cross-sectional correlation structures.

4. Data and variables

The panel used in this thesis consists of 73 countries observed over the period 2000 – 2019. An advantage of using a panel is the possibility to include a larger number of observations. It is also the most used setup when analysing the relationship in question.

Three different variables for insurance premiums are included as proxies for the insurance market: total, life, and nonlife premium volumes. The observations are extracted from the annual Sigma publications from the Swiss Re Institute and the choice of countries and time periods is based on the availability of data. Due to inconsistency in the publications, a few countries have been excluded to get a more balanced panel. The Sigma publications are the only provider of yearly data for a relatively large number of countries (Petrova, 2019). The fact that most studies are based on data from the same source is desirable for the comparability of the results, but it also raises concerns since it is hard to validate the results.

There are three main ways of measuring insurance premiums: in levels, density (average annual per capita) or penetration (ratio of premiums to GDP). They all have benefits and limitations and there is no consensus regarding which of these three proxies is preferred. While levels measure the overall scale of the insurance market, it fails to consider the population factor. Insurance density does consider population but neglects the connection between the insurance market and the economy. Lastly, penetration adjusts for the economy but fails to reflect that different levels of insurance penetration are connected to different stages of economic development (Zheng et al., 2009).

The overall assessment is that measuring the total effect of the insurance market by using premium levels is the most appropriate for this thesis. Although not optimal, it will avoid potential misinterpretation due to differences in market characteristics between countries such as product designs and price levels. Another advantage is that the raw data from the Sigma publications does not need further transformation.

A dummy variable is included to enable analysis of potential differences between advanced and emerging countries. This binary division is based on the classification made by the International Monetary Fund (IMF, 2019). The dummy takes the value one for advanced and zero for emerging economies. 31 countries in the dataset are classified as advanced and 42 as emerging. While 21 of the advanced countries are European, there is a larger spread across continents among the emerging countries. Although this division into advanced and emerging economies has been criticised for being obsolete in its simplification, it follows previous research and is assessed as the most appropriate for this thesis.

Annual real GDP is included as the measure for economic development. CPI, with the base year 2010, is used to transform the nominal premium values of the Sigma publications to real. Data on both real GDP and CPI is collected from UNCTAD. All variables are transformed into logarithms following previous research.

The construction of the dataset allows for various ways of analysing the interaction between real GDP and the insurance market. While premiums can be distinguished into life and nonlife sectors, the market can also be analysed using total insurance premiums. In addition, further analysis is possible by applying the dummy variable and thereby separating advanced and emerging countries. An overview of the variables included in this study is presented in table 1.

Table 1. Review of the used variables

Variable	Name	Unit of measure	Frequency	Source
Real GDP	*ln rgdp*	US dollars at constant prices (2015) in millions	Yearly	UNCTAD
Total insurance premium	*ln tot*	US dollars at constant prices (2010) [5]	Yearly	Swiss Re Institute, Sigma publications 2000 - 2019.
Life insurance premium	*ln life*			
Nonlife insurance premium	*ln nonlife*			
Dummy of economic development	*advanced*	1 for advanced and 0 for emerging countries	-	Classification by IMF, October 2019

4.1 Descriptive statistics and test

Table 2 presents summary statistics of the variables in the thesis together with Pesaran's pre-estimation test for CD and average pairwise correlations. A list of the included countries can be found in the appendix (Table A1).

[5] Values have been converted from nominal to real through the UNCTAD consumer price index (CPI) with base year 2010.

Table 2. Descriptive statistics, Pesaran's CD-test and average pairwise correlations.

All countries								
Variable	**Obs**	**Mean**	**Std.dev.**	**Min**	**Max**	**CD-test**	**corr**	**abs(corr)**
ln rgdp	1460	12.4513	1.4673	9.4755	16.8147	198.82 ***	0.867	0.892
ln tot	1460	8.9232	2.1303	4.2748	14.8748	206.22 ***	0.900	0.900
ln life	1460	7.9289	2.5618	2.0478	13.5102	187.42 ***	0.817	0.825
ln nonlife	1460	8.2175	1.9136	3.6921	14.5798	208.00 ***	0.907	0.907

Advanced countries								
Variable	**Obs**	**Mean**	**Std.dev.**	**Min**	**Max**	**CD-test**	**corr**	**abs(corr)**
ln rgdp	620	13.0211	1.4376	9.6476	16.8147	76.51 ***	0.793	0.841
ln tot	620	10.3566	1.7078	5.7736	14.8748	83.06 ***	0.861	0.862
ln life	620	9.7410	1.8505	4.7165	13.5102	73.08 ***	0.758	0.766
ln nonlife	620	9.3934	1.6614	4.8869	14.5798	84.62 ***	0.877	0.877

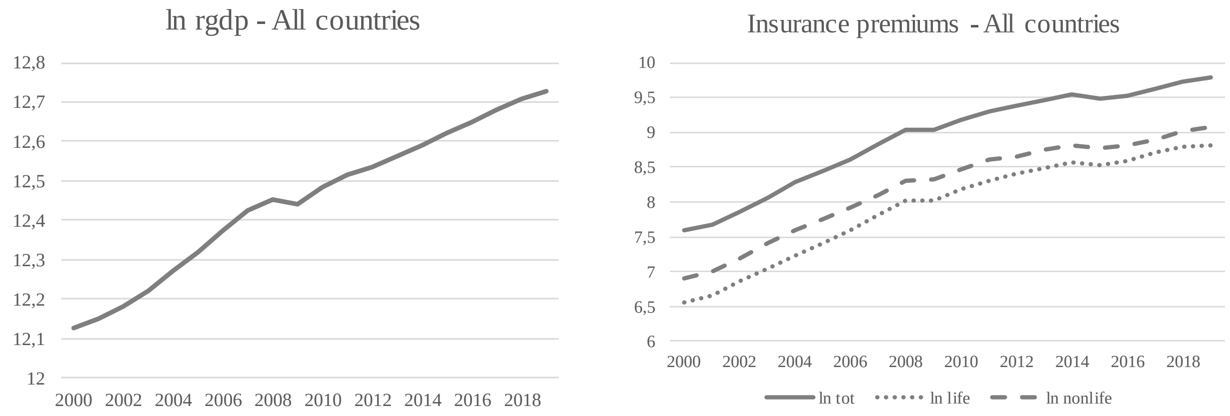
Emerging countries								
Variable	**Obs**	**Mean**	**Std.dev.**	**Min**	**Max**	**CD-test**	**corr**	**abs(corr)**
ln rgdp	840	12.0307	1.3425	9.4754	16.4770	123.03 ***	0.938	0.938
ln tot	840	7.8653	1.7610	4.2748	13.5571	125.07 ***	0.953	0.953
ln life	840	6.5915	2.1606	2.0478	12.9289	119.07 ***	0.907	0.907
ln nonlife	840	7.3496	1.5986	3.6921	12.7944	124.75 ***	0.951	0.951

Notes: "corr" presents the average pairwise correlation, "abs(corr)" present the average pairwise correlation based on absolute values. The null hypothesis of the CD-test is cross-sectional independence. *** indicate significance at 0.1% level.

The means presented in the table show that advanced countries on average have a higher level of real GDP as well as insurance premiums. Independent of the sample considered, the standard deviations indicate that the spread of life insurance is higher than that of nonlife insurance, which is similar to total insurance. The results of the CD test are in line with previous research, indicating CD in all series. It is also apparent from the table that the average pairwise correlation between countries is greater within the emerging compared to the advanced. There is little difference in average pairwise correlation when the averages are based on absolute values indicating that the correlation is in general positive.

Figure 1 presents cross-sectional averages of logged values of real GDP and logged values of insurance premiums when all countries are considered. As shown by the graphs all series are highly trending and persistent. Because of the small number of years, it is hard to distinguish a cointegrating relationship while looking at the graphs. Therefore, additional testing is required before further conclusions regarding a potential relationship between the series are possible.

Figure 1. Cross-sectional averages of the included variables, all countries considered.



As expected, there is a clear decline in all series after the financial crisis of 2008. There is also a decline in insurance premiums after 2014 which could partly be explained by changes in the European insurance market after the implementation of Solvency II, a directive from the European Union stipulating a new risk-based regulatory framework for the insurance market (Kočović et al., 2017). See appendix (Figure A1 & A2) for graphs over cross-sectional averages when advanced and emerging countries are separated.

5. Empirical results

5.1 Preliminary tests

5.1.1 Panel Unit root tests

Given the presence of CD in the data, the second-generation CADF of Pesaran (2006) is preferred when testing for unit root. Previous analysis of the cross-sectional averages (Figure 1) together with an ocular inspection of the countries individually shows that the series are trending. A time trend is therefore included in the estimations. The results are presented in table 3.

Table 3. Pesaran's CADF unit root test on levels and first difference

	All countries				Advanced countries					Emerging countries		
Variable:	***ln rgdp***	***ln tot***	***ln life***	***ln nonlife***	***ln rgdp***	***ln tot***	***ln life***	***ln nonlife***	***ln rgdp***	***ln tot***	***ln life***	***ln nonlife***
Level	-1.487 (1.000)	-1.911 (0.999)	-2.173 (0.838)	-1.890 (1.000)	-2.202 (0.686)	-2.016 (0.934)	-2.089 (0.866)	-1.585 (1.000)	-2.086 (0.905)	-2.118 (0.866)	-2.369 (0.305)	-1.861 (0.997)
First difference	-1.997 * (0.013)	-2.837 *** (0.000)	-3.014 *** (0.000)	-2.789 *** (0.000)	-2.071 * (0.032)	-3.024 *** (0.000)	-3.122 *** (0.000)	-2.803*** (0.000)	-2.280 *** (0.000)	-2.855 *** (0.000)	-3.086 *** (0.000)	-3.024 *** (0.000)

Notes: T-bar values are presented together with p-values in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Lag length is set to 3 in accordance with $T^{1/3}$

As shown by table 3, the null hypothesis that all series are non-stationary cannot be rejected when the variables are tested in levels. When the first differences are considered, the null is rejected. These results hold for all variables, independent of the countries included in the sample, which indicate that they are integrated by order 1, henceforth I(1).

Breitung's unit root test, presented in the appendix (Table A2), has been carried out as a check for robustness. The estimated equation includes a constant and a trend. In addition, cross-sectional means are subtracted as a way of mitigating the CD (Levin et al., 2002). The results are similar to the ones from the CADF test. A difference is that the test for total insurance premiums rejects the null of non-stationarity at the 5% significance level when evaluated in levels if only advanced countries are considered. However, as previously discussed, the CADF test is more suitable when dealing with cross-sectional data since it allows for CD. Therefore, it is reasonable to proceed assuming that all series are nonstationary and I(1).

5.1.2 Cointegration

Given that real GDP and insurance premiums (total, life, and nonlife) are concluded to be I(1), we proceed on to test for cointegration. As previously discussed, the test of Westerlund (2005) is preferred. Since the series are trending and cross-sectionally dependent, all tests include a panel-specific linear time trend and cross-sectional means have been subtracted. Both of Westerlund's tests are carried out. The alternative hypothesis in the first is that *all* panels are cointegrated, and the alternative in the second is that *some* panels are cointegrated. It should also be noted that an intercept is included in all tests. The results are presented in table 5.

Table 5. Westerlund's cointegration tests

	All panels are cointegrated			Some panels are cointegrated		
Samlpe	***ln tot***	***ln life***	***ln nonlife***	***ln tot***	***ln life***	***ln nonlife***
All countries	6.4382 *** (0.0000)	5.9577 *** (0.0000)	4.9943 *** (0.0000)	7.0226 *** (0.0000)	6.9796 *** (0.0000)	6.3349 *** (0.0000)
Advanced countries	2.8114 ** (0.0025)	3.0331 ** (0.0012)	2.5234 *** (0.0058)	1.9677 * (0.0246)	1.9050 * (0.0284)	2.1948 * (0.0141)
Emerging countries	4.6106 *** (0.0000)	4.5411 *** (0.0000)	3.1202 *** (0.0009)	5.2343 *** (0.0000)	5.3711 *** (0.0000)	4.7830 *** (0.0000)

Notes: Test statistics are presented together with p-values in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Test includes panel-specific linear time trend and cross-sectional means have been subtracted.

The results from the two tests provide clear evidence of cointegration between real GDP and insurance premiums. It is also apparent that the relationship holds for total, life, and nonlife insurance premiums. This indicates that there is a long-run relationship between the insurance market and real GDP in the used dataset, which is independent of whether all countries are taken into consideration or if divided into advanced or emerging by the dummy variable.

As previously mentioned, the study of Petrova (2019) raises concerns regarding the panel size dependency when analysing cointegrating relationships. Although the test of Pedroni (2004) is likely to over-reject the null hypothesis of no cointegration when CD is present, it has been applied as a robustness check [6]. The results confirm the ones from Westerlund's test, indicating cointegration.

5.1.3 Factor analysis

Before estimating the regressions, factor analysis is carried out to investigate if the requirement $m \leq k+1$ of the CCE model is fulfilled. The analysis is a technique for reducing the data into linear combinations of the variables which accommodate most of the information (StataCorp, 2019). Since each regression consists of one explanatory variable, two cross-sectional averages are used in each regression. Specifically, the cross-sectional average of real GDP and the cross-sectional average of the variable used for insurance premiums. This implies that the maximum number of factors allowed is two. The result from the factor analysis shows that all combinations of real GDP and the three different proxies for insurance premiums have one factor. The results do not change when taking the dummy of advanced/emerging countries into account. This implies that the number of factors is less than the number of cross-sectional averages used, the requirement is therefore satisfied.

5.2 Regression estimations

5.2.1 Regression output

Table 6 presents regression coefficients together with the standard errors in parenthesis from all three models. The p-values from the two-way fixed effects (TWFE) and the fixed effects (FE) models are calculated using robust standard errors to account for autocorrelation and

[6] The cointegration test of Pedroni (2004) includes panel-specific time trends and cross-sectional averages have been subtracted to mitigate the impact of the cross-sectional dependence.

heteroskedasticity which is likely to be present [7]. The CCE model is calculated using fixed T adjusted standard errors following the findings of Westerlund et al. (2019).

Table 6. Regression output from the three models: CCE, TWFE and FE

	All countries			Advanced countries			Emerging countries		
Model	***ln tot***	***ln life***	***ln nonlife***	***ln tot***	***ln life***	***ln nonlife***	***ln tot***	***ln life***	***ln nonlife***
CCE	0.1033 *** (0.0156)	0.0594 *** (0.0135)	0.1094 *** (0.0150)	0.1004 ** (0.0349)	0.0559 * (0.0277)	0.1171 *** (0.0300)	0.0926 *** (0.0175)	0.0221 (0.0201)	0.0422 * (0.0195)
TWFE	0.1779 *** (0.0341)	0.1223 *** (0.0242)	0.1717 *** (0.0359)	0.2390 *** (0.0390)	0.1646 *** (0.0292)	0.1708 *** (0.0426)	0.1038 * (0.0484)	-0.0411 (0.0312)	0.0483 (0.0298)
FE	0.2434 *** (0.000)	0.2151 *** (0.0154)	0.2463 *** (0.1720)	0.2550 *** (0.0211)	0.2362 *** (0.0228)	0.2459 *** (0.0204)	0.2413 *** (0.0190)	0.1345 * (0.0551)	0.2118 *** (0.0173)

Notes: The table presents coefficients and standard errors in parentheses. TWFE and FE are estimated with robust standard errors. CCE is estimated with fixed T-adjusted standard errors. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The number of observations: 1480 when considering all countries, 620 and 860 respectively when considering advanced and emerging countries. The dependent variable is real GDP.

The overall assessment when evaluating the regression output is that there is a significant and positive long-run relationship between the insurance market and real GDP. Given the cointegrated relationship, the estimated coefficients are even assumed to be "super-consistent". When comparing coefficients, it is apparent that the estimated values differ greatly depending on which model that is used to estimate the relationship. Take the variable *ln nonlife* for advanced countries as an example. While controlling for time-specific effects decreases the coefficient for the fixed effects estimates from approximately 0.25 to 0.17, the estimate decreases to 0.12 when considering the CD using the CCE model.

These results of a positive relationship between the insurance market and real GDP are in line with most previous research, independent of their econometric approach. There are however differences. While previous studies have found that life insurance tends to be more important for advanced countries and nonlife insurance is more important for emerging countries, this relationship is not as clear when evaluating the coefficients from the regression estimates. Instead, the general pattern is that nonlife insurance has greater influence, independent of countries' level of development. A potential reason for this difference is the time periods of this study since it, in contrast to most previous research, includes both the aftermath of the great financial crisis as well as the implementation of the Solvency II directive.

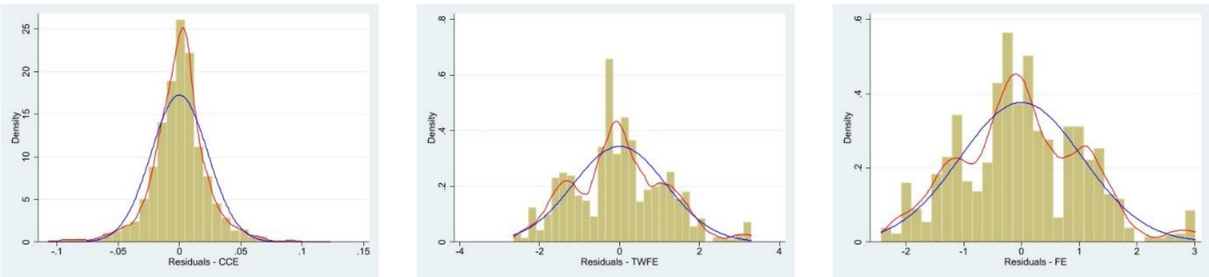
[7] An initial Hausman test rejects the null of random effects for all samples.

Although there are great differences in coefficients, the level of significance is similar across the output. In fact, most are significant at the 0.1% level. The main exceptions are the coefficient for emerging countries while using the CCE and TWFE model and separating the premiums into life and nonlife. Among these four coefficients, only *ln nonlife* evaluated by the CCE model comes out significant. To get further information regarding the validity of the estimated results, the next section will investigate the residuals of the models.

5.2.2 Residual diagnostics

As a first way of checking the validity of the estimates, the assumption of normally distributed residuals is inspected via histograms. A desirable result would be a symmetric bell-shaped distribution around zero. Figure 2 presents residuals from the three models, illustrating the differences in their distribution. The histograms are overlapped by a blue line indicating normal density and a red line which is a kernel density estimate. The pattern is similar when the countries are divided into advanced and emerging, as well as when the insurance market is divided into life and nonlife premiums. Therefore, only histograms over residuals from total insurance premiums regressed on real GDP when all countries are considered are provided.

Figure 2. Histogram over residuals from CCE, TWFE and FE. All countries included.



Notes: Blue line represents normal density which has the same mean and standard deviation as the data. The red line is a scaled kernel density estimate of the density.

As indicated by the graphs, the CCE model produces relatively even distributed residuals around zero, indicating normality. In comparison, the residuals estimated by TWFE and FE have a greater spread and there are tendencies of positive outliers. Although the distribution is satisfying in all three models, the normality of the residuals provided by the CCE model stands out.

As a second step, we move on to investigate correlations in the residuals. Table 7 presents average pairwise correlations and the absolute average pairwise correlation in the residuals. The latter is based on absolute values, thereby disregarding the direction of the correlation.

Table 7. Average pairwise correlations in the residuals.

	All countries			Advanced countries			Emerging countries		
Model	***ln tot***	***ln life***	***ln nonlife***	***ln tot***	***ln life***	***ln nonlife***	***ln tot***	***ln life***	***ln nonlife***
CCE	-0.004 [0.295]	-0.002 [0.318]	-0.002 [0.299]	0.001 [0.315]	-0.006 [0.353]	0.012 [0.322]	-0.014 [0.322]	-0.004 [0.360]	-0.015 [0.313]
TWFE	-0.008 [0.533]	-0.005 [0.555]	-0.007 [0.585]	-0.030 [0.483]	-0.028 [0.482]	-0.002 [0.564]	-0.017 [0.584]	-0.017 [0.560]	-0.018 [0.589]
FE	0.202 [0.499]	0.162 [0.508]	0.218 [0.486]	0.325 [0.519]	0.321 [0.524]	0.321 [0.485]	0.123 [0.490]	0.073 [0.483]	0.159 [0.503]

Notes: The table presents the average pairwise correlation and absolute average pairwise correlation in brackets.

The output shows that the average pairwise correlation in the residuals from the CCE model and the TWFE model is similar. Almost all are negative and close to zero. In comparison, the values from the residuals based on the FE model are substantially larger and positive. However, since residuals are being evaluated, it is more informative to investigate correlation based on absolute values. When interpreting the absolute average pairwise correlations, the pattern is quite different. The similarities now lie between the two separate fixed effects models and the residuals from the CCE model have far less absolute average pairwise correlation. The lower values suggest that the approach of including cross-sectional averages in the regression removes a great amount of cross-correlation in the residuals.

The results indicate that CCE model produces more reliable estimates of the cointegrating relationship between the insurance market and real GDP. The model incorporates more cross-correlation in the estimation which implies that more information in the variables is being used while estimating the regression. Although there is absolute correlation remaining in the residuals, the lower degree indicates that the estimates from the CCE models are more reliable compared to the TWFE and FE model.

The findings support the ones from Fuleky et al. (2017) as well as Chudik & Pesaran (2015b). Using the CCE model, thereby accounting for CD, could avoid substantial overestimations followed by a misleading perception while studying economic relationships in cross-sectional data. It is therefore important to question conventional methods and choose the econometric approach carefully.

6. Concluding remarks

There has been an increased interest in investigating the relationship between the insurance market and real GDP in recent decades. However, most studies rely on methods that assume cross-sectional independence. This assumption is unrealistic and contradicts recent research stipulating that most cross-sectional panels are dependent. In contrast, this study relaxes this assumption by using an approach that allows for cross-sectional heterogeneity that has not been used before. This is possible due to new findings making the CCE model applicable even in the case of a small T panel. To compare the results of the CCE model, the same data is used on the fixed effects model as well as the two-way fixed effects model.

The empirical results show that there is a positive cointegrating relationship between the insurance market and real GDP which holds for all three models. If disregarding the results for life insurance in emerging countries, all three models indicate a highly significant relationship. There is however a great difference in the magnitude of the estimated effects. While comparing the residuals, it is apparent that the residuals from the CCE model have a substantially lower absolute average pairwise correlation and a higher degree of normality in its distribution. This highlights the potential pitfalls of ignoring CD while using cross-sectional panel data. It also suggests that the CCE estimates of the relationship between the insurance market and real GDP are more reliable than the ones of the fixed effects models.

6.1. Limitations

Since non-stationary variables are applied in the regressions, the results rely heavily on the cointegration tests. Since all series are trending with time, there is a risk of spurious results if the cointegrating relationship does not hold. Given that three different tests imply cointegration, and that these results support previous research, further analysis on this issue has been considered outside the scope of this thesis.

6.2. Further research

A central problem when investigating the insurance market is the availability of data. The Swiss Re Institute is the most popular source of data but the earliest observations which they have published are from 2000. This makes the time horizon relatively short. However, the new econometric approach of using the CCE model with fixed T opens for further possibilities. A suggestion would be to use this method together with a more detailed division of countries. For example, by investigating the impact of the Solvency II directive on the member states of the European Union. The method could also be of use in further analysis of the impact of different insurance markets in emerging countries, helping policymakers decide on future insurance investments aimed to stimulate growth. Given the fast-growing tendencies of the insurance market, it would also be interesting to see if the result of this thesis holds when applied to an updated dataset in the future.

7. References

Arena, Marco. (2008). Does insurance market activity promote economic growth? A cross-country study for industrialized and developing countries. *The Journal of Risk and Insurance,* Vol 75(4), pp. 921-946.

Baltagi, B.H. (2013). *Econometric analysis of panel data*. 5 edition. Cornwall: John Wiley & Sons, inc.

Beck, T. Levine, R. (2004). Stock markets, banks, and growth: Panel evidence. *Journal of Banking & Finance.* Vol 28(3), pp. 423-442.

Breitung, J. (1999). The local power of some unit root tests for panel data. Humboldt University. Discussion paper.

Chudik, A. Pesaran, M.H. (2015a). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics.* Vol 188, pp. 393-420.

Chudik, A. Pesaran, M.H. (2015b). Large panel data models with cross-sectional dependence: A survey. In Baltagi, B.H (Ed.). *The Oxford Handbook on Panel Data.* New York: Oxford University Press.

Chudik, A. Pesaran, M.H., Tosetti, E. (2011). Weak and strong cross-section dependence and estimation of large panels. *The Econometrics journal.* Vol 14. pp. 45-90.

Das, U. Davies, N. Podpiera, R., (2003). Insurance and Issues in Financial Soundness. *IMF Working Paper,*

De Hoyos, R. Sarafidis, V., (2006). Testing for cross-sectional dependencies in panel-data models. *The Stata journal.* Vol 6(4), pp. 482-496

Din, S. Abu-Bakar, A. Regupathi, A., (2017). Does insurance promote economic growth: A comparative study of developed and emerging/developing economies. *Cogent Economics & Finance,* Vol 5(1), pp. 1-12.

Eberhardt, M. Helmers, C. Strauss, H. (2013). Do spillovers matter when estimating private returns to R&D? *The Review of Economics and Statistics.* Vol 95(2), pp. 436-448.

Eberhardt, M. Teal, F. (2011). Econometrics for Grumblers: A new look at the literature on cross-country growth empirics. *Journal of Economic Surveys.* Vol 25(1), pp. 109-155.

Enders, W. (2010). *Applied Econometric Time Series*. 3 edition. Hoboken: John Wiley & Sons, inc.

Fuleky, P. Ventura, L. Zhao, Q. (2017). Common Correlated Effects and International Risk Sharing. John Wiley & Sons Ltd.

Haiss, P. Sümegi, K. (2008). The relationship between insurance and economic growth in Europe: a theoretical and empirical analysis. *Empirica*. Vol 35, pp. 405-431.

Hlouskova, J. Wagner, M. (2006). The performance of panel unit root and stationarity tests: Results from a large scale simulation study. *Econometric Reviews.* Vol 95, pp. 85-116.

Hlouskova, J. Wagner, M. (2009). The Performance of panel Cointegration methods: Results from a large scale simulation study. *Econometric Reviews.* Vol 29(2), pp. 182-223.

International Monetary fund. (2019). World economic outlook – Global manufacturing downturn, rising trade barriers. Washington, DC.

Juodis, A. Reese, S. (2021). The Incidental Parameters Problem in Testing for Remaining Cross-section Correlation. *Journal of Business & Economic Statistics* (Forthcoming)

Kapetanios, G. Pesaran, M.H. Yamagata, Y. (2010). Panels with non-stationary multifactor error structures. *Journal of Econometrics*. Vol 160, pp. 326-348.

King, R.G., Levine, R. (1993). Finance and Growth: Schumpeter Might be Right. *Oxford University press.*Vol 108(3), pp. 717-737.

Kočović, J. Paunovic, B. Koprivica, M. (2017). Initial effects of Solvency II Implementation in the European Union. *Ekonomika Preduzeca*. Vol 65(7-8), pp. 436-452.

Kugler, M. Ofoghi, R. (2005). Does Insurance Promote Economic Growth? Evidence from the UK. University of Southampton Working Paper

Le, T. Chang, Y. Park, D. (2018). Economic development and environmental sustainability: evidence from Asia. *Empirical Economics*. Vol 57, pp. 1129-1156.

Levin, A. C-F, Lin. Chu, C-S. J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics*. Vol 108(1), pp. 1-24.

OECD. (2020). OECD *Institutional investors Statistics 2020,* Paris: OECD Publishing

Outreville, F.J. (2013). The relationship between insurance and economic development: 85 empirical papers for a review of the literature. *Risk Management and Insurance Review.* 16(1), pp. 71-122

Pedroni, P. (2004). Panel Cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Economitric Theory*. Vol 20(3), pp. 597-625.

Pesaran, M.H. (2004). General Diagnostic Test for Cross Section Dependence in Panels. IZA Discussion Paper No. 1240.

Pesaran, M.H. (2006). Estimation and Inference in large heterogenous panels with a multifactor error structure. *Econometrica*. Vol 74(4), pp. 967-1012.

Petrova, Y. (2019). On cointegration between the insurance market and economic activity. *Empirical Economics.* Vol 59, pp. 1127-1138.

Reese, S. (2017). *Estimation and Testing in Panel Data with Cross-section Dependence*. Lund: Lund University

Sigma, Swiss Re institute. No 4/2020. (2020). World insurance: riding out the 2020 pademic storm. Available at: https://www.swissre.com/institute/research/sigma-research/sigma-2020-04.html [Accessed: 2021-05-14]

StataCorp. (2019). Stata multivariate Statistics reference manual – Release 16. Texas: StataCorp LLC.

UNCTAD. (1964). Proceeding of the United Nations Conference on Trade and Development, First Session. Vol 1. Final Act and Report. United Nations.

Ward, D. Zurbruegg, R. (2000). Does insurance promote economic growth? Evidence from OECD countries. *The journal of Risk and Insurance*. Vol 67(4), pp. 489-506.

Webb, I.P. Grace, M.F. Skipper, H.D. (2002). The effect of banking and insurance on the growth of capital and output. *Center for risk management and insurance*. Working paper.

Westerlund, J. (2005). New simple test for panel cointegration. *Econometric Reviews.* Vol 24(3), pp. 297-316

Westerlund, J. Edgerton, D.L. (2008). A Simple Test for Cointegration in Dependent Panels with Structural Breaks. *Oxford bulletin of economics and statistics.* Vol 70(5), pp. 665-704.

Westerlund, J. Petrova, Y, Norkute, M. (2019). CCE in fixed-T panels. *Journal of applied econometrics.* Vol 34, pp. 746-761

Westerlund, J. Urbain, J.P. (2015). Cross-sectional averages versus principal components. *Journal of Econometrics*. Vol 135, pp. 372-377.

Zheng, W. Liu, Y. Deng, Y. (2009). A comparative study of international insurance markets. *The Geneva Papers on Risk and insurance. Issues and Practice.* Vol 34(1), pp. 85-99.

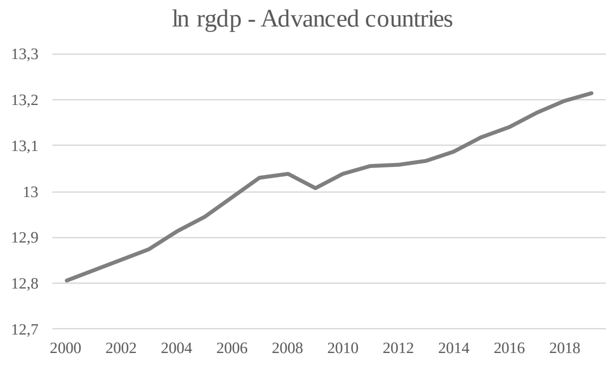
8. Appendix

8.1 Table A1. List of countries included

Advanced countries			Emerging countries		
Australia	Italy	Taiwan	Algeria	Iran	Philippines
Austria	Japan	United Kingdom	Argentina	Jamaica	Poland
Belgium	Luxembourg	United States	Brazil	Jordan	Romania
Canada	Netherlands		Bulgaria	Kenya	Russia
Cyprus	New Zealand		Chile	Kuwait	Saudi Arabia
Czech Republic	Norway		Colombia	Lebanon	South Africa
Denmark	Portugal		Costa Rica	Malaysia	Sri Lanka
Finland	Singapore		Croatia	Mexico	Thailand
France	Slovakia		Dominican Republic	Morocco	Trinidad and Tobago
Germany	Slovenia		Ecuador	Nigeria	Tunisia
Greece	South Korea		Egypt	PR China	Turkey
Hong Kong	Spain		Hungary	Pakistan	United Arab Emirates
Ireland	Sweden		India	Panama	Uruguay
Israel	Switzerland		Indonesia	Peru	Vietnam

8.2 Figure A1-2. Cross-sectional averages – advanced/emerging countries

Figure A1. Cross-sectional averages – Emerging countries



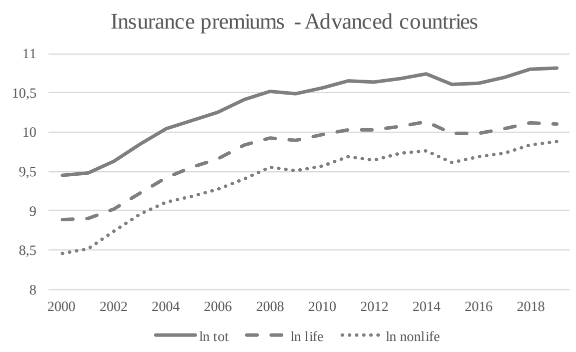
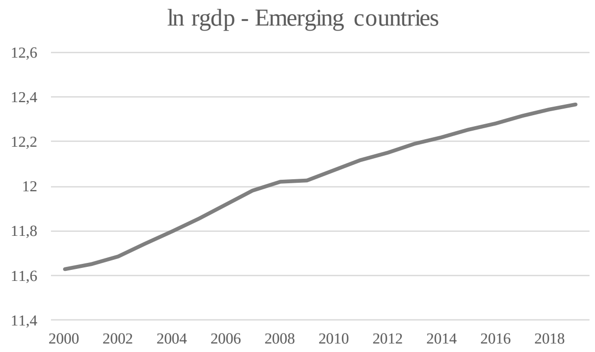
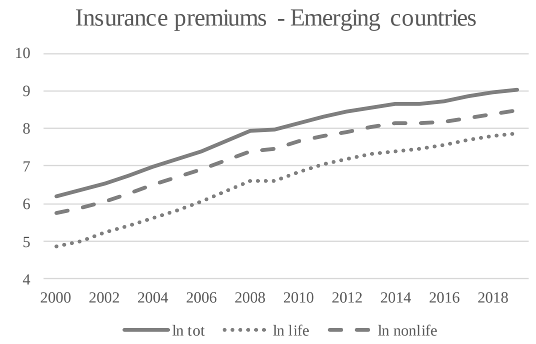


Figure A2. Cross-sectional averages – Advanced countries





8.3 Table A2. Breitung's Unit root test

	All countries				Advanced countries				Emerging countries			
Variable:	***ln rgdp***	***ln tot***	***ln life***	***ln nonlife***	***ln rgdp***	***ln tot***	***ln life***	***ln nonlife***	***ln rgdp***	***ln tot***	***ln life***	***ln nonlife***
Level	1.9349 (0.9735)	-0.0195 (0.4922)	-0.9080 (0.1819)	1.6401 (0.9495)	-0.0533 (0.4788)	-1.9662 * (0.0246)	-1.1372 (0.1277)	-0.8870 (0.1875)	1.0173 (0.8455)	-0.0421 (0.4832)	-0.3125 (0.3773)	0.9302 (0.8239)
First difference	-3.1479 *** (0.0008)	-3.2807 *** (0.0005)	-4.0433 *** (0.0000)	-3.1720 *** (0.0008)	-4.4604 *** (0.0000)	-2.7867 ** (0.0027)	-3.1723 *** (0.0008)	-1.7564 * (0.0395)	-2.8001 ** (0.0026)	-3.0260 ** (0.0012)	-3.4910 *** (0.0002)	-3.1324 *** (0.0009)

Notes: Test statistics are presented together with p-values in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$% significance. Test includes a constant and trend, cross-sectional means are subtracted. Lag length is set to 3 in accordance with $T^{1/3}$