Interconnectedness Among Sovereign Yield Curve Factors - Working title

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Abstract

Ezt megirjuk kesobb

1 Introduction

The subprime crisis renewed the interest in analyzing the co-movement of different financial instruments and systemic risk related studies came to the forefront. Shocks can be transmitted differently across various assets, therefore it is convenient to achieve awareness both for regulators and other market participanst in order to react more efficiently. Understanding such network structures are valuable for reducing potential damage and making appropriate future decisions. Analysis of the interconnectedness of different assets plays crucial role in systematic risk assessment. Furthermore, during crises the strength of connections sharply increases and risk spills over across financial institutes and sovereign bonds, as it happened during the Financial Crisis of 2007-2009 and during the European Sovereign Crisis (Diebold and Yilmaz (2012)). IDE KELL MAJD HIVATKOZÁST KERESNI

Because the financial system is a huge complex interactive system, in recent years scholars began using complex network theory to investigate the interconnectedness of financial institutions. Acemoglu et al. (2015) pointed out that in smaller financial systems, shocks make the densely interconnected network steadier, however after a certain size the opposite applies. According to Elliott et al. (2014), diversification initially allows failure cascades to travel within the system, but as it increases further, organizations are better insured against one another's failures. Depending more on other participants makes personal sensitivity lower on own investments. SZERINTEM ITT VAN MÉG 1-2 FONTOS CIKK RÁNÉZEK MAJD

In the empirical literature there are several methods to measure connectedness. In the last decade the widespread methods are Granger causality network (Billio et al. (2012)), CoVaR (Adrian et al. (2008)), MES (Acharya et al. (2012)) and numerous studies appeared based on the Vector AutoRegressive Diebold-Yilmaz (DY) framework (Diebold and Yilmaz (2009), Diebold and Yilmaz (2012)). Compared to CoVaR and MES methods the advantage of Granger causality based frameworks is the ability to examine the network both micro (pairwise connectedness) and macro (total connectedness) level. As a result, these methods have been often used to analyse the network on different asset classes like equities, bonds, exchange rates or commodity prices. Most analysis focus on the whole system or some subpart.The dynamics of individual assets' role in the system have not been explored yet. IDE KELL hivatkozások összeszednem

KELLENE EGY KOINTEGRÁCIÓT Nem szokta vizsgálni bekezdés

Central banks traditionally rely on the co-movement of different maturities of yield curves to make effective monetary policy decisions. According to the expectations hypothesis, long-term interest rates are influenced by current and expected future short-term interest rates. However, increasing globalization of financial systems and structural changes across economies have disrupted the integration of the maturity spectrum of different yield curves. Short-end movements are more exposed to monetary policy decisions, so their interconnectedness is more consistent with the alternation of business cycles. The long end of the yield curve is mainly affected by global investment, with current preferences and risk appetite being the primary drivers. The integration of distant maturity points is driven by global capital flows and the volume of investments. IDE MINDENKÉPP KELLENEK HIVATKOZÁSOK

Usually, a tenor structure consists of multiple maturities which means one-one individual time series. It is challenging to deal with such a magnitude of data, therefore in raw format the yield curve itself is not used. Fernández-Rodríguez et al. (2016) examined only the 10Y yield curve point on EMU countries while Claeys and Vašíček (2014) chose the spread between EU government bond yieldsand German sovereign bondyield, also considering 10 years of maturity. Ahmad et al. (2018) picked bond indices to analyze and Sowmya et al. (2016) decomposed the yield curve to Level, Slope and Curvature factors with the Diebold-Li dimension reduction technique. Multilayer networks, in which the links in each layer represent different types of connections between the same nodes, can combine different measures of interconnectedness to effectively describe complex financial systems. Such networks are already widely used in dependency networks of financial markets. However, few literatures consider multilayer networks to study the interconnectedness of the financial system from the perspective of information propagation. EZT KI KELL BŐVÍTENEM

We are eager to find the less and most interconnected participants of our system via understanding the connections not only between particular factors, but involving all three of them. We are also curious for the behavior of such linkages during time, thus besides static analysis we performed rolling window-based tests as well. Our contribution to the existing literature is fourfold. We analyze the interconnectedness of different yield curve factors with the consideration of cointegration among the time series. This is the first study which examines the crosswise causality connections among Level, Slope and Curvature. We chose developed economies from all over the World in order to achieve a wide geographical coverage. ITT LEHET KELLENE MÉG MAGYARÁZAT

We find, that there is cointegration between the yield curve factors, therefore our modelling approach (Toda-Yamamoto method) is justified. There is a not negligible amount of significant cross connections among these factors. The Level drives the highest number of linkages while the Curvature is the main receiver. Slope is ranked as second in both comparisons. USD factors have the most net connections (outgoing –incoming) thus it can be considered as the driver of the system. Our dynamic approach shows that during a recession period the sum of the connections in the network increases which statement is supported with different window sized robustness checks.

2 Literature review

An overview of existing literature on bond market reveals that there are a few early studies on the interdependence of international bond markets (Ilmanen, 1995; Clare and Lekkos, 2000; Driessen et al., 2003; Laopodis, 2004; Dewachter et al., 2004, among others). Ilmanen (1995) examines the predictable variation in long-maturity government bond returns in six countries using a linear regression model with local and global instruments. Clare and Lekkos (2000) decompose the relationship between the government bond markets of Germany, the United Kingdom, and the United States. They find that global factors influence the yield curves for each of these markets and the impact of these factors increases significantly during times of financial stress. Driessen et al. (2003) estimate and interpret the factors that jointly determine bond returns of different maturities in the US, Germany, and Japan. They find that the positive correlation between bond markets is driven by the term structure levels, not by term structure slopes. Dewachter et al. (2004) develop a benchmark against which the effects of ECB (European Central Bank) mone- tary policy on the German bond market can be evaluated. They find that yield spreads increased substantially during the EMU (European Monetary Union) period. Laopodis (2004) examines the monetary policy implications of the greater integration of the capital markets using long-term interest rates. He finds greater convergence among countries in the EU (European Union) as Germany still retains its hegemonic status.

There are papers on sovereign yield spreads (Balli, 2009; Favero and Missale, 2012; Antonakakis and Vergos, 2013; Costantini et al., 2014). Balli (2009) examines the time-varying nature of European government bond market integration by employing multivariate GARCH models. He states that global factors are sufficient for the volatility of yield differentials among euro government bonds. Favero and Missale (2012) provide new evidence on the determinants of sovereign yield spreads and market sentiment effects in the Eurozone to evaluate the rationale for a common Eurobond jointly guaranteed by Eurozone member states. Antonakakis and Vergos (2013) examine sovereign bond yield spread spillovers between Eurozone countries using the VAR-based spillover index model of Diebold and Yilmaz (2012) and impulse response analyses. Their findings highlight the increased vulnerability of the Eurozone from the destabilizing shocks originating mostly from the Eurozone countries in the periphery and to a lesser extent from the Eurozone core. Costantini et al. (2014) find that fiscal imbalances – namely expected government debt-to-GDP differentials – are the primary long-run drivers of sovereign spreads.

The literature on volatility spillovers in bond markets is scanty. Skintzi and Refenes (2006) examine dynamic linkages among the European bond markets. They find that significant volatility spillovers exist from both the aggregate Euro and US bond markets to the individual European markets. They also conclude that the introduction of the Euro has strengthened the volatility spillover effects and the cross-correlations for most European bond markets. Christiansen (2007) examines volatility spillover from the US and aggregate European bond markets into individual European bond markets using a GARCH volatility-spillover model. Results indicate that for EMU countries, the US volatility spillover effects are rather weak (in economic terms) whereas the European volatility spillover effects are substantial. The bond markets of EMU countries exhibit high integration after the introduction of the euro. The post-Euro period has further strengthened the integration process. They find interest rate convergence as one of the primary drivers of bond market integration.

Gómez-Puig et al. (2014) apply the Granger-causality approach and endogenous breakpoint test to offer an operational definition of contagion to examine (EMU) countries public debt behaviour. A database of yields on 10-year government bonds issued by 11 EMU countries covering fourteen years of monetary union is used. The main results suggest that the 41 new causality patterns, which appeared for the first time in the crisis period, and the intensification of causality recorded in 70% of the cases provide clear evidence of contagion in the aftermath of the current euro debt crisis. Sibbertsen et al. (2014) study tests for a break in the persistence of EMU government bond yield spreads examining data from France, Italy and Spain and using German interest rates as a kind of benchmark. Their results provide evidence for breaks between 2006 and 2008. The persistence of the yield spreads against German government bonds has increased significantly after this period.

Besides this, few studies have also examined volatility spillovers in bond markets using Diebold and Yilmaz (2009, 2012) methodology. Claeys and Vašíček (2014) measure direction and extent of sovereign bond markets linkages among sixteen EU (European Union) using a factor-augmented version of the VAR model in Diebold and Yilmaz (2009). Fernández-Rodríguez et al. (2015) examine volatility spillovers in EMU sovereign bond markets. They find that slightly more than half of the total variance of the forecast errors is explained by shocks across countries rather than by idiosyncratic shocks. They also report that during the pre-crisis period, most of the triggers in the volatility spillovers were central EMU countries – peripheral countries imported credibility from them – while during the crisis, peripheral countries became the dominant transmitters. Fernández-Rodríguez et al. (2016) examine the time-varying behavior of net pair-wise directional connectedness at different stages of the recent sovereign debt crisis.

Under emerging market setting, a limited number of studies have responded to the need of bond market making in emerging economies. Kim et al. (2006) examine the time-varying bond market integration in case of European emerging countries and report the evidence of weak bond market integration. Examining the bond markets of Asian countries with USA and Australia, Vo (2009) reports moderate level of interdependence because of the different institutional structure. Cifarelli and Paladino (2006) examines the volatility comovement between spreads for ten selected emerging economies. The study reports that volatility comovements between spreads are higher for within countries than across spatially distributed countries. Bunda et al. (2009) assess comovements in emerging markets bond returns and disentangles roles of external and domestic factors during episodes of heightened market volatility. Piljak (2013) investigates the time-varying dependence of bond markets of emerging including frontier economies with the USA and also examines the major factors that determine the comovement. The study finds that the impact of domestic factors are higher than the factors on the bond market integration of these countries. Piljak and Swinkels (2017) examine the dynamic interdependence of sovereign debt markets of frontier economies with US bond markets. The study reports that there is a limited interdependence between frontier and US bond markets because of the limited diversification opportunities.

3 Methodology

3.1 The Nelson-Siegel yield curve model and the Diebold-Li decomposition

The target of the yield curve models is to enable the fitting of the yield curve, then the parametric interpolation and extrapolation afterwards, which is in line with the non-parametric (statistics based) fitting methods, such as smoothing splines. Besides the statistical approaches, the model of Diebold and Li (2006) spread widely both in the academic literature and in industrial applications. This method is the dinamic extension of the yield curve modelling elaborated by Nelson and Siegel (1987). The observed yield curve can be described with the following equation:

$$y_\tau = \beta_1 + \beta_2 \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} \right) + \beta_3 \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau} \right) \tag{1}$$

where y_τ are the realized values for τ maturity, β_1, β_2 és β_3 are time varying parameters, and λ is the exponential decay factor. The Nelson-Siegel model is a simple way of yield curve fitting, while the approach is capable to capture the stylized facts observable in the market, such as the usual shape of yield curves (forward sloping, inverse, humped). The β_i parameters have an economic meaning, β_1 represents the long end of the yield curve, β_2 is the short term component, while β_3 mimics the middle interval. According to the interpretation of Litterman and Scheinkman (1991) these factors can be considered as the Level, Slope and Curveture of the yield curve, accordingly. These components can be utilized for interest-rate asset immunization as well. Besides simple estimation, the model of Diebold and Li (2006) has two further advantages compared to non-parametric approaches. First is, that the extrapolation is more accuratge thanks to the model being exponential. The other is the upper mentioned Litterman interpretation with which understanding and comapring results being much easier.

With the extension of Diebold and Li (2006) the Nelson-Siegel model becomes dynamic (the curve fits on multiple observations). The parametrization of the yield cureve can be done at every point in time to form a set of time-dependent parameters. This is achieved in a two steps procedure.

- First, the λ paramater gets fixed such that the second factor attains its maximum at τ = 30 months and the β parameters get derived.
- Next, an AR(1)-process is fitted to these time dependent parameters to model the dynamics over time, which results the Dynamic Nelson Siegel model.

Additional stylized facts achieved by the Diebold-Li model is the high persistance of time dynamics (same yield curve tenors are highly dependent on past values) and the fact that the long end of the curve is less volatile than the short end.

3.1.1 The Toda-Yamamoto model

The Today-Yamamoto framework is a popular causality testing method. It is widely used in time series analysis. Zhang and Cheng (2009) check the relationship between economic growth and carbon emissions or energy consumption and find that neither of the proposed variables leads to economic growth. Hansen and Rand (2006) look for dependencies between foreign direct investments and increase of the GDP, in a sample of 31 developing countries. They find evidence that FDI causes growth. While checking Healthcare related expenditures and GDP growth, Amiri and Ventelou (2012) conclude that bidirectional causality is predominant. Basher et al. (2012) say that there is an evidence that increases in emerging market stock prices increase oil prices. The common factor in the upper mentioned researches, that the authors has to deal with integrated or cointegrated time series sets.

The Toda and Yamamoto (1995) method uses the followig premise: the classic Granger causality test (Granger (1969)) obtained by a VAR model, may cause a non-stationarity problem, since it does not account the potential cointegration between the used time series. Toda and Yamamoto (1995) point out, that the usual Wald test leads to integrated or cointegrated VAR model, which eventually results spurious Granger causal connections. The Toda-Yamamoto approach eliminates this shortcoming by introducing a modified Wald test (MWald) which has restrictions on the parameters of the VAR(p) model. The test is based on a χ_p distribuiton, where $p' = p + d^{max}$. The order of VAR is increased artificially, p gets increased by d^{max} which is the maximal order of the integration. Then a VAR with order of $(p + d^{max})$ is estimated, where the last d^{max} lag coefficient is ignored. A VAR($p + d^{max}$) model is desribed by equations a (2) and (3):

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \delta_{1i} Y_{t-i} + \sum_{j=p+1}^{d^{max}} \alpha_{1j} Y_{t-j} + \sum_{j=1}^{p} \theta_{1j} X_{t-j} + \sum_{j=p+1}^{d^{max}} \beta_{1j} X_{t-j} + \omega_{1t} \tag{2}$$

$$X_t = \alpha_1 + \sum_{i=1}^{p} \delta_{2i} Y_{t-i} + \sum_{j=p+1}^{d^{max}} \alpha_{2j} Y_{t-j} + \sum_{j=1}^{p} \theta_{2j} X_{t-j} + \sum_{j=p+1}^{d^{max}} \beta_{2j} X_{t-j} + \omega_{2t} \tag{3}$$

where α, δ, θ and β are model parameters, p is the optimal lag of the original VAR model, ω_{1t} és ω_{2t} are the errors of the VAR model, and d^{max} is the maximal order of integration in terms of the Toda-Yamamoto model. hereby based on (2), there is a Granger causality between X and Y, $\delta_{1i} \neq 0$ for all i. In the same manner, based on (3), Granger causality is observable between Y and X, if $\delta_{2i} \neq 0$ for all i. From the VAR($p + d^{max}$) model, the Toda–Yamamoto approach is realized in three steps:

- Perform d^{max} ordered stationarity test on all time series with applying ADF (Augmented Dickey-Fuller test), KPSS (Kwiatkowski-Phillips-Schmidt-Shin test) and PPE (Phillips-Perron test) tests individually or in combination.
- Determine the optimal lag, (p) with the maximal consistency of the AIC (Akaike's Information criterion), the FPE (Akaike's Final Prediction Error), the BIC (Bayesian Information Criterion), the HQ (Hannan-Quinn criterion) and the LR (Lielihood Ratio test) criteria.
- With the application of the upper mentioned parameters, rejecting the Granger test between X and Y means a causality relation in Toda-Yamamoto terms. Bivariate rejection suggests a mutual causal relationship between the variables.

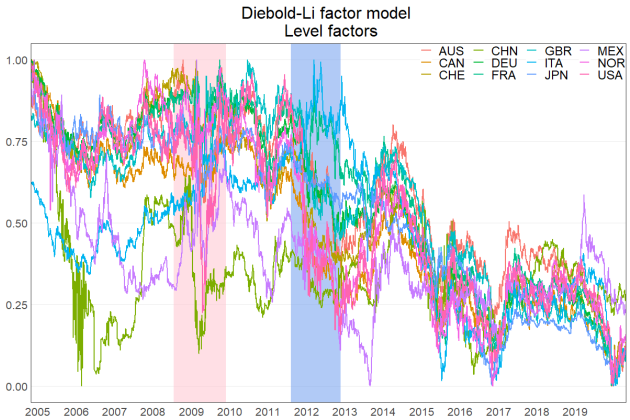
The Toda-Yamamoto procedure has three main advantages. First and foremost, as mentioned above, it can be utilized on integrated an cointegrated time series without any preliminary testing. Second, according to Rambaldi and Doran (1996) the computaion of MWald test is simple, since it can be calulated with a set of Seemingly Unrelated Regressions. Third, Zapata and Rambaldi (1997) shows that in an intentionally overfitted environment, the MWALD test performs as well as more complicated procedures (if the sample size is at least 50).

4 Data

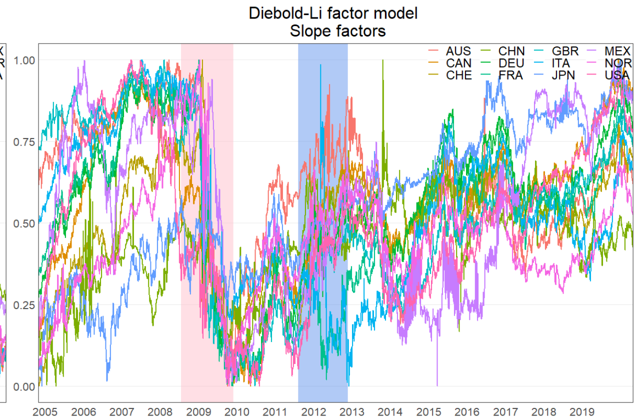
The yield curve time series of the countries were downloaded from Bloomberg. Twelve developed countries were involved into the examination universe, which cover more geographic regions, since they were selected from different continents. Evenually four regions were defined with three-three suvereigns in each. These are the *Pacific* (Australia, China, Japan), *American* (Canada, Mexico, United States), *Euro-zone* (France, Germany, Italy) and the *Non Euro-zone* (United Kingdom, Norway, Switzerland). Ongoingly they are referred as the three letter abbreviation introduced by Worldbank. Respectively: AUS, CHN, JPN, CAN, MEX, USA, FRA, DEU, ITA, GBR, NOR, CHE. During the empirical analysis, the yield curve is examined by its whole tenor structure with fifteen different maturities: 3, 6, 12, 24, 36, 48, 60, 72, 84, 96, 120, 180, 240 and 360. These apply for all countries. The first observation day is 7/1/2004 while the last one is 12/31/2019. The uniusual period is determined by the Chinese yieldcurve since in this case data is available form July 2014 only. Furthermore the effects of recent COVID19 pandemic is exluded from this study, therefore we chose the last day of 2019 for ending the time horyzone. Altogether we work with 4045 daily observations. Missing data points are forward filled from the previous day.

Note1: Kik hasznaltak ezeket az orszagokat? nem nagyon talaltam erre forrast

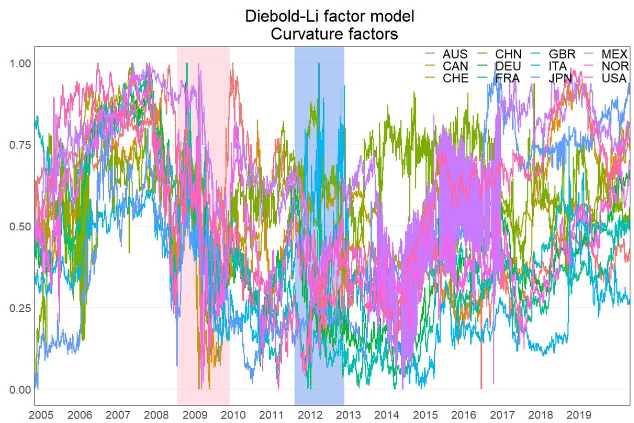
The inputs of the country yield curves are always zero-coupn bonds, denominated in the local currency of the sovereing. Debt in local currency represents the different interest rate cicle of the economy and represents the domestic monetary policy better. Furthermore the debt denominated in local currency has better liquidity and credit rating then holding the same in USD (Sowmya et al. (2016)). Table 2 in the appendix provides descriptive statistics for the 1, 5, 10 and 30 years tenors of each country yield curves. The Level (L), Slope (S) and Curvature (C) factors are calculated by Diebold and Li (2006), Diebold et al. (2008), assuming a dynamic Nelso-Siegel model. Figure 1 shows the normalized time series of the factors. On the below figure period denoted with red shading represents the subprime crysis, while blue shading stands for the European sovereign debt crysis. These periods were determined based on Bostanci and Yilmaz (2020) and Hué et al. (2019).



(a) **Level**



(b) **Slope**



(c) **Curvature**

Figure 1: Normlized factor time series

Start of the subprime crysis: J.P. Morgan takes over Bear Stearns, the troubled investment bank (03/16/08);
End of subprime crysis: 6/30/2009;
Start of the European sovereign debt crysis: Portuguese government calls on EU for bailout (04/06/11);
End of the European sovereign debt crysis: Draghi makes the famous Whatever It Takes speech (07/26/12).

Es itt mondtad, hogy van egy eros faktorkomponens, arra egyelore nem nagyon tudok reagalni, azzal kapcsolatban mi lenne a tervunk?

The descriptive statistics of the factors are represented in Table 1. The average Level factor is positive in all cases, highest for Mexico and lowest for Japan. Average Slope refers to the tipical increasing shape of the yield curves (negative values). Slope is negative for all countries meaning that longer maturities have higher values than shorter ones. In absolute terms the USA has the highest Slope, while Australia has the lowest. Potential positive values of Slope represent restricittive monetary politics. Curvature is always negative too, highest for France and lowest for China (in absoluter terms).

Factor	Average	Std. dev.	Minimum	Maximum	Jarque-Bera t-stat.	P value
Germany						
Level	2.92	1.54	-0.34	5.41	347	0.00
Slope	-1.86	1.06	-4.54	0.14	210	0.00
Curvature	-3.72	1.72	-7.15	0.73	234	0.00
Italy						
Level	4.78	1.29	1.98	8.00	106	0.00
Slope	-3.43	1.57	-7.01	-0.44	183	0.00
Curvature	-4.25	2.24	-8.60	4.75	194	0.00
France						
Level	3.39	1.37	0.26	5.48	417	0.00
Slope	-2.24	1.19	-4.73	0.02	162	0.00
Curvature	-4.29	1.96	-7.82	1.07	210	0.00
USA						
Level	3.96	0.99	1.88	5.87	323	0.00
Slope	-2.41	1.55	-5.52	0.71	139	0.00
Curvature	-3.63	2.50	-9.58	0.72	228	0.00
Canada						
Level	3.43	1.10	1.23	5.90	274	0.00
Slope	-1.73	1.23	-4.84	0.58	251	0.00
Curvature	-2.49	1.63	-6.26	1.31	206	0.00
Mexico						
Level	8.58	1.28	5.56	13.41	834	0.00
Slope	-2.36	1.83	-6.14	0.67	340	0.00
Curvature	-4.16	2.85	-14.84	0.49	321	0.00
Japan						
Level	1.70	0.83	-0.02	3.26	406	0.00
Slope	-1.28	0.63	-2.83	-0.02	155	0.00
Curvature	-3.69	1.28	-6.03	-0.87	278	0.00
China						
Level	4.02	0.62	2.70	6.52	2047	0.00
Slope	-1.53	0.81	-3.87	1.65	275	0.00
Curvature	-1.24	0.92	-5.20	1.25	1128	0.00
Australia						
Level	4.63	1.23	1.40	6.77	262	0.00
Slope	-0.89	0.98	-3.87	1.00	105	0.00
Curvature	-2.08	1.84	-6.59	2.25	296	0.00
Norway						
Level	3.22	1.12	1.02	5.23	333	0.00
Slope	-1.22	1.07	-4.04	2.26	167	0.00
Curvature	-1.59	1.22	-4.68	1.73	337	0.00
United Kingdom						
Level	3.66	1.23	0.87	5.80	329	0.00
Slope	-1.76	1.75	-5.42	1.35	211	0.00
Curvature	-3.33	3.02	-8.77	3.65	159	0.00
Switzerland						
Level	1.77	1.18	-0.76	3.86	289	0.00
Slope	-1.18	0.70	-3.32	0.91	219	0.00
Curvature	-2.94	1.21	-7.77	0.62	543	0.00

Table 1: Descriptive statistics of yield curve factors

Factor time sereies are tested with (Bera and Jarque (1981)) test for normality. Neither of them passes the acceptance criteria therefor null-hypothesis for normaility is rejected. Furthermore ADF and KPSS unit-root tests for stationarity is applied. Curvature for China and Slope for Japan is stationary on the usual 95% confidence level. The tests can be applied for first difference of the remaining time series. The unit-root test results are represented in Table 5 in the Appendix.

Before differentiating, a pairwise (Engle and Granger (1987) test is applied for determining cointegration. Table 2. represents the ratio of the cointegrated time series aggregated by factors.

Besides the diagonal, the Slope - Curvature and the Curvature - Slope pairs both show a value more than 70%. Since the time series are not stationary on the same order and the ratio of cointegrated time series are high, we consider the Toda-Yamamoto approach to be justified for analyzing connections.

Table 2: Pairwise Engle-Granger test

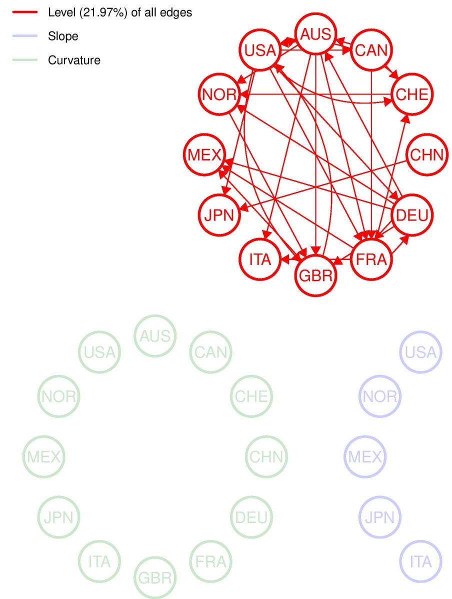
	Level	Slope	Curvature
Level	75.7%	44.4%	64.6%
Slope	29.2%	74.3%	71.5%
Curvature	29.2%	78.5%	75.0%

5 Results

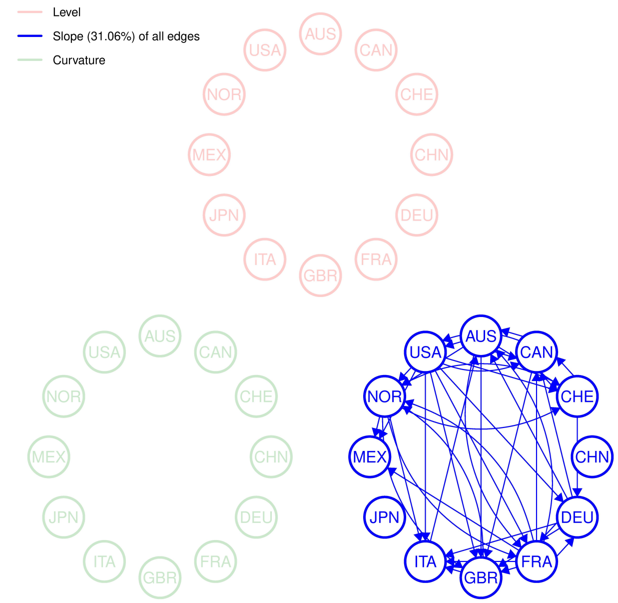
5.1 Static interconnectedness

We perform statical and dynamical analysis of the factor interconnectedness resulted by the Toda-Yamamoto model. All of the available data points were used in the static method. Time series are differenciated once at maximum, and the optimal lag number is determined based on AIC. Figure textcolormagenta2 shows the causailiy relationships on 1 % sigificance level. Level factors are red, while Slope is blue and the Curvature is shwed in green. The arrow between two factors shows the direction of tha causality and its color represent the factor which it is started from.

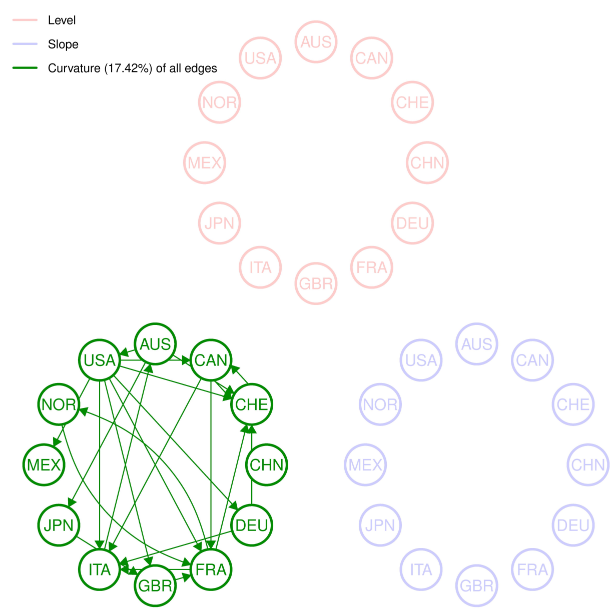
From the three subsystems, the Slope network is the most dense. 31.06% of the potential relationships are significant. It is followed by Level (21.97%), then Curvature (17.42%). Considering cross connections, 31.25% of the possible edges going out from Level factors are significant. This ratio is 26.39% for Slope, and Curvature is the least interconnected factor in these terms, only 24.49% of the outgoing edges are significant.



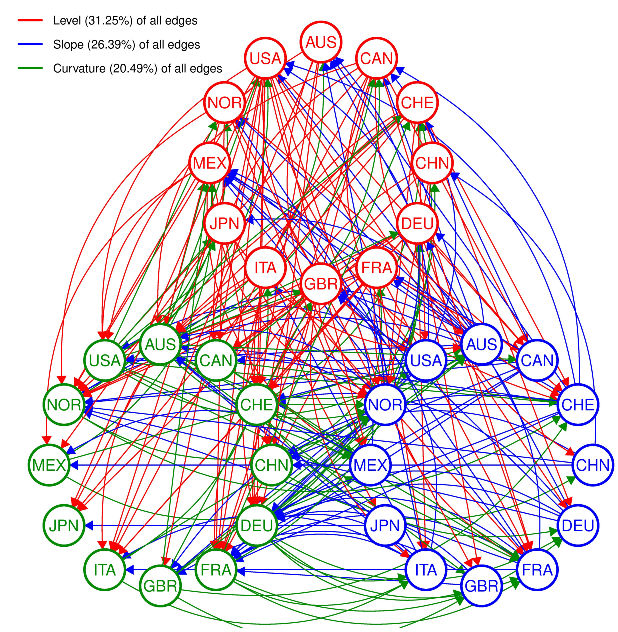
(a) **Level subnetwork**



(b) **Slope subnetwork**



(c) **Curvature subnetwork**



(d) **Cross connections**

Figure 2: Interconnectedness in subnetworks

The (a) part of Table 4 contains the number of edges defined in the system. Rows of the table represent the origin of the relationship, while columns stand for the endpoints of the arrows. On 1% significance level, the graph has 318 edges which is 25.24% of the total potential edges . (b) part of Table 4 shows the ratio of the edges defined within subnetworks compared to the total potential edges definable in that given relationship system. Based on this, density of causality is the highes for Level - Curvature par, 36.1% followed by Slope - Curvature which is 31.94%. The third place goes for the Level subnetork with 31.06%. The relationship matrix is simmetrical for the diagonal, in total, from the Curvature factor there is less arrows going out both internally and towards other subnetworks.

	Level	Slope	Curvature	Sum
Level	29	38	52	119
Slope	30	41	46	117
Curvature	25	34	23	82
Sum	84	113	121	318

(a) **Number of edges, grouped by factors**

	Level	Slope	Curvature	Sum.
Level	22.0%	26.4%	36.1%	84.5%
Slope	20.8%	31.1%	31.9%	83.8%
Curvature	17.4%	23.6%	17.4%	58.4%
Sum.	60.2%	81.1%	85.5%	25.2%

(b) **Distribution of edges, grouped by factors**

Table 3: The number and distibution of the sygnificant edges defined in the system

5.1.1 Top nodes

Table 5 contains the fators with the most edges. The first quarter of the list stands for the summarized relationships, then the following columns represent the nodes having the most incoming and outgoing edges separatedly. In total, Level factor of the United States has the most edges, which is 30. from this 30, there are 23 outgoing and 7 incoming arrows. This relationship system is shown on Figure 5. Generally speaking, one can say, that all three factors of the USA lead the list regarding both outgoing, both net (outgoing-incoming) edges. This can be interpreted as the USA causes the values of the factors of the remaining participants of the system and in the meanwhile it is not affected by the others. In the list of outgoing edges, Curvature of Asutralia is ahd of the Level of Germany which node is on the fourth place of the net chart, before the Level of Canada. The most causality effect is arriving towards the French Curvature followed by the Italian Slope, then the Curvature of the same country.

Top 5 Sum				Top 5 Incoming		Top 5 Outgoing		Top 5 Net	
Node	Total	In	Out	Node	In	Node	Out	Node	Net
USA_L	30	7	23	FRA_C	19	USA_L	23	USA_L	16
AUS_S	28	11	17	ITA_S	16	USA_S	18	USA_S	12
FRA_S	28	14	14	ITA_C	16	USA_C	17	USA_C	10
NOR_S	27	16	11	MEX_L	14	AUS_S	17	DEU_L	9
FRA_C	27	19	8	FRA_S	14	DEU_L	16	CAN_L	7

Table 4: Factors having most edges

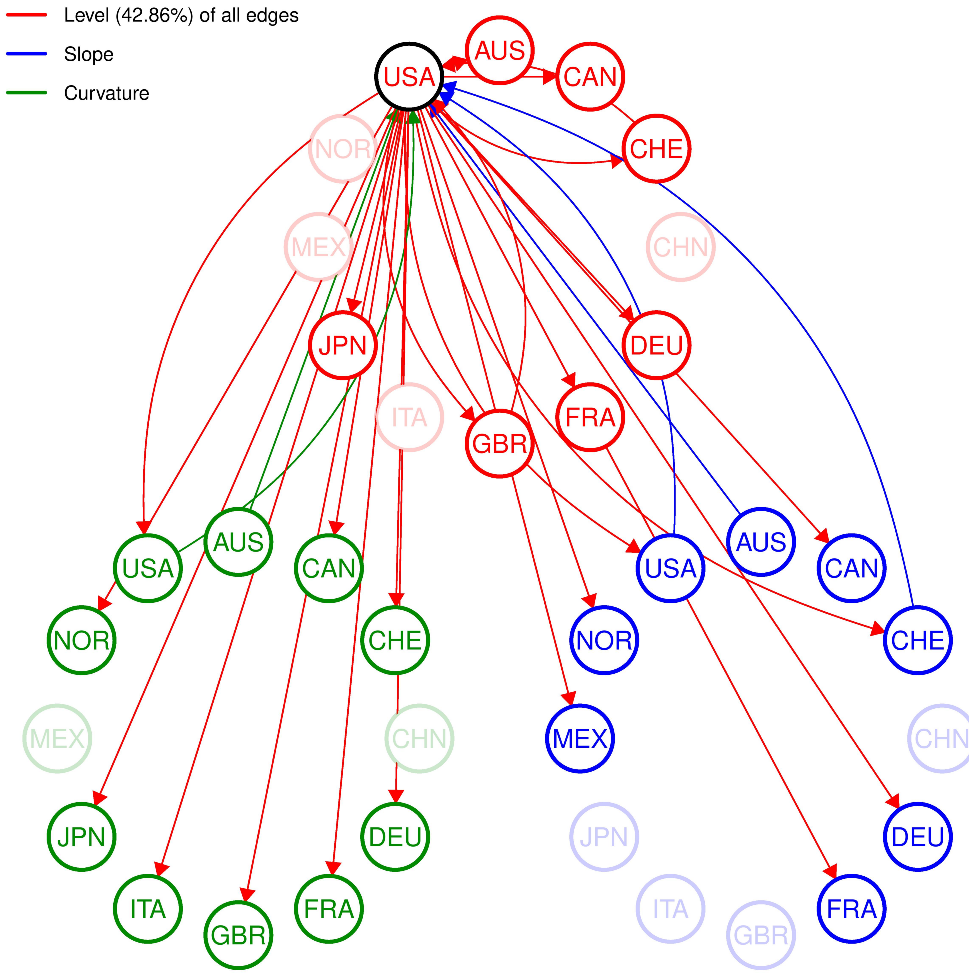


Figure 3: Node having most summarized edges

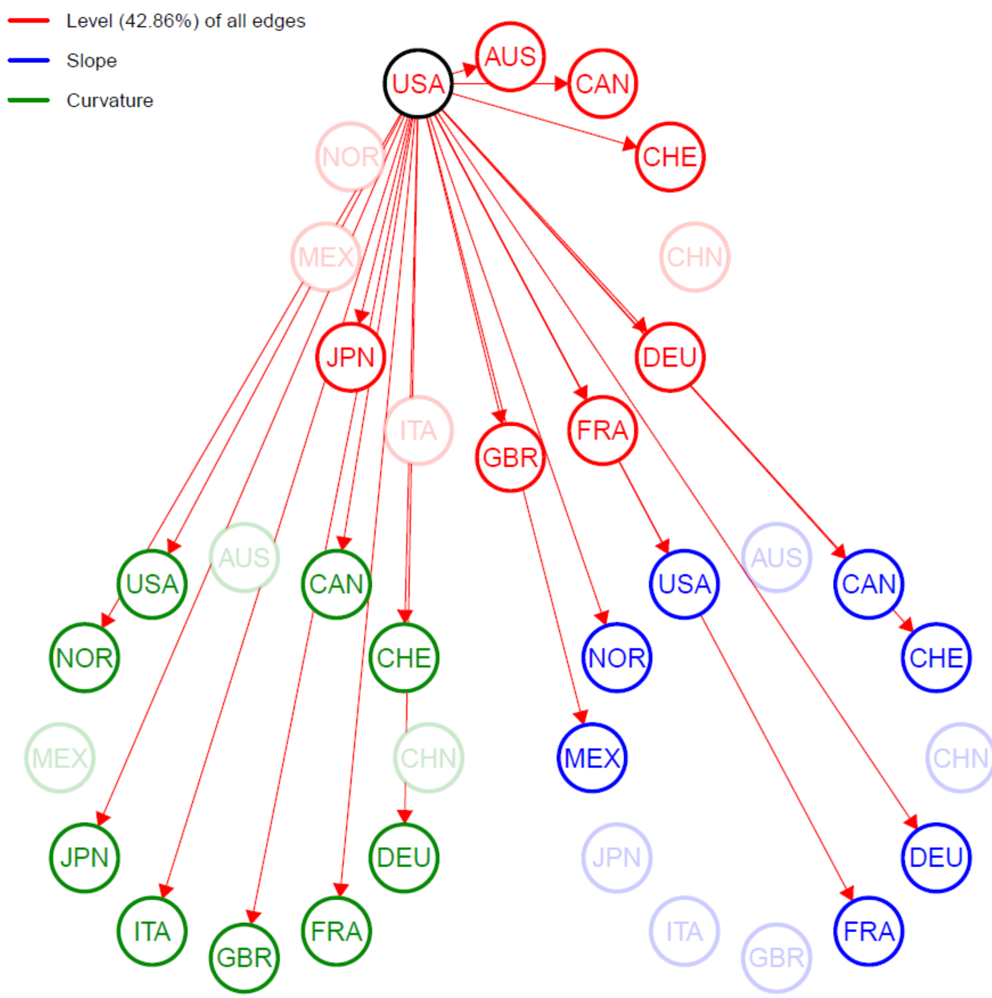


Figure 4: Node having most outgoing edges

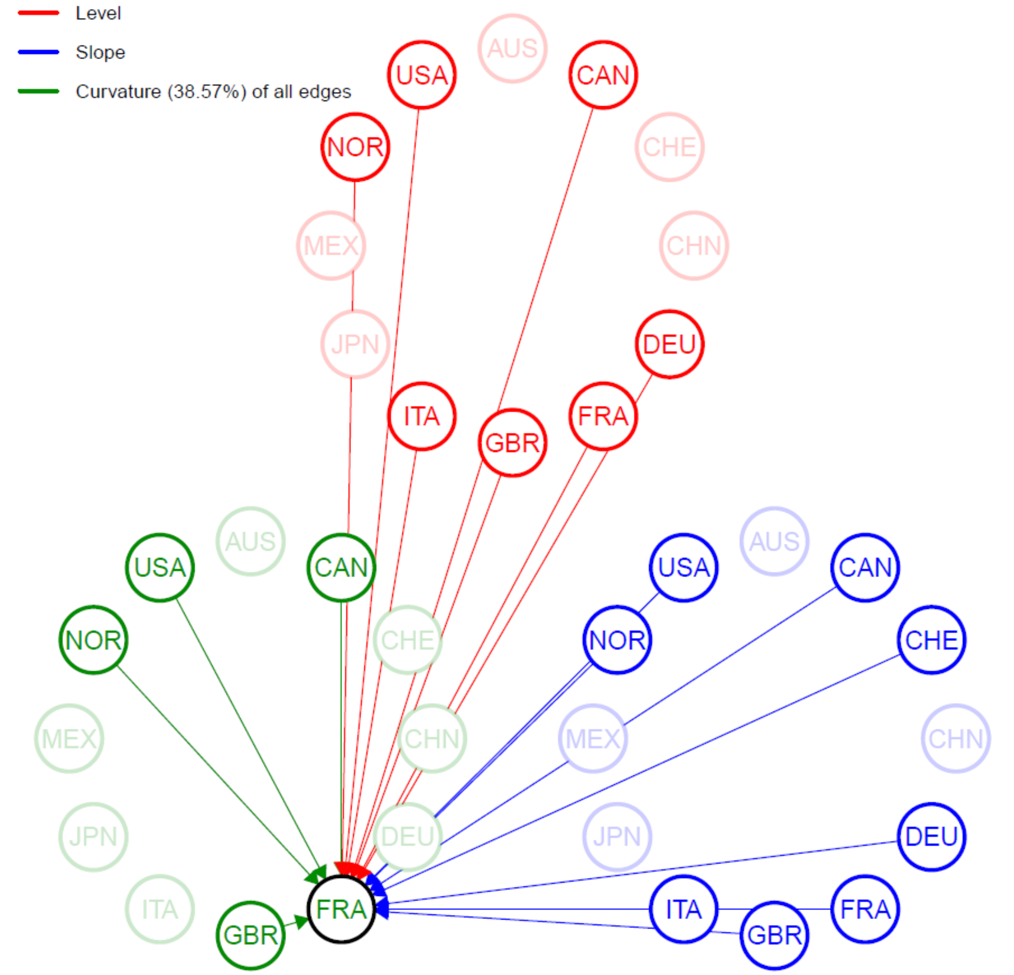


Figure 5: Node having most incoming edges

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Appendices

Node	Average	St. dev	Minimum	Maximum	ρ(1)	ρ(10)
Germany						
1 year	0.026	1.628	-0.969	4.690	1.000	0.996
5 years	0.026	1.632	-0.941	4.767	0.999	0.993
10 years	0.024	1.545	-0.722	4.686	0.993	0.964
30 years	0.023	1.448	-0.244	5.195	0.999	0.988
Italy						
1 year	0.024	1.533	-0.484	8.394	0.998	0.986
5 years	0.024	1.520	0.237	7.895	0.998	0.985
10 years	0.022	1.388	0.875	7.492	0.998	0.986
30 year	0.019	1.197	2.043	7.584	0.998	0.985
France						
1 year	0.025	1.589	-0.801	4.657	1.000	0.996
5 years	0.025	1.573	-0.773	4.910	0.999	0.993
10 years	0.023	1.467	-0.415	4.851	0.999	0.991
30 years	0.019	1.235	0.419	5.116	0.999	0.986
USA						
1 year	0.025	1.613	0.054	5.323	1.000	0.998
5 years	0.019	1.232	0.559	5.301	0.999	0.980
10 years	0.016	1.039	1.389	5.388	0.998	0.983
30 years	0.015	0.962	1.992	5.839	0.997	0.976
Canada						
1 year	0.019	1.230	0.300	4.809	1.000	0.995
5 years	0.018	1.146	0.484	4.801	0.999	0.989
10 years	0.017	1.098	0.983	5.076	0.999	0.987
30 years	0.016	1.012	1.306	5.612	0.998	0.985
Mexico						
1 year	0.032	2.025	1.512	10.570	0.979	0.988
5 years	0.024	1.511	3.786	10.897	0.986	0.981
10 years	0.021	1.352	4.619	12.413	0.992	0.970
30 years	0.020	1.238	5.873	12.726	0.993	0.947
Japan						
1 year	0.004	0.272	-0.371	0.850	0.999	0.992
5 years	0.008	0.485	-0.396	1.631	0.999	0.990
10 years	0.010	0.656	-0.285	2.050	0.999	0.990
30 years	0.012	0.761	0.053	3.295	0.998	0.985
China						
1 year	0.012	0.730	0.957	4.382	0.992	0.966
5 years	0.009	0.594	1.782	4.874	0.997	0.973
10 years	0.009	0.570	2.481	5.503	0.993	0.964
30 years	0.010	0.615	2.470	6.009		
Australia						
1 year	0.028	1.775	0.675	7.376	0.999	0.992
5 years	0.026	1.677	0.639	6.960	0.999	0.990
10 years	0.024	1.497	0.885	6.873	0.999	0.988
30 years	0.019	1.207	1.558	6.888	0.998	0.983
Norway						
1 year	0.022	1.410	0.199	6.243	0.999	0.994
5 years	0.020	1.273	0.545	5.335	0.999	0.991
10 years	0.019	1.194	0.888	5.276	0.999	0.989
30 years	0.018	1.113	0.882	5.273	0.999	0.987
United Kingdom						
1 year	0.031	1.956	0.024	5.883	0.999	0.995
5 years	0.026	1.644	0.161	5.821	0.999	0.991
10 years	0.022	1.418	0.400	5.543	0.999	0.989
30 years	0.018	1.110	0.939	5.070	0.999	0.987
Switzerland						
1 year	0.020	1.241	-1.165	3.375	1.000	0.996
5 years	0.019	1.192	-1.196	3.200	0.999	0.993
10 years	0.019	1.198	-1.138	3.455	0.999	0.991
30 years	0.017	1.101	-0.644	3.733	0.998	0.986

Table 5: Descriptive statistics of country yield curve nodes

Country	DEU		ITA		FRA		USA		CAN		MEX	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	-2.30	0.45	-1.47	0.81	-2.16	0.51	-3.66	0.03	-3.06	0.13	-3.97	0.01
Slope	-2.09	0.54	-2.26	0.47	-1.64	0.73	-1.50	0.79	-1.57	0.76	-1.88	0.63
Curvature	-2.22	0.49	-3.59	0.03	-2.36	0.43	-1.62	0.74	-2.35	0.43	-2.71	0.28

Country	JPN		CHN		AUS		NOR		GBR		CHE	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	-2.97	0.17	-3.69	0.02	-2.90	0.20	-2.63	0.31	-2.16	0.51	-2.50	0.37
Slope	-4.85	0.01	-3.69	0.03	-2.30	0.45	-2.72	0.27	-0.95	0.95	-3.14	0.10
Curvature	-2.03	0.57	-5.52	0.01	-2.61	0.32	-3.67	0.02	-1.62	0.74	-3.14	0.10

(a) **ADF test results**

Country	DEU		ITA		FRA		USA		CAN		MEX	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	32.89	0.01	14.58	0.01	29.87	0.00	26.85	0.01	32.18	0.01	15.24	0.01
Slope	4.26	0.01	7.61	0.01	4.50	0.01	5.30	0.01	5.40	0.01	4.78	0.01
Curvature	8.96	0.01	10.21	0.01	15.21	0.01	7.34	0.01	4.59	0.01	4.92	0.01

Country	JPN		CHN		AUS		NOR		GBR		CHE	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	33.94	0.01	3.55	0.01	29.17	0.01	30.06	0.01	28.70	0.01	31.96	0.01
Slope	33.21	0.01	14.99	0.01	7.32	0.01	1.25	0.01	7.53	0.01	5.49	0.01
Curvature	15.95	0.01	2.91	0.01	24.67	0.01	11.56	0.01	13.33	0.01	5.67	0.01

(b) **KPSS test results**

Country	DEU		ITA		FRA		USA		CAN		MEX	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	-17.05	0.01	-16.01	0.01	-15.99	0.01	-15.79	0.01	-16.35	0.01	-16.56	0.01
Slope	-15.90	0.01	-14.62	0.01	-14.59	0.01	-16.55	0.01	-16.32	0.01	-15.19	0.01
Curvature	-18.52	0.01	-18.67	0.01	-17.65	0.01	-17.45	0.01	-16.02	0.01	-18.88	0.01

Country	JPN		CHN		AUS		NOR		GBR		CHE	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	-16.55	0.01	-16.99	0.01	-15.61	0.01	-16.43	0.01	-16.48	0.01	-15.57	0.01
Slope			-18.90	0.01	-17.87	0.01	-17.61	0.01	-16.12	0.01	-14.59	0.01
Curvature	-17.51	0.01			-18.06	0.01	-17.04	0.01	-16.45	0.01	-14.27	0.01

(c) **ADF(1) test results**

Slope	DEU		ITA		FRA		USA		CAN		MEX	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	0.04	0.10	0.13	0.10	0.06	0.10	0.03	0.10	0.06	0.10	0.08	0.10
Slope	0.08	0.10	0.07	0.10	0.12	0.10	0.16	0.10	0.17	0.10	0.09	0.10
Curvature	0.05	0.10	0.02	0.10	0.05	0.10	0.08	0.10	0.08	0.10	0.01	0.10

Slope	JPN		CHN		AUS		NOR		GBR		CHE	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	0.03	0.10	0.16	0.10	0.05	0.10	0.04	0.10	0.07	0.10	0.04	0.10
Slope	0.03	0.10	0.03	0.10	0.04	0.10	0.08	0.10	0.24	0.10	0.14	0.10
Curvature	0.06	0.10	0.05	0.10	0.04	0.10	0.03	0.10	0.16	0.10	0.05	0.10

(d) **KPSS(1) test results**

Table 6: Results of unit-root tests