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Author(/s): **González Sánchez, Mariano**

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Causality in the sovereign bond markets

González, Mariano

Business Administration Department, School of Economics,
CEU San Pablo University,
Julian Romea, 23. 28003 Madrid (Spain)

Abstract

The results of empirical studies aboutn causality among sovereign bonds could be biased, since its use only some bonds, depending on the maturity, or analyze bond market indexes; by contrast, we test causality in-mean and in-variance on full interest rate curve. For that, we propose a method for estimating the curve factors (Nelson-Siegel) avoiding multicollinearity, and then we study asymmetric causalilty among them. On a daily sample of sovereign bonds market prices (France, Germany, Italy, Spain, Switzerland, UK and USA), we found that USA (long-term) and Germany (short-term) are main drivers of causality in-mean. The causality in-variance results shows that the effect is miostly in the EMU area, highlighting Spain as the main driver.

Keywords: Asymmetric causality, sovereign bond market, volatility spillovers, Nelson-Siegel.
JEL: E58, F34, F36, G12, G15.

*Corresponding author
Email address: gonsan@ceu.es (González, Mariano)

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1. Introduction

The recent financial crisis has revealed the existence of strong connections among different markets and assets. This is most evident in the case of sovereign debt, where its special nature, as key investment in many portfolios and financial institutions,has involved that the regulator introduces in the stress tests the relationship among the behavior of different sovereign bonds. Besides, given the high volume of sovereign debt issues and its characteristics, in the financial literature there is an abundant number of studies analyzing the integration between sovereign debt markets, even more so since the birth of the EMU area (see Ehrmann et al. (2011)).

In this context, we would highlight empirical evidence found by previous works, such as: nonstationarity of a long-term yield (Gómez-Puig & Sosvilla-Rivero (2013) or Sibbersten et al. (2014)); heteroskedasticity, causality in-variance and volatility-spillover (Laopodis (2004); Christiansen (2007); Li et al. (2008); Babalos et al. (2015)); and asymmetric causality (Beirne & Fratzcscher (2013); Caporin et al. (2013); Babalos et al. (2015)), mainly in the case of bad news. It is noteworthy that we have not found any work that includes all these features to analyze causality in the bonds market, for example Caporin et al. (2013) use a regression quantiles to estimate asymmetry but does not consider causality in-variance, or Babalos et al. (2015) indicate that long-term yields are stationary unlike the rest of literature.

Regarding the methodologies used in the study of causality among financial variables in-mean and in-variance, there are two approaches, on the one hand, the approach using multivariate models as Vector Autorregresive and Multivariate Generalized Autorregresive Conditional Heterokedasticity or VAR-$MGARCH$ models (Weber (2010)); and the other that uses Cross Correlation Function or CCF (Cheung & Ng (1996); Hong (2001); Qadan & Yagil (2012)).

From Cheung & Ng (1996) we know that CCF is robust against non-symmetrical and leptokurtic behavior, usually in financial data. Also, Pantelidis & Pittis (2004) showed that simultaneously test the causality in-mean and in-variance is not feasible since, the first results condition the second ones. In addition, the computational complexity for a multivariate $GARCH$ increases when individual distribution of each series or/and the univariate model $GARCH$ fitted are different. González (2016) implements an analysis of causality in-mean and in-variance, which in a first stage, analyzes and models the stylized facts of data, and later, on standardized residuals, using the Wald test, he checks the causality asymmetric. In this line, our aim is to determine whether a shock on the sovereign bonds involves an asymmetric effects on the other bonds, that is, if the effects are the same when the movements are up and down.

Another issue to review is the lack of homogeneity in the analyzed samples to test the bond market causality. There are works using only a few references as: prices or yields of long-term (Dungey et al. (2006); Gómez-Puig & Sosvilla-Rivero (2013); Sibbersten et al. (2014); Babalos et al. (2015)); prices or yields of short-term (Laopodis (2004)); or spreads on another reference asset. Others papers use bond indexes (Christiansen (2007); Ciner (2007); Li et al. (2008)); and others study Credit Defaults Swap for some maturities (Beirne & Fratzcscher (2013); Caporin et al. (2013); Groba et al. (2013); Gorea & Radev (2014)) but in this case, because its objective is to analyze mostly credit risk. So the main problem of previous works is that sample is incomplete, since not all references traded daily on the market, independently of maturity, are used.

Then, to make our study feasible and given the dispersion of maturities and continued emissions, we must perform the analysis of causality in-mean and in-variance not on specific bonds, but on the daily interest rate curve obtained from market prices of all references traded. In this regard, and in order to correctly interpret the results, we have to consider two preliminary issues. On the one hand,it is necessary that the factors explaining the curve have a clear and common meaning to all bonds (that would restrict the use of factor decompositions that do not allow to identify the factors); and on the other, these factors have to be independent of each other, because otherwise we could not identify the causality for the same type of factor from different curves.

A standard model use to value and analysis the sovereign bonds is Nelson & Siegel (1987); for which Coroneo et al. (2011) found that is free arbitrage. This approach has already been applied by Afonso & Martins (2012) with the aim to study the dynamic relation between fiscal developments (government debt and the budget deficit) and the shape of the sovereign yield curves for the U.S. and for Germany. For our purposes, the problem is the model estimation. In this regard there are two ways to study the parameters. On the one hand, in serial time, which is called dynamic approach (Diebold & Li (2006); Koopman et al. (2010)), but it carries the disadvantage of fixing a priori the behavior of the parameters. And secondly, in cross-section (see a comparative study on De Pooter (2007)). Additionally, the method to estimate the parameters is also double, since the model is not linear. This has been solved in two ways in the literature: either estimating all parameters together by techniques of nonlinear optimization, because the optimization function is not convex; or previously estimating the nonlinear parameter model (even setting its value), and then estimating the rest by least squares.

There are several drawbacks in a joint estimation such as: the outliers, which forces to delimit the intervals where we run the optimization problem, the treatment of multicollinearity between the regressors and the sensitivity to initial values (Gimeno & Nave (2009)). Meanwhile, the two-stage estimate (Gauthier & Simonato (2012)) is not absent problems: the multicollinearity, which increases when the nonlinear parameter is fixing and, the heterogeneity of the references in each estimation date.

As our aim is to obtain the explanatory (and independent) factors of the interest rate curve without setting a priori their behavior, we follow a two-step process that guarantees that such factors or regressors are independent of each other. For that, we propose a estimation methodology similar to Annaert et al. (2013).

In short, our goal is to study the asymmetric causality in-mean and in-variance on the interest rates curves of sovereign bonds, for which we must first estimate the parameters that define it, but under the assumption of independence among the explanatory factors of the curve and, subsequently we use a methodology CCF multivariate on standardized residuals, as González (2016), to test if there are causality between these parameters from different curves.

The rest of the paper is organized as follows: section 2 describes the methodology used; section 3 analyzes the data and to check the validity of the proposed approach; section 4 shows the results for the test of causality. The paper ends with the main conclusions of the study.

2. Methodology

The methodology used is two-stage; first, we estimate the parameters that fitting the interest rate curves and, secondly, after a preliminary analysis of the results, we test the asymmetric causality. Subsequently both phases are described.

2.1. Estimation of the Nelson-Siegel model

We write the Nelson-Siegel model as follows, for purposes of estimation:

$$y_{i,j,k} = \beta_{0,i,j} + \beta_{1,i,j}X_{1,i,j,k} + \beta_{2,i,j}X_{2,i,j,k} + \epsilon_{i,j,k} \tag{1}$$

Where $i = 1, \cdots, N$ is the issuer of sovereign debt; $j = 1, \cdots, T$ is date; $k = 1, \cdots, K_{i,j}$ is each bond of emisor i traded on date j; $y_{i,j,k}$ is the yield of bond k, issued by i and, estimated from market bond price on date j and its characteristics (coupon and maturity). In equation(1), the regressors X are defined as:

$$\begin{aligned} X_{1,i,j,k} &= \frac{1-\exp(-\frac{t_{i,j,k}}{\tau_{i,j}})}{\frac{t_{i,j,k}}{\tau_{i,j}}} \\ X_{2,i,j,k} &= X_{1,i,j,k} - \exp(-\frac{ti,j,k}{\tau_{i,j}}) \end{aligned} \tag{2}$$

Where $t_{i,j,k}$ is the time remaining until the maturity of the bond k, on date j and the sovereign issuer i. As can be seen, by construction, there is collinearity between regressors. Furthermore τ is the nonlinear parameter of the model.

In this model, each parameter is a factor of the interst rate curve:

- β_0: the constant shows the level of interest rate long-term or long-term factor.
- β_1: is the slope (or steepness) of the curve, if $\beta_1 < 0$ is downward and, else if $\beta_1 < 0$ is upward. It represents the short-term factor.
- β_2: is the curvature, if $\beta_2 > 0$ is hump, else if $\beta_2 < 0$ is trough. It shows the medium-term factor.
- τ: its inverse is the speed with which forward rates converge at long-term rates, thus, for smaller value (always positive), the speed of convergence is higher. It represents the form (shape) of the function and, it shows the maturity for that the medium-term factor takes the maximum value.

Diebold & Li (2006) found that multicollinearity, as measured by the correlation between the regressors model, is related to τ. So, in order to achieve that the regressors are *i.i.d.* and taking into account the effect of τ on this relationship, in this paper we propose the following procedure to estimate the Nelson-Siegel model:

1. For the date j and the issuer i, we calculate the yield (continuous compounding) y from each bond traded k.

2. We estimamos $\tau_{i,j}$ such that $X_{1,i,j,k}$ and $X_{2,i,j,k}$ are linearly independent. So, if Σ is correlation matrix of regressors (X_1, X_2) then, we seek τ to maximize its determinant: $max\{\det(\Sigma)\}$. Note that the maximum value is reached when the correlation is zero; in this case, there is no collinearity and factors are independent.
3. Replacing optimal $\tau_{i,j}$ in equation(2) we obtained the regressors uncorrelated and, we estimated $\beta_{0,i,j}$, $\beta_{1,i,j}$ and $\beta_{2,i,j}$ by least squares on equation(1).
4. Repeat steps 1 to 3 for each date $j = 1, \cdots, T$ and each issuer $i = 1, \cdots, N$.

2.2. Asimmetric causalilty test

Firslty, we analize the time series of Nelson-Siegel model parameters, we check stationarity, autocorrelation and heterokedasticity and, according the statistics test, we model each parameter. So, if $\lambda_{i,j}$ is any stationary transformation of parameters (β_0, β_1, β_2 or τ) then, we fit a univariate *AR-GARCH* model, for example for one lag, we estimate this expression:

$$\begin{aligned} \lambda_{i,j} &= \gamma_{0,i} + \gamma_{1,i}\lambda_{i,j-1} + e_{i,j} \\ e_{i,j} &\sim i.i.d.(0, \sigma^2_{i,j}) \\ \sigma^2_{i,j} &= \alpha_{0,i} + \alpha_{1,i}e^2_{i,j-1} + \alpha_{2,i}\sigma^2_{i,j-1} \end{aligned} \tag{3}$$

Once the univariate suitable processes are estimated, it is feasible to extract the standardized residuals (z). In the second stage, we determine the effects on the set of variables using a VAR model. Thus, for example, if the lag optimal by informtation criterion (AIC) was one (to simplify) then, the expression is:

$$\begin{aligned} &\begin{bmatrix} z_{1,j} \\ \vdots \\ z_{N,j} \end{bmatrix} = \begin{bmatrix} 0 & \cdots & \omega^-_{1,N,1} \\ \vdots & \ddots & \vdots \\ \omega^-_{N,1,1} & \cdots & 0 \end{bmatrix} \cdot \begin{bmatrix} \delta_{1,j-1} \cdot z_{1,j-1} \\ \vdots \\ \delta_{1,j-1} \cdot z_{N,j-1} \end{bmatrix} + \begin{bmatrix} 0 & \cdots & \omega^+_{1,N,1} \\ \vdots & \ddots & \vdots \\ \omega^+_{N,1,1} & \cdots & 0 \end{bmatrix} \cdot \begin{bmatrix} (1-\delta_{1,j-1}) \cdot z_{1,j-1} \\ \vdots \\ (1-\delta_{1,j-1}) \cdot z_{N,t-1} \end{bmatrix} + \begin{bmatrix} u_{1,j} \\ \vdots \\ u_{N,j} \end{bmatrix} \\ &\forall i = 1, \cdots, N \\ &\delta_{i,j} = \begin{cases} 1 & \text{if } \lambda_{i,j} \leq 0 \\ 0 & \text{otherwise} \end{cases} \end{aligned} \tag{4}$$

The expression (4) is non-constant and non-autoregressive since these characteristics are in the mean equation(3). The variable δ depends on the parameter daily variationsr (up or down movement of explanatory interest rate factor), but not the shock sign (error term in the univariate model), to avoid the influence of the adjusted univariate model on the causality test. Then, in equation(4), the following hypotheses are tested as González (2016):

- If the variable i does not cause in-mean the variable s, then $H_0 : \omega^-_{i,s,1} = \omega^+_{i,s,1} = 0$.
- If the variable i causes in-mean the variable s, then the asymmetric causality in-mean is tested as: $H^{sym}_0 : \omega^-_{i,s,1} = \omega^+_{i,s,1}$.

- Finally, if the variables i and s cause each other, we check whether the bidirectional effects are the same: $H_0^*: \omega_{i,s,1}^* = \omega_{s,i,1}^*$. Where $*$ is $(+)$ or/and $(-)$.

From the results of expression(4), and to test the causality in-variance without the impact of the possible causality in-mean (see Pantelidis & Pittis (2004)), a new variable (η) is defined as:

$$\forall i = 1, \cdots, N$$
$$\eta_{i,j} = \begin{cases} z_{i,j}^2 - 1 & \text{if } \forall s \neq i, \omega_{i,s,t}^* = 0 (nocausalityin - mean) \\ u_{i,j}^2 - 1 & \text{otherwise} \end{cases} \tag{5}$$

The residual η is non-autoregressive, since this characteristic is in the variance equation(3) and, it is not constant because the original residuals (z) are standardized (zero mean and unit variance). Newly, we use a VAR model to estimate the asymmetric causality in-variance as in equation(4). To simplify, we write a $VAR(1)$ model:

$$\begin{bmatrix} \eta_{1,j} \\ \vdots \\ \eta_{N,t} \end{bmatrix} = \begin{bmatrix} 0 & \cdots & \psi_{1,N,1}^- \\ \vdots & \ddots & \vdots \\ \psi_{N,1,1}^- & \cdots & 0 \end{bmatrix} \cdot \begin{bmatrix} \delta_{1,j-1} \cdot \eta_{1,j-1} \\ \vdots \\ \delta_{1,t-1} \cdot \eta_{N,j-1} \end{bmatrix} + \begin{bmatrix} 0 & \cdots & \psi_{1,N,1}^+ \\ \vdots & \ddots & \vdots \\ \psi_{N,1,1}^+ & \cdots & 0 \end{bmatrix} \cdot \begin{bmatrix} (1 - \delta_{1,t-1}) \cdot \eta_{1,j-1} \\ \vdots \\ (1 - \delta_{1,t-1}) \cdot \eta_{N,j-1} \end{bmatrix} + \begin{bmatrix} \upsilon_{1,j} \\ \vdots \\ \upsilon_{N,j} \end{bmatrix}$$
$$\forall i = 1, \cdots, N$$
$$\delta_{i,j} = \begin{cases} 1 & \text{if } \lambda_{i,j} \leq 0 \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

In this case, the hypotheses are:

- No causality in-variance: $H_1: \psi_{i,s,1}^- = \psi_{i,s,1}^+ = 0$.
- No asymmetric causality in-variance: $H_1^{sym}: \psi_{i,s,1}^- = \psi_{i,s,1}^+$.
- If there is bidirectional causality in-variance, the effects are the same: $H_1^*: \psi_{i,s,1}^* = \psi_{s,i,1}^*$.

Both expressions (4) and (6) are estimated by Full Information Maximum Log-likelihood ($FIML$) procedure, i.e. maximizing the follow log-likelihood function:

$$\ell_0 = -\frac{TN}{2} \cdot log(2\pi) + \frac{TN}{2} log(|\Omega^{-1}|) - \frac{TN}{2}$$
$$\Omega = \frac{1}{T} \cdot \begin{bmatrix} \mathbf{r}_1 & \cdots & \mathbf{r}_N \end{bmatrix} \cdot \begin{bmatrix} \mathbf{r}_1 \\ \vdots \\ \mathbf{r}_N \end{bmatrix} \tag{7}$$

where $\mathbf{r}$ is the residuals vector for each variable. Thus, any hypothesis is tested with an LR test (log-likelihood ratio) as:

$$LR_{m-s} = -2 \cdot log \frac{\ell_m}{\ell_s} \sim \chi_{m-s}^2 \tag{8}$$

Where (m-s) is the number of restrictions for a χ^2 distribution.

3. Data: Description and Econometric Modeling

In order to check whether the causality found by the previous studies, above mentioned, during the recent financial crisis it still remains, our data sample consists of daily prices closing from 1 January 2010 until 31 December 2015, both included. From Bloomberg and, since the evidence of previous work found causality in EMU zone, we have selected the sovereign bonds issuers for major economies within this area (France, Germany, Italy and Spain); additionally, we include United Kingdom (UK), this is due to its special relationship with this area; United Stated of America (USA) is included too, as a consequence of its weight in the world economy. Finally, Switzerland (Swiss) is included as a control variable, since it is a country geographically close to the EMU zone (to avoid problems of asynchrony with prices) with a good financial health.

First, we have estimated the Nelson-Siegel model to fit the daily interest rate curves. The estimates were made following four methods. For three of them, we have estimated first the nonlinear parameter (τ), as it is described above, and then the linear parameters (β_0, β_1, and β_2) are estimated by three different methods: Ordinary Least Squares (OLS), Generalized Least Squares (GLS) and Non-linear Least Squares ($partial\ NLS$) using nonlinear optimization Simulated Annealing (SA). Finally, the fourth estimate is a NLS applying SA, where the start values of parameters are the values obtained previously in $partial\ NLS$.

Table(1) shows the data used, the computational time estimation of each method and root mean square error percentage, both on yield and on observed prices.

Table 1: Nelson-Siegel estimation results

Method / Data	Results	France	Germany	Italy	Spain	Swiss	UK	USA
Total references		76	52	121	64	29	56	523
Total observations		78,934	57,477	106,595	56,285	32,236	60,443	407,739
Max references by day		60	40	85	44	23	42	307
Min references by day		41	29	39	28	6	36	192
OLS	Time	35.5707	26.6033	51.5757	12.5891	11.8547	30.5461	117.8603
	RMSE on rate	0.75%	0.12%	0.49%	0.15%	0.09%	0.17%	0.10%
	RMSE on price	9.80%	3.04%	5.31%	2.27%	2.71%	2.97%	2.94%
GLS	Time	37.0313	32.8537	57.2076	20.3317	18.3207	34.3953	121.4946
	RMSE on rate	0.78%	0.11%	0.36%	0.14%	0.08%	0.15%	0.08%
	RMSE on price	8.40%	3.04%	5.25%	2.26%	2.71%	2.96%	2.29%
NLS partial	Time	43.0313	38.8537	63.2076	26.3317	24.3207	40.3953	127.4946
	RMSE on rate	0.81%	0.14%	0.51%	0.16%	0.10%	0.17%	0.10%
	RMSE on price	10.24%	3.04%	5.65%	2.27%	2.70%	2.95%	2.94%
NLS	Time	50.0313	45.8709	70.2364	33.3397	31.3325	47.4107	134.5520
	RMSE on rate	0.90%	2.37%	3.06%	0.81%	3.28%	2.10%	4.10%
	RMSE on price	9.69%	2.67%	5.23%	2.09%	2.09%	2.44%	3.65%

Note: $Time$ is the computation time for a standard PC expressed in minutes and $RMSE$ is Root Mean Square Error in percentage.

First, it is noteworthy that USA is the issuer with the highest number of references, followed by Italy and France. About the results, we found, as expected, that as the method becomes more complex or more parameters involved, the computation time is higher. As regards the degree of fit, except in the case of French bonds, NLS better fits over prices than on yields. Among the methods, the best adjusted on prices and yields is GLS and, therefore we take the parameters obtained by this procedure. But, to ensure that it is a right choice, we compare, in table(2), the adjusted R^2 from OLS and GLS.

Table 2: Adjusted R^2

Method	Adjusted R^2	France	Germany	Italy	Spain	Swiss	UK	USA
OLS	Max	0.7009	0.9509	0.9292	0.9986	0.9968	0.9958	0.9978
	Mean	0.5371	0.9744	0.7909	0.9821	0.9710	0.9759	0.9858
	Min	0.0761	0.5928	0.0022	0.5666	0.5075	0.3024	0.6343
GLS	Max	0.9992	0.9999	0.9991	0.9999	0.9999	0.9995	0.9999
	Mean	0.8087	0.9999	0.9940	0.9998	0.9994	0.9942	0.9997
	Min	0.3974	0.9844	0.7486	0.9802	0.9385	0.9849	0.9963

As shown the results are superior to GLS. Finally, in order to justify this difference, we check if it is caused by a possible heterogeneity of the data, and the corresponding effect on OLS results. For this, we estimate (see table-3) the White test on the OLS results.

Table 3: White test

OLS estimation	France	Germany	Italy	Spain	Swiss	UK	USA
Max	47.522 [**]	39.452[**]	47.856 [**]	37.863[**]	22.994[**]	37.191[**]	158.448[**]
Mean	11.698[**]	16.773[**]	11.155 [**]	15.865[**]	9.773[**]	17.464[**]	73.779[**]
Min	2.014	2.761	2.339	0.340	0.253	2.730	5.778[*]

Note: [∗∗] and [∗] mean that the null hypothesis of non-heteroskedasticity is rejected at 1% and 5%, respectively.

As seen in table(3), there is an obvious problem of heteroskedasticity that justifies the use of GLS.

Finally, in tabe(4), we show the nonlinear parameter (τ) estimated individually, using the methodology proposed, and jointly with others parameters by NLS. The τ values are accompanied by the corresponding correlation between the regressors, to check the collinearity between regressors.

Note that NLS estimations show multicolinearity and higher variability than GLS estimation, and even some values are absurd.

The statistics of parameters estimated by GLS are in table(5) and, in figure(1), we plot the parameters obtained for US bonds.

In table(5), note that, except for τ, the other parameters are not stationary in levels. So, in order to check the causality, previously we have to make a transformation (first difference) stationary and analyze the behavior of these variations.

As seen in table(6), the parameters variations (or in level, where it is appropiate, τ) are not Gaussian, are stationary and have autocorrelation and heteroskedasticity. Therefore, we have to fit a model that allows us to correct these characteristics before studing causality. Following González (2016), we have tested different models (from FIEGARCH to FIAPARCH, with and without effects on mean equation) and,we have selected the model based on the information criterion AIC, but considering the above characteristics, and

Table 4: Parameter τ and collinearity

Method		GLS			NLS		
Countries	Parameters	Max	Mean	Min	Max	Mean	Min
FRANCE	τ	4.1530	3.3143	2.4653	84.4453	13.3018	0.0942
	Correlation	0.0000	0.0000	0.0000	0.9893	-0.4874	-1.0000
GERMANY	τ	4.2923	3.3608	2.2828	25.5365	3.9091	0.0279
	Correlation	0.0000	0.0000	0.0000	1.0000	0.1132	-0.9908
ITALY	τ	3.1218	2.4826	2.0442	75.7670	32.5275	0.0116
	Correlation	0.0000	0.0000	0.0000	0.9977	-0.4000	-1.0000
SPAIN	τ	4.4386	2.4947	1.9706	28.3911	2.4735	0.0242
	Correlation	0.0000	0.0000	0.0000	1.0000	0.1498	-0.9929
SWISS	τ	4.3101	3.4800	1.6333	44.0759	3.0982	0.0127
	Correlation	0.0000	0.0000	0.0000	1.0000	0.3087	-0.9964
UK	τ	7.3052	4.5483	3.6816	19.6061	5.5718	0.1944
	Correlation	0.0000	0.0000	0.0000	0.9906	-0.0674	-1.0000
USA	τ	2.0449	1.8011	1.6025	2.3030	0.6303	0.0304
	Correlation	0.0000	0.0000	0.0000	0.8662	0.5381	-0.1891

Table 5: Statistics of parameters by GLS

Countries	β_0					β_2				
	min	mean	max	std. dev	ADF	min	mean	max	std. dev	ADF
France	0.0108	0.0346	0.0452	0.0069	-1.5230	-0.0591	-0.0173	0.0334	0.0214	-2.4301
Germany	0.0068	0.0308	0.0439	0.0080	-1.4183	-0.0475	-0.0200	0.0178	0.0146	-2.5223
Italy	0.0217	0.0480	0.0663	0.0093	-0.6764	-0.0771	-0.0140	0.0605	0.0249	-2.3361
Spain	0.0220	0.0512	0.0720	0.0108	-0.8811	-0.0806	-0.0138	0.0651	0.0244	-2.5186
Swiss	0.0045	0.0179	0.0291	0.0053	-1.7939	-0.0317	-0.0127	0.0111	0.0093	-2.5579
UK	0.0228	0.0376	0.0485	0.0061	-0.7408	-0.0449	0.0023	0.0513	0.0179	-2.3475
USA	0.0233	0.0366	0.0522	0.0077	-1.9373	-0.0678	-0.0400	-0.0082	0.0138	-1.0857
Countries	β_1					τ				
	min	mean	max	std. dev	ADF	min	mean	max	std. dev	ADF
France	-0.0527	-0.0352	-0.0112	0.0076	-1.9076	2.4653	3.3143	4.1530	0.3419	-3.6781
Germany	-0.0455	-0.0304	-0.0079	0.0076	-1.8867	2.2828	3.3611	4.2923	0.3261	-4.0220
Italy	-0.0552	-0.0393	0.0019	0.0091	-2.4473	2.0442	2.4827	3.1218	0.1750	-4.2607
Spain	-0.0637	-0.0418	-0.0103	0.0086	-2.4662	1.9706	2.4947	4.4386	0.3423	-3.5732
Swiss	-0.0311	-0.0208	-0.0019	0.0043	-1.8023	1.6333	3.4766	4.3101	0.4037	-4.7353
UK	-0.0482	-0.0378	-0.0190	0.0070	-1.0671	3.6816	4.5483	7.3052	0.3740	-3.8042
USA	-0.0529	-0.0347	-0.0189	0.0085	-1.9520	1.6025	1.8011	2.0449	0.0982	-3.8258

Note: ADF is Augmented Dickey-Fuller stationary test, with critical value -3.46 an -2.86 at 1% and 5% of confidence level, respectively.

also ensuring that the variance was stationary. Table(7) shows that in all cases, the selected model for the variance is a $GARCH(1,1)$ with a *t-Student* or $Normal$ distribution and, sometimes accompanied by an $AR(1)$ model for the mean equation.

Note that after fitting univariate models, the residuals are not autocorrelated and heteroskedastics. It also, we found that the variations of linear parameters are not Gaussian, whereas τ, estimated under our

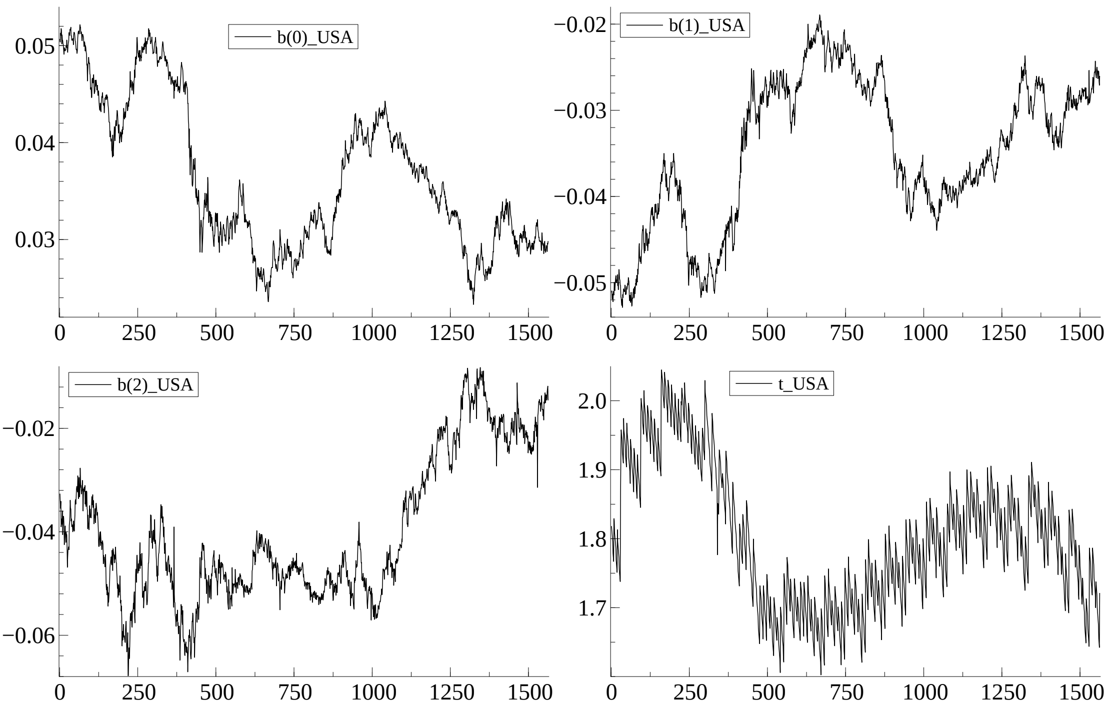

Figure 1: Parameters estimated by GLS for USA

proposal, has Gaussian residuals.

4. Results of Asymmetric Causality Tests

Before analyzing causality, figure(2) shows the linear parameters estimated by GLS for France and Germany. As seen, there is a clear similarity in their behaviors, which justify our empirical study.

First, we test assymetric causality in-mean on standardize residuals obtained from the above univariate models. For this, we estimate a simultaneous equations by $FIML$. In table(8), we show the signficant parameters.

From the results of table(8), we observe that causality in-mean for all curve parameters is asymmetric ,i.e., the causality effect has place for upward (+) or downward (-) factors movements, but not both. Differentiating for each explanatory factor of interest rate curves, we conclude on causality in-mean the following:

- Long-term factor (β_0): USA is the most important driver, since it affects most countries and is not influenced by anyone. This influence only occurs when a negative shock in long-term rates arises, leading to a decline in long rates of other countries. The area EMU effect is not evident in this factor, except for bilateral and opposite relationship between Italy and Spain; for example, Germany is affected by long-term factor decreases in France and USA, and the increases in UK. Finally, note that UK is the most affected, even by EMU countries (France, Germany and Italy).

Table 6: Descriptive Statistics of parameters

countries	France	Germany	Italy	Spain	Swiss	UK	USA
statistics				$\Delta\beta_0$			
min	-0.00431	-0.00450	-0.00559	-0.00418	-0.00287	-0.00841	-0.00282
mean	-0.09806	-0.14864	-0.12697	-0.08902	-0.11496	-0.08066	-0.13342
max	0.00616	0.00462	0.00474	0.00432	0.00325	0.00794	0.00277
std. dev	0.00061	0.00055	0.00088	0.00074	0.00050	0.00057	0.00063
skw	0.44162	-0.07656	0.20631	-0.11274	0.08616	-0.58388	0.14016
exc. Kur	10.54100	9.33380	4.34370	4.43710	6.77280	60.43100	1.48680
JB	7282.1 [**]	5671.5 [**]	1239.1 [**]	1284.7 [**]	2987.3 [**]	237770 [**]	148.98 [**]
ADF	-23.98 [**]	-24.58 [**]	-28.12 [**]	-23.43 [**]	-27.57 [**]	-26.18 [**]	-23.93 [**]
ARCH 1-2	7.84 [**]	129.98 [**]	30.99 [**]	34.02 [**]	47.14 [**]	290.60 [**]	45.49 [**]
BP(5) on data	9.5123	8.79868	48.87 [**]	4.9415	72.25 [**]	81.39 [**]	18.71 [**]
BP(5) on sq	148.15 [**]	223.12 [**]	111.35 [**]	125.94 [**]	187.94 [**]	338.67 [**]	179.71 [**]
statitisc				$\Delta\beta_1$			
min	-0.01324	-0.01059	-0.00733	-0.01187	-0.00501	-0.00626	-0.00474
mean	0.00001	0.00001	0.00001	0.00001	0.00002	0.00001	0.00002
max	0.00826	0.01069	0.01412	0.00951	0.01731	0.00745	0.00377
std. dev	0.00092	0.00093	0.00127	0.00141	0.00078	0.00086	0.00081
skw	-2.43930	-0.29956	0.50592	-0.97056	6.41320	-0.13149	-0.21854
exc. Kur	40.75000	43.17400	13.26600	11.18500	153.62000	15.51000	1.88900
JB	1096200 [**]	1213400 [**]	11521 [**]	8388.1 [**]	1546700 [**]	15661 [**]	244.68 [**]
ADF	-25.09 [**]	-26.15 [**]	-23.29 [**]	-24.33 [**]	-26.14 [**]	-27.32 [**]	-24.91 [**]
ARCH 1-2	99.75 [**]	135.06 [**]	43.40 [**]	77.96 [**]	52.43 [**]	61.08 [**]	51.82 [**]
BP(5) on data	53.13 [**]	86.48 [**]	6.49	16.25 [**]	28.13 [**]	150.07 [**]	36.89 [**]
BP(5) on sq	161.91 [**]	323.67 [**]	128.98 [**]	192.24 [**]	207.88 [**]	205.52 [**]	122.71 [**]
statitisc				$\Delta\beta_2$			
min	-0.02582	-0.03133	-0.02397	-0.03797	-0.02209	-0.05645	-0.01301
mean	-0.00003	-0.00003	-0.00002	-0.00003	-0.00001	-0.00003	0.00001
max	0.03553	0.03756	0.02624	0.02852	0.03020	0.05965	0.01554
std. dev	0.00285	0.00236	0.00407	0.00425	0.00310	0.00399	0.00181
skw	2.23770	2.16130	0.01562	0.41659	1.44970	1.10000	0.58668
exc. Kur	33.31100	81.55300	5.37460	13.32200	20.18700	69.75400	9.44820
JB	73521 [**]	4340800 [**]	1880.1 [**]	11596 [**]	27069 [**]	3169900 [**]	5899.5 [**]
ADF	-24.95 [**]	-29.41 [**]	-27.43 [**]	-26.08 [**]	-34.39 [**]	-27.95 [**]	-27.26 [**]
ARCH 1-2	66.29 [**]	133.57 [**]	34.17 [**]	46.28 [**]	32.30 [**]	267.36 [**]	97.64 [**]
BP(5) on data	42.31 [**]	95.09 [**]	34.45 [**]	32.97 [**]	165.92 [**]	185.76 [**]	53.02 [**]
BP(5) on sq	122.71 [**]	234.55 [**]	103.07 [**]	113.91 [**]	229.97 [**]	331.56 [**]	158.82 [**]
statitisc				τ			
min	2.46530	2.28280	2.04420	1.97060	1.63330	3.68160	1.60250
mean	3.31430	3.36110	2.48270	2.49470	3.47660	4.54830	1.80110
max	4.15300	4.29230	3.12180	4.43860	4.31010	7.30520	2.04490
std. dev	0.34191	0.32611	0.17500	0.34230	0.40374	0.37398	0.09822
skw	0.03260	-0.52167	0.17120	1.33570	-0.21108	0.08164	0.39213
exc. Kur	-0.57558	0.18568	-0.64905	1.64050	-0.43873	1.03780	-0.65930
JB	21.85 [**]	73.14 [**]	35.07 [**]	640.05 [**]	24.14 [**]	71.88 [**]	68.36 [**]
ADF	-3.68 [**]	-4.02 [**]	-4.26 [**]	-3.57 [**]	-4.74 [**]	-3.80 [**]	-3.83 [**]
ARCH 1-2	17007 [**]	6354.1 [**]	8496.8 [**]	8212.8 [**]	5215.88 [**]	4961.6 [**]	10506 [**]
BP(5) on data	6952.37 [**]	6215.68 [**]	6375.65 [**]	6699.36 [**]	3039.4 [**]	6394.64 [**]	6504.70 [**]
BP(5) on sq	6963.67 [**]	6117.39 [**]	6330.55 [**]	6521.53 [**]	5372.15 [**]	6100.34 [**]	6539.90 [**]

Note: JB is the Jarque-Bera test.ADF is stationarity test. $ARCH$ is a LM-test of heterokedasticity. BP is Breusch-Pagan test (lags) on data (autocorrelation test) and square data (conditional heterokedasticity test). The null hypothesis is normality, non-stationarity, non-heterokedasticity, non-autocorrelation and no conditional heterokedasticity, respectively. Thus [*] and [**] show that null hypothesis is rejected to 5% and 1%, respectively.

- Short-term factor (β_1): again note that UK is the most affected by the other countries. In this case Germany is the driver with an influence in case of positive shocks in the short-term rates. Regarding the EMU area, a bidirectional relationship appears in case of positive shocks between France and Germany, and Italy over Spain.

- Medium-term factor (β_2): this factor has the highest number of causal relationships, which are concentrated mostly in the EMU area. There is a bidirectional relationship between Italy and Spain when

Table 7: Results of AR-GARCH model estimation

countries	France	Germany	Italy	Spain	Swiss	UK	USA
parameters				$\Delta\beta_0$			
Const			-0.0001 [*]				
AR(1)			-0.1212 [**]	0.0653 [*]	-0.0961 [**]		-0.0957 [**]
Cv x 10^6	0.0201 [**]	0.0104 [*]	0.0209 [*]	0.0325 [**]	0.0163 [*]	0.0325 [*]	0.0043 [*]
ARCH(1)	0.1605 [**]	0.1437 [**]	0.1808 [**]	0.1702 [**]	0.1341 [**]	0.2903 [**]	0.0361 [**]
GARCH(1)	0.8026 [**]	0.8380 [**]	0.8118 [**]	0.7951 [**]	0.8070 [**]	0.6105 [**]	0.9528 [**]
df Student	4.2074 [**]	4.2306 [**]	4.4631 [**]	4.1623 [**]	3.8587 [**]	4.174 [**]	10.4466 [**]
ARCH 1-2	2.5223	2.407	0.1162	0.4732	0.442	0.0165	1.9238
BP(5) on data	4.0311	4.0080	1.1155	4.1316	5.9039	6.3391	3.3096
BP(5) on sq	6.0850	6.407	1.5144	1.5998	7.5226	0.1081	4.2743
parameters				$\Delta\beta_1$			
Const					0.0001 [*]		
AR(1)					-0.0893 [**]		-0.1317 [**]
Cv x 10^6	0.1726 [**]	0.0695 [*]	0.0208 [*]	0.1857 [*]	0.1252 [**]	0.3431 [**]	0.0080 [*]
ARCH(1)	0.3003 [**]	0.2588 [**]	0.1183 [**]	0.3388 [**]	0.2492 [**]	0.2556 [**]	0.0291 [**]
GARCH(1)	0.4937 [**]	0.6570 [**]	0.8814 [**]	0.6624 [**]	0.4925 [**]	0.6918 [**]	0.9581 [**]
df Student	3.6707 [**]	4.6974 [**]	3.5178 [**]	3.1298 [**]	3.5907 [**]	3.1254 [**]	10.8411 [**]
ARCH 1-2	0.3597	2.0879	2.904	0.4266	0.0083	1.4095	1.6963
BP(5) on data	3.9069	1.7283	4.4991	6.0985	3.3726	5.6211	4.3774
BP(5) on sq	0.9494	6.5469	7.8519	1.0792	0.0262	4.7103	6.1472
parameters				$\Delta\beta_2$			
Const	-0.0002 [*]	-0.0001 [**]		-0.0002 [**]	-0.0001 [**]	-0.0001 [*]	
AR(1)			-0.0567 [*]			-0.1223 [**]	-0.1675 [**]
Cv x 10^6	1.5688 [*]	1.0612 [**]	1.2870 [*]	1.7433 [**]	0.7501 [**]	1.5224 [**]	0.0117 [*]
ARCH(1)	0.1415 [**]	0.2220 [**]	0.3010 [**]	0.3214 [**]	0.3229 [**]	0.1537 [**]	0.0142 [**]
GARCH(1)	0.7076 [**]	0.7508 [**]	0.6910 [**]	0.6718 [**]	0.6087 [**]	0.7785 [**]	0.9717 [**]
df Student	2.4180 [**]	3.4057 [**]	3.3285 [**]	2.6927 [**]	2.004 [**]	2.7443 [**]	4.6548 [**]
ARCH 1-2	0.0148	0.1587	1.166	0.352	0.2963	0.2895	1.6265
BP(5) on data	3.8661	3.9698	3.728	5.8764	5.8895	5.5217	5.4589
BP(5) on sq	0.2308	0.577	4.3221	1.2778	1.8184	3.5457	6.2653
parameters				τ			
Const	3.3969 [**]	3.5447 [**]	2.5234 [**]	2.5270 [**]	3.668 [**]	4.6006 [**]	1.7422 [**]
AR(1)	0.9705 [**]	0.8394 [**]	0.9612 [**]	0.9791 [**]	0.8460 [**]	0.9733 [**]	0.9702 [**]
Cv x 10^6	0.2547 [*]	0.2425[*]	0.1646 [*]	0.1447 [*]	0.1965 [*]	0.1518 [*]	0.1612 [*]
ARCH(1)	0.15024 [**]	0.2505 [**]	0.1918 [**]	0.3049 [**]	0.1185 [**]	0.2353 [**]	0.1354 [**]
GARCH(1)	0.7551 [**]	0.7274[**]	0.7427 [**]	0.7337 [**]	0.8764 [**]	0.7488 [**]	0.8018 [**]
ARCH 1-2	0.0843	0.2214	2.7502	1.1939	1.4176	0.0276	1.0997
BP(5) on data	0.2937	5.1410	5.3776	1.4618	4.2534	3.1766	3.9302
BP(5) on sq	6.6059	1.0679	4.8928	2.4665	3.4776	0.1052	2.0552

Note: *Const* and *Cv* are the constant in mean and variance equations, respectively. *dfStudent* is degree of freedom for t-Student distribution. [**] and [*] mean that the parameter is significant at 1% and 5% confidence level, respectively.

shocks are negatives. It also highlights the causality in case of negative shocks of Spain over France, Germany and UK.

Table 8: Asymmetric causality in-mean

	Causality sign	France	Germany	Italy	Spain	Swiss	UK	USA
Causation countries		Causality in-mean for $\Delta\beta_0$						
France	(+)						-0.1366 [*]	
	(-)		0.1062 [**]					
Germany	(+)						0.1337 [*]	
Italy	(+)	0.1389 [**]						
	(-)				0.0825 [*]		-0.1290 [*]	
Spain	(+)			0.0960 [*]				
UK	(+)		0.0789 [*]		0.0924 [*]			
USA	(-)	0.1136 [*]	0.1806 [**]			0.1271 [*]	0.1952 [**]	
Causation countries		Causality in-mean for $\Delta\beta_1$						
France	(+)		0.1386 [**]					
Germany	(+)	0.0971 [*]					0.1252 [*]	0.1949 [**]
Italy	(+)				0.1394 [**]			
Swiss	(-)						0.0979 [*]	
UK	(-)					-0.1104 [*]		
USA	(+)						0.1050 [*]	
Causation countries		Causality in-mean for $\Delta\beta_2$						
France	(-)		0.1085 [*]					
Germany	(+)	0.1022 [**]						
Italy	(+)							-0.0881 [*]
	(-)	0.1039 [*]			0.1013 [**]			
Spain	(+)							0.0975 [*]
	(-)	-0.1987 [**]	-0.1088 [*]	0.1599 [**]			-0.1356 [*]	
UK	(-)	-0.0709 [*]		-0.1233 [**]	-0.0845 [*]			
USA	(-)			-0.1073 [**]	-0.1003 [**]			
Causation countries		Causality in-mean for τ						
France	(+)					-0.0868 [**]		
	(-)				0.1842 [*]			0.1520 [*]
Germany	(-)				-0.1136 [**]	0.1127 [**]		
Italy	(-)		0.3035 [*]			0.3525 [**]		
Spain	(-)	0.1937 [*]		0.1440 [*]				
Swiss	(-)		0.1946 [**]					
USA	(+)			0.1787 [**]				
	(-)		0.5002 [**]					

Note: From AIC criterion, we estimate a model with 1-lag. [**] and [*] mean that the parameter is significant at 1% and 5% confidence level, respectively.

- Decay factor (τ): in this case, the causal relations are mainly negative, that is, causality in-mean is statistically significant when this factor decreases.

Table(9) shows that causality in-variance is low, but for statistically significant cases, it is asymmetric. Differentiating by factors we conclude:

- Long-term factor (β_0): when this factor increases, there is causality in-variance from Spain to France and from UK to Germany. However when this factor decreases, we observe causality in-variance from USA to Italy.

- Short-term factor (β_1): France is affected by the volatility of Germany factor down shocks and Spain up shocks. Finally, UK affects Italy when this factor decreases.

- Medium-term factor (β_2): this factor, as happened with causality in-mean, has the highest number of asymmetric causal relationships within the EMU zone. In particular, Germany and Spain are the main drivers of causality. Note again the effect of UK on Italy.

- Decay (τ): we observe an asymmetric causality (only with decay increases) bidirectional between Spain and Italy, whose effects are the same (the same bidirectional effect hypothesis is not rejected: 2.087 Wald test with p-value 0.1492).

5. Conclusions

The financial literature has analyzed, repeatedly over time, the causality among movements in interest rates of sovereign debt. After the recent financial crisis, the studies find higher connections between interest rates, mainly in the EMU area; also the results of several studies show that the cause-effect relationships are not symmetrical. In this context, we have not found any work to analyze simultaneously the asymmetry of causality in-mean and in-variance for the sovereign bond markets. Neither, we know studies on causality for the full interest rate curve, not only on some maturities or indexes. As a result of this, this paper aims to analyze whether there is an asymmetric causality in-mean and in-variance for the full interest rate curve of sovereign bonds; in particular, on a sample of the major economies of the EMU zone (France, Germany, Italy and Spain), as well as a country with important relations with this area (UK) and, the main economy of the developed world (USA). We have also added a country, as a control variable, given its sound financial standing and its geographical proximity to the rest (Switzerland).

For the study, we need to define a priori an interest rate curve model from which we identify the factors i.i.d.; later to study the causality among these factors from different interest rate curves. Thus, within the set of potential models, we selected the Nelson-Siegel model given its properties, but we made a first contribution by a bi-stage estimation proposal, that avoids the usual problem of multicollinearity between factors of the curve. Then, in a first phase we estimate the nonlinear parameter maximizing the determinant of the correlation matrix of the regressors and; in a second phase, we apply GLS to estimate the remaining

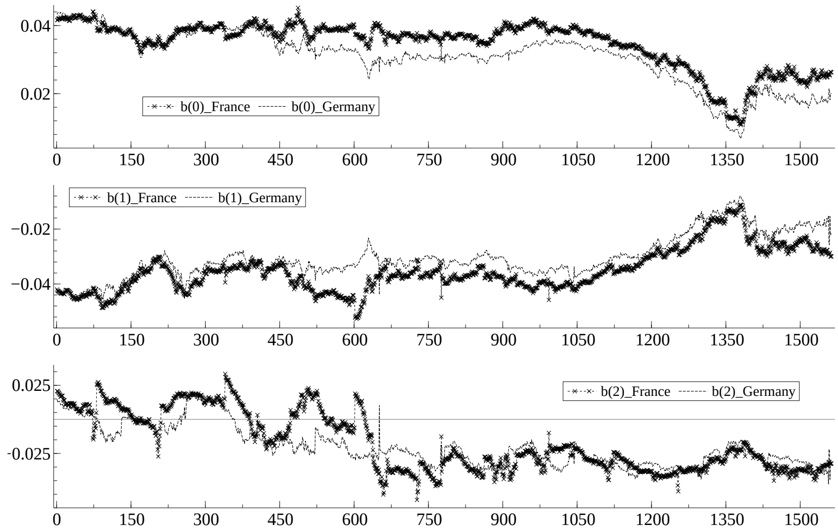

Figure 2: Parameters estimated by GLS for France and Germany

Table 9: Asymmetric causality in-variance

	Causality sign	France	Germany	Italy	Spain
Causation countries		Causality in-variance for $\Delta\beta_0$			
Spain	(+)	0.0988[*]			
UK	(+)		0.1193[**]		
USA	(-)			0.1699[**]	
Causation countries		Causality in-variance for $\Delta\beta_1$			
Germany	(-)	0.1618[**]			
Spain	(+)	0.4843[**]			
UK	(+)			0.1153[**]	
Causation countries		Causality in-variance for $\Delta\beta_2$			
Germany	(+)	0.1578[**]			
	(-)			0.4539[**]	0.9281[**]
Spain	(-)	0.4516[**]			
UK	(-)			0.0864[**]	
Causation countries		Causality in-variance for τ			
Italy	(+)				0.0627[*]
Spain	(+)			0.0258[*]	

Note: From AIC criterion, we estimate a model with 1-lag. [**] and [*] mean that the parameter is significant at 1% and 5% confidence level, respectively.

linear parameters. With this proposal we obtain results absent of multicollinearity among factors, financial consistency parameters values, with a high level of adjustment over prices and yiels, at a reduced computation time (since, it is not necessary to find suitable initial values) and, without problems of heterogeneity (heteroskedasticity).

After estimating the parameters that define the behavior of the interest rate curve, we have observed that, like the most financial variables in high frequency (daily), these show so called stylized facts. As a result, and from previous studies on asymmetric causality, we adjust such statistical properties and extract the standardized residuals, on which we test the causality (CCF approach).

On the results of causality in-mean, we emphasize that UK interest rate curve is the most affected by the rest, while the least affected is Swiss, as expected to be a control variable. Also we note the relationship in south of the EMU zone (Italy-Spain). Differentiating by factors, we have found the following drivers of causality in-mean: for long term are the movements down in the US, for short-term are the upward in Germany, in the medium-term highlights the relation of EMU area, while the decay factor shows only causality when decreases.

As for the results of causality in-variance, they are much less important than in-mean, although the cases found are also asymmetric. Note that the EMU area shows the highest number of causality relationship in-variance and, Spain is the main driver, especially when the factors of the curve are upward.

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