Interconnectedness Among Sovereign Yield Curve Factors - Working title

Milan Csaba Badics - Balazs Kotro

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Abstract

We are investigating the interconnectedness of the yield curve factors of 12 developed economies worldwide. From the yield curve time series we extract the Level, Slope and Curvature factors by the Diebold-Li decomposition technique for every day. On the recieved 36 observation series a pairwise Toda-Yamamoto causality test is performed in order to identify connections. Our static results show that there is a significant amount cross connections among the different factos. On average Level is the most connected factor, followed by Slope and Curvature. We also identify the USA to be the main driver of the observation universe. Our dynamic results show that during turbulent economic periods the density of the connections gets higher. On the chosen time horizone, USD Level, USD Curvature and Norwegian Slope are the most interconnected factors.

1 Introduction and literature review

The subprime crisis renewed the interest in analyzing the co-movements 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 crisises the strength of connections sharply increases and risk spills over across financial institutes and sovereign bonds, as it happened during the Financial Crisis of 2008-2009 and during the European Sovereign Crisis (Diebold and Yilmaz (2012), Diebold and Yılmaz (2014), Demirer et al. (2018)). itt ezt annyira nem erzem jonak, csak felsoroltam 3 diebold cikket

Since the financial system is a huge, complicated, interactive system, in recent years scholars began using complex network theories to investigate the interconnectedness of financial institutions. Acemoglu et al. (2015) points out that in smaller financial systems, shocks make the densely interconnected network steadier, however after a certain size the opposite applies. Glasserman and Young (2015) has some common features with the previously mentioned article, however they allow continuous distributions of the shocks. By doing so, they state that the probability of default of a firm is lower when a shock hits some of its neighbors compared with when the firm is directly hit. 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 anothers' failures. Depending more on other participants makes personal sensitivity lower on own investments. An other mechanism of shock transmission is the decrease of interbank loan availability as known as funding liquidity shock. Gai and Kapadia (2010) examine the liquidity hoarding that formed on the interbank funding markets. They find that such accumulation of liquidity can flow through a banking network, with serious consequences. As soon as one bank draws down or shortens the terms of its interbank loans, the related banks are eager to do the same. This results a liquidity shock that is not characterized by the damping of interbank default shocks.

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), Diebold and Yılmaz (2014)). Compared to CoVaR and MES methods, the advantage of Granger causality based frameworks is the ability to examine the network both on micro (pairwise connectedness) and macro (total connectedness) level. As 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 focuses on the whole system or some subpart. The dynamics of individual assets' role in the system have not been explored yet.

Central banks traditionally rely on the co-movements 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 (Laopodis (2004)). 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 (Ilmanen (1995)). ezek hellyel-kozzel erintik ennek a bekezdesnek a tartalmat, nem tudom hogy jo lesz-e

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) examines only the 10Y yield curve point on EMU countries while Claeys and Vašíček (2014) choose the spread between EU government bond yields and German sovereign bond yield, also considering 10 years of maturity. Ahmad et al. (2018) pick bond indices to analyze and Sowmya et al. (2016) decompose the yield curve to Level, Slope and Curvature factors with the Diebold-Li dimension reduction technique.

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 choose developed economies from all over the World in order to achieve a wide geographical coverage.

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 main 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 Methodology

2.1 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 dynamic 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 on 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 becomes 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.

2.1.1 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 described 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:

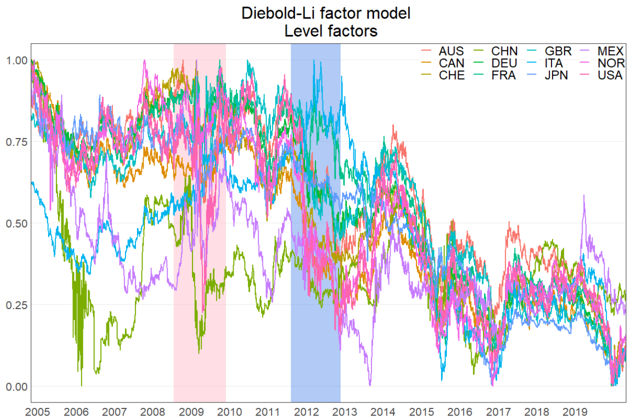
- Perform d^{max} ordered stationarity test on all time series with applying ADF (Augmented Dickey-Fuller test), KPSS (Kwiatkowski-Phillips-Schmidt-Shin test) and PPE (Phillips-Perron test) tests individually or in combination.
- Determine the optimal lag, (p) with the maximal consistency of the AIC (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).

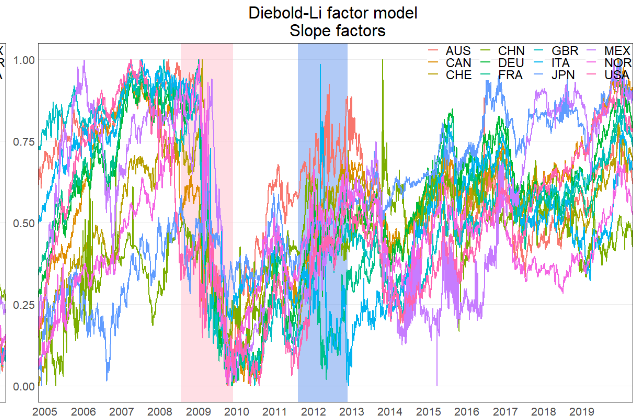
3 Data

The yield curve time series of the countries are downloaded from Bloomberg. Twelve developed countries are involved in the examination universe, which cover more geographic regions, since they are selected from different continents. Evenually four regions are defined with three-three sovereigns 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 yield curve 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 choose the last day of 2019 for ending the time horizone. Altogether we work with 4045 daily observations. Missing data points are forward filled from the previous day.

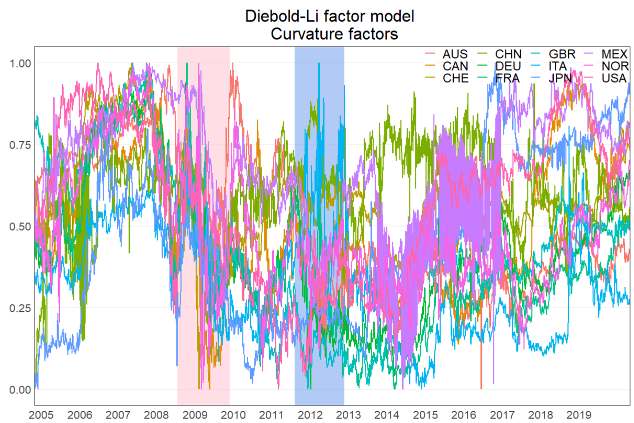
The inputs of the country yield curves are always zero-coupon bonds, denominated in the local currency of the soverein. Debt in local currency represents the different interest rate cycles of the economy and represents the domestic monetary policy better. Furthermore the debt denominated in local currency 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 Y 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 Nelson-Siegel model. Figure 1 shows the normalized time series of the factors. On the below figure period denoted with red shading represents the subprime crisis, while blue shading stands for the European sovereign debt crisis. These periods are 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 crisis: J.P. Morgan takes over Bear Stearns, the troubled investment bank (03/16/08); End of subprime crisis: 6/30/2009; Start of the European sovereign debt crisis: Portuguese government calls on EU for bailout (04/06/11); End of the European sovereign debt crisis: Draghi makes the famous "Whatever It Takes" speech (07/26/12).

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 restrictive monetary politics. Curvature is always negative too, highest for France and lowest for China (in absolute 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 therefore the null-hypothesis for normaility is rejected. Furthermore ADF and KPSS unit-root tests for stationarity are 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 too. 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 cointegrations. 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 is high, we consider the Toda-Yamamoto approach to be justified for analyzing connections.

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

Table 2: Pairwise Engle-Granger test

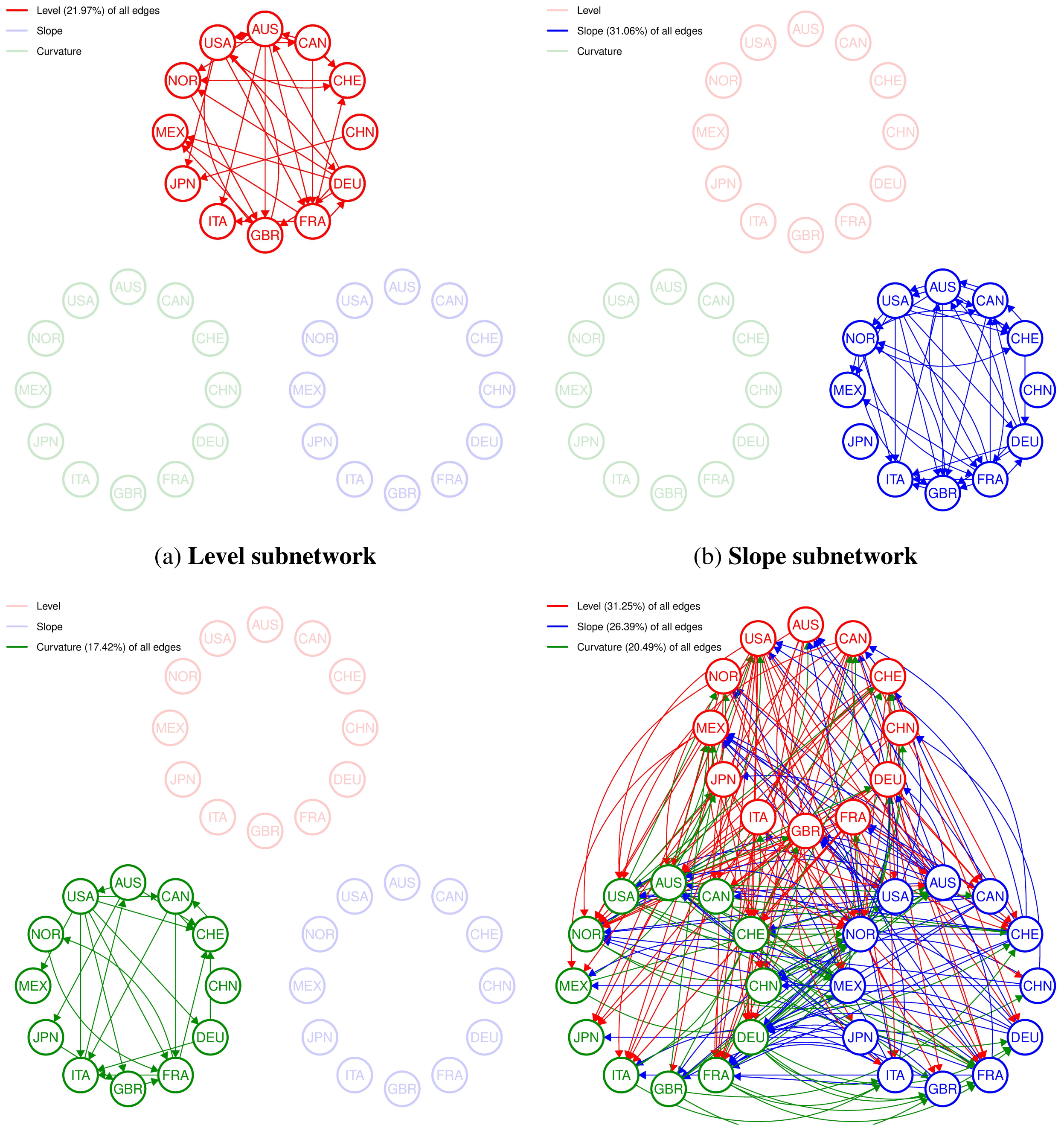
Instead of the 36 x 36 matrix which we obtain from the pairwise Engle-Granger test, we highlight only the factor-wise aggregated values in this table.

4 Results

4.1 Static interconnectedness

We perform static and dynamic analysis of the factor interconnectedness resulted by the Toda-Yamamoto model. All of the available data points are used in the static method. Time series are differenciated once at maximum, and the optimal lag number is determined based on AIC. Figure 2 shows the causailiy relationships on 1 % sigificance level. Level factors are red, while Slope is blue and the Curvature is showed in green. The arrow between two factors shows the direction of the 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 is 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 is 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 is significant.



(a) **Level subnetwork**

(b) **Slope subnetwork**

(c) **Curvature subnetwork**

(d) **Cross connections**

Figure 2: Interconnectedness in subnetworks

The (a) part of Table 3 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 3 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 highest for Level - Curvature pair, 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 symmetrical 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

4.1.1 Top nodes

Table 4 contains the factors 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. Fom this 30, there are 23 outgoing and 7 incoming arrows. This relationship system is shown on Figure 5. Generally speaking, all three factors of the USA leads the list regarding both outgoing and net (outgoing-incoming) edges. This can be interpreted as the USA has a high affecting power on the values of the factors of the remaining participants in the system and in the meanwhile it is not affected by the others. In the list of outgoing edges, Curvature of Asutralia is ahead 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

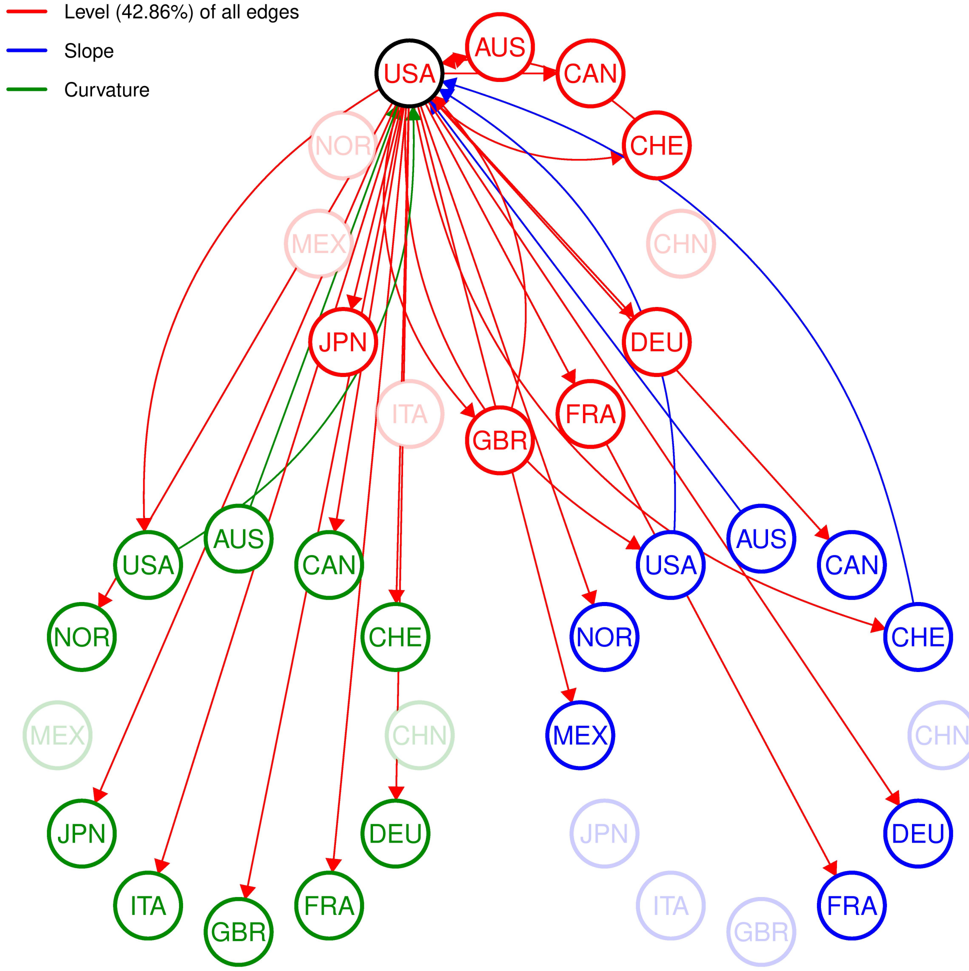


Figure 3: Node having most summarized edges

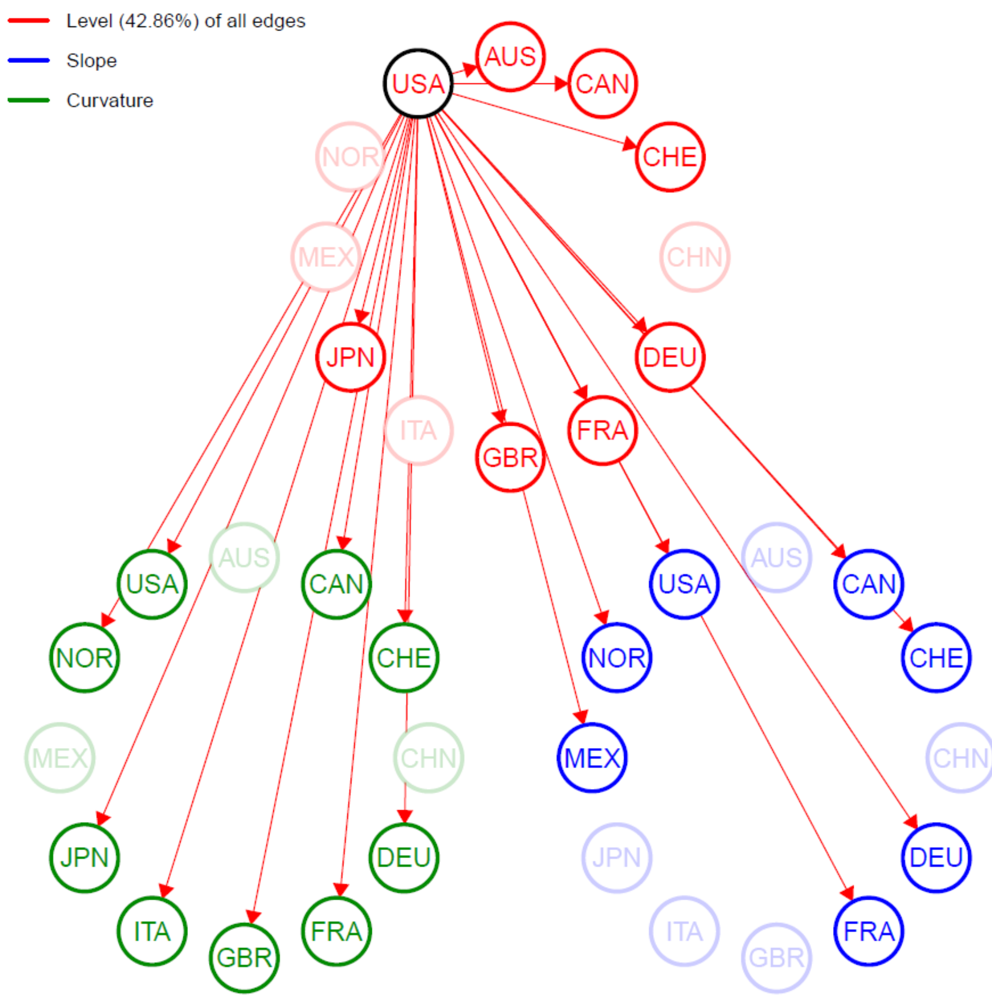


Figure 4: Node having most outgoing edges

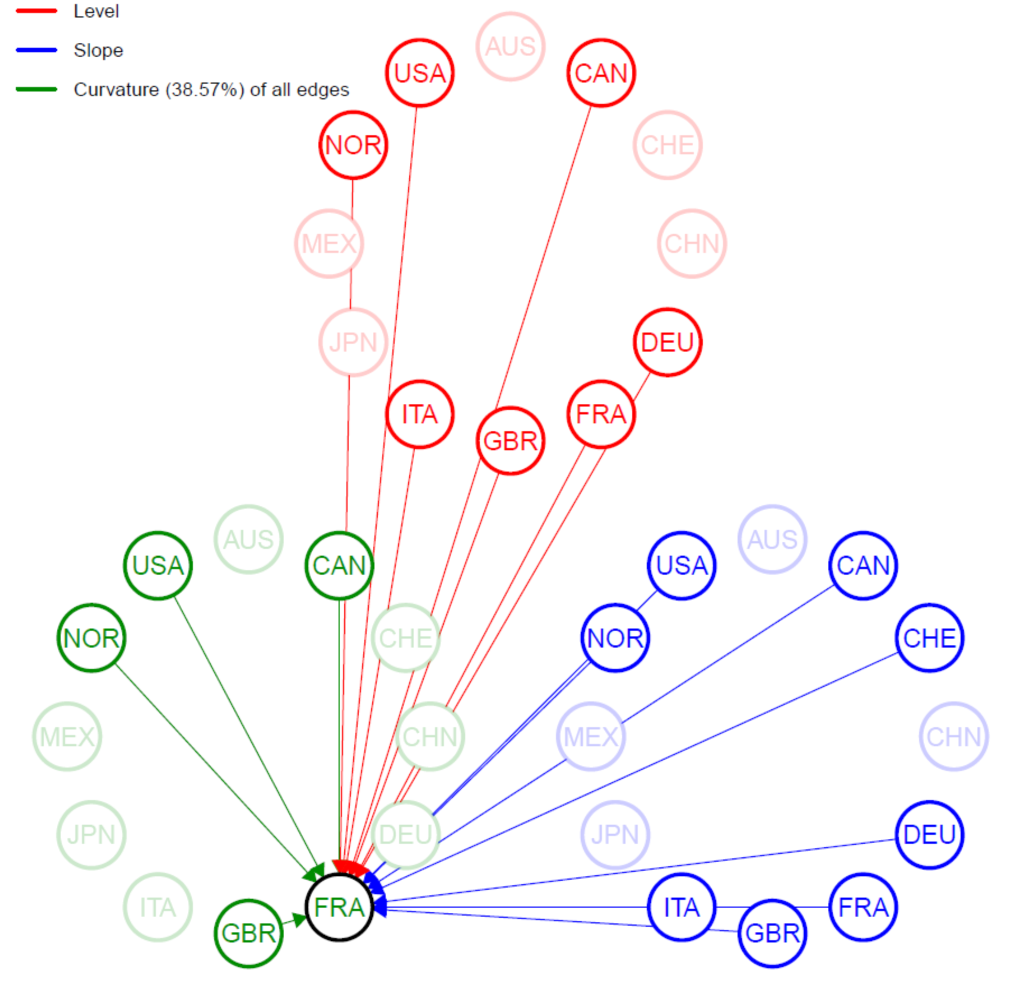


Figure 5: Node having most incoming edges

4.2 Time series analysis

After the static examination we performed a dynamic analysis of the factor interconnectedness. We chose a rolling window mrthod with size of 750 observations. Considering 250 business days long years, this can be interpreted as a three years long period. With each shifting we move 5 observations ahead which can be seen as one business week. By doing so, we define 659 separeted models. The time series coming from these models are shown on Figure 6. Purple line stands for the ratio of the singnificant edges in the whole newtwork, cyan is the sum of the edges in different subnetworks and yellow represents edges coming from cross connections. As stated before, the subprime crysis is displayed by the red shaded area and the blue field covers the European sovereign debt.

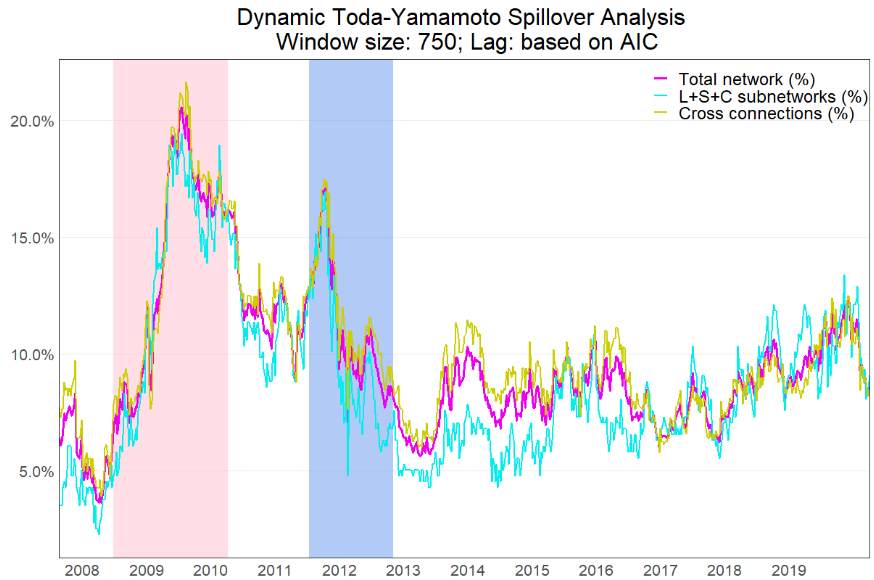


Figure 6: Dynamic Toda-Yamamoto analysis - 750 observations long window size

Figure 7 shows the factors having the most edges during the whole observation period. In ascending order, these are Norwegian Slope, American Curvature and American Level. Subprime crisis had an effect on both three of them, time series have a peak during this period. The Slope factor of Norway increased drastically during the European Sovereign crisis. This can be explained by the fact that in the end of 2011, the sovereign investment fund of Norway sold whole of its Irish and Portugal sovereign debt, and decreased the ownership ratio in Spanish and Italian bonds.

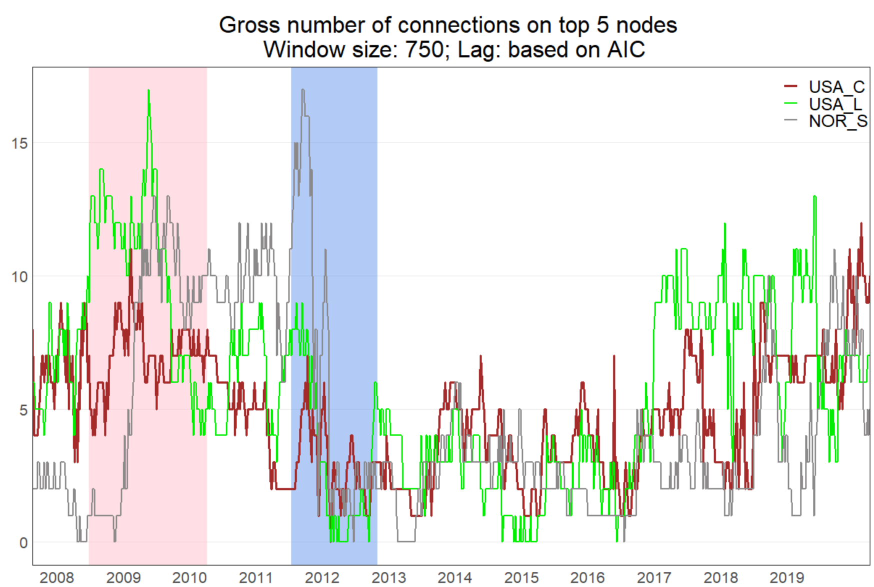


Figure 7: Edges having the most edges during the observation period - 750 observations long window size

By defining two turbulent periods, which are colored on the plots, and three calm ones we devide our observation horizone to five subsets. Table 5 shows the average edge count for such periods aggregated by factors. One can see that during the subprime crisis, all of the edge numbers increases to more than double. This is followed by a slow decrease, the second turbulent period is not even represented by the numbers. The reason is that the crisis of 2008 was global, while the Europen soverein crisis had affect mainly on the European countries and especially on the Eurozone.

	Whole period	1. calm	1. crisis	2. calm	2. crisis	3. calm
Level	29	7	16.2	13.4	12.1	12
Slope	41	6	25.5	22.5	16.2	8.6
Curvature	23	7.3	20.7	9.7	9.2	9.9
Cross connections	225	61.8	142.2	109.1	101.2	76.1

Table 5: Average edge count by edges during the five sub-periods - 750 observations long window size

5 Robostness checks

Yet to come...

Bibliography

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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 6: 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 7: Results of unit-root tests