LINEAR AND NONLINEAR RELATIONSHIPS BETWEEN INTEREST RATE CHANGES AND STOCK RETURNS: INTERNATIONAL EVIDENCE

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Linear and nonlinear relationships between interest rate changes and stock returns: International evidence

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Abstract

This paper examines the linear and nonlinear relationships between changes in 10-year government bond yields and stock returns for nine developed countries over the period 1999 and 2017 using different methodologies such as linear and nonlinear Granger causality and the NARDL model.

The empirical results show linear Granger causality relationship exists in seven to nine countries. Most of them, from stock market to interest rate changes consistent with the forward-looking nature of the stock market. In the nonlinear Granger approach, we also found six to nine significant relationships. Highlighting the bidirectional strong found in Italy and Greece. Similarly, NARDL model results show a consistency as the only two asymmetric long-term relationships found are in Italy and Greece.

Finally, we have analyzed these conclusions in economic crisis period and we detect asymmetric long-run relationships tend to increase as in this situation four countries have asymmetric linkage. These results should be considered by investors, portfolio managers, hedgers and policy makers as we show linkage between interest rate changes and stock market returns should be considered dynamic and not necessarily linear.

Keywords: Granger causality, linear, nonlinear, asymmetry, stock returns, interest rate changes

Contents

1 Introduction

The relationship between interest rate changes and stock returns is a well-studied and debated topic in the financial literature. This is due to its central role in several key areas of finance such as asset allocation, portfolio diversification, risk management, asset pricing or monetary policy transmission. Modern financial theory postulates that the price of a stock is equal to the present value of all expected future cash flows discounted at the appropriate discount rate. In this context, interest rate can affect stock prices through various channels. On the one hand, variations in interest rate have a direct impact on the discount rate used in standard equity valuation models, thus modifying the value of company's share. On the other hand, interest rate fluctuations may alter the cost of financing of firms, especially those without negotiation power or heavily indebtedness, thus impacting expected future cash flows and, hence, stock prices. In addition, interest rates movements can also affect stock prices through portfolio rebalancing strategies between financial assets. For example, if yields on fixed-income grow up, stocks would be probably seen by investors as less interesting than bonds.

Traditionally, it has been widely accepted that the link between interest rate fluctuations and stock returns has negative sign, i. e., when one variable raises up, the another variable is expected to go down. However, the linkage between interest rates and stock returns is not necessarily negative and constant. In this regard, Kuenen (2015) concludes that the correlation between asset returns increases during financial crises because investors doubt about what asset is the most secure and all relevant financial markets tend to follow the same trend as is argued by Sandoval and Franca (2012). In addition, Korkeamäki (2011) shows that there was a negative correlation between changes in interest rates and equity returns in European countries before 1999, but this correlation becomes insignificant after the launch of the euro in 1999, possibly as a result of increased financial markets integration.

The stock and bond markets are, surely, the most important and well-known by investors as they usually tend to combine investment in both markets. They will allocate more money in one or another market depending on their risk aversion and specific market situation. It is known that in financial crisis times many investors allocate more money in government bond markets rather than in stock markets. This phenomenon is called "flight to quality". However, they feel secure investing in government bonds as they think if one country fails, others will bail out to maintain the economic stability.

There is a great deal of literature investigating the interest rate-stock market link. The classical linear OLS (ordinary least squares) regression has been the most common approach used to address this issue. There are, however, several reasons to suspect that the relationship may be nonlinear as stock prices depend on interest rates both through the discount factor and the effect of interest rate changes on expected future cash flow, according to this situation is seems reasonable to expect a nonlinear impact from interest rate to stocks. Moreover, the presence of nonlinearity becomes highly plausible when the sample includes major economic shocks such as the global financial crisis of 2008-2009 or the European sovereign debt crisis since the end of 2009. Another reason, which has been supported by some researchers like Bildirici and Turkmen (2015) is the belief that financial markets may have an asymmetrical response to movements of different sign in relevant economic and financial variables. That is, financial markets do not react equally when the shock is positive than when it is negative. That is the reason, for example, that asymmetric GARCH[1] models have been used.

The main aim of this paper is to revisit the relationship between changes in 10-year government bond yields and stock market returns. To achieve it, a number of time series methods are implemented to get more reliable conclusions. Most of the empirical research on the linkage between interest rate changes and stock market returns has assumed a linear and symmetric relationship between these variables. However, we are going to use different methodologies without assuming always a linear relationship. In particular, the methods applied in this study are linear and nonlinear Granger causality relationship, the Johansen cointegration analysis and the nonlinear autoregressive distributed lag (NARDL hereafter) approach.

The NARDL model, recently developed by Shin et al. (2014), allows for modeling simultaneously asymmetric nonlinearity and cointegration among the underlying variables in a single equation framework, providing various significant advantages over standard cointegration techniques (i.e. Engle-Granger and Johansen methods). It is, in essence, a dynamic error-correction representation, which provides robust empirical results even for small sample sizes. Another advantage of the NARDL model is its flexibility as this approach does not require all the variables have the same order of integration, that is, the variables can be integrated of order one or not integrated. In addition, this framework permits testing for hidden cointegration[2] and to differentiate among linear cointegration, nonlinear cointegration and lack of cointegration.

Our study considers a selection of nine developed countries, all of them European except the USA, in order to obtain a more general view of links between interest rate changes and stock returns. Our results contribute to a better understanding of the relationship between interest rate changes and stock returns. They may be helpful for investors and portfolio managers in making better asset allocation decisions and designing improved portfolio diversification and risk management strategies. Our results may be also useful for policy makers for preserving financial stability, especially during periods of market turmoil and financial crisis.

[1] Generalized AutoRegressive Conditional Heterokedasticity

[2] The concept was introduced by Granger and Yoon (2002). Hidden cointegration occurs when no cointegration is detected using conventional techniques but it is found between positive and negative components of the series.

Our findings contribute to the idea that the relationship between interest rates and stock market returns does not have to be necessarily linear as have been found nonlinear Granger causality relationship in many countries and also, long-run asymmetric linkage in two cases. Furthermore, these last asymmetric relationship tend to increase when analyses is carried out in extreme economic situations.

The paper is structured as follows. Section 2 reviews the more relevant related literature. Section 3 details the data has been used in this study. Section 4 describes different methodologies used to reach a conclusion. Finally, Section 5 describes major empirical findings in the analysis.

2 Literature Review

The relationship between interest rate changes and stock returns has given rise to an extensive body of literature over the last decades. According to Ballester et al. (2011), most of this literature has concentrated on the banking industry due to the especial interest rate sensitivity that banks have because of their main role as a financial intermediary. This role causes a maturity mismatch between financial assets and liabilities as a result from the maturity transformation function of banking firms (i.e. financing long-term loans with short-term deposits). Nevertheless, it is worth to notice that companies of nonfinancial sectors can be also significantly influenced by interest rates, primarily through their effect on the cost of capital and the impact of movements in interest rates on the market value of financial assets and liabilities held by nonfinancial firms.

A wide range of empirical methodologies have been utilized to analyze the relationship between interest rate changes and stock market returns. Linear regression constitutes the most widely used approach in this field, mainly in early studies like Flannery and James (1984), Korkeamaki (2011) and Sweeney and Warga (1986) among others. These papers have employed APT-type models. Subsequently, a number of more sophisticated time series methods have been applied to examine the interest rate-stock market nexus. For example, Vector autoregressive (VAR) models have been widely used in this context by authors such us Laopodis (2010), Campbell and Ammer (1993) or Baek and Brock (1992). Other authors have used cointegration techniques like Eita (2014) or Hatemi-J and Roca (2008). Otherwise, linear Granger causality tests have been also used by Alaganar and Bhar (2003), Eita (2014) and Amarasinghe (2015), among others. It is also possible to find some contributions that used a nonlinear approach to model the relationship between interest rates and stock returns such as Ballester et al. (2011), Bartram (2002) or Ferrer et al. (2010). Different types of GARCH models have been also employed by many authors like Elyasiani and Mansur(1998) or Alaganar and Bhar (2003). A more recent methodology like the Quantile regression model has been applied in this framework by Ferrando et al. (2017) and Jareño et al. (2016).

In addition, the novel Quantile-on-Quantile (QQ) approach has been used by Maizonada (2016). Finally, there are a few studies which have used wavelet methodology to analyze this relationship like Martínez-Moya et al. (2015).

Earlier studies in this field provided evidence of a negative relationship between interest rate changes and stock returns of both financial and nonfinancial companies (Flannery and James (1984); Sweeney and Warga (1986)). Nevertheless, several recent studies have shown that this connection does not remain constant over time and it is influenced by economic conditions. In this respect, Kuenen (2015) shows that the correlation between bond yields and stock prices becomes higher during crisis periods because of the "flight to quality" phenomenon, but this effect is minor or even negative in riskier countries because they are forced to offer higher yields to maintain investors.

As indicated above, linear Granger causality tests have been utilized in a number of studies such as Eita (2014), Amarasinghe (2015) or Alaganar and Bhar (2003). In essence, the causality in the sense of Granger is based on the idea that a variable precedes another variable and is typically tested in the framework of VAR or vector error correction models. Eita (2014) finds a bidirectional linear Granger causality relationship between interest rate changes and stock returns in Namibia. In turn, Amarasinghe (2015) detects linear Granger causality between interest rates and the stock market in his study of the Colombo stock exchange. Instead, Alaganar and Bhar (2003) reach a different conclusion as they find that there are countries where stock market returns [3] cause innovations in interest rate changes, being these stock markets forward-looking of the general economic situation.

Nevertheless, the idea that the relationship between stock market returns and interest rate changes could be of nonlinear nature has gained importance in several studies. Paralel, there has been an important progress in nonlinear Granger testing. One of the first techniques was created by Baek and Brock (1992). These authors developed a nonparametric method which can be used for detecting nonlinear causal relations. This technique depends on the assumption that the variables are mutually i.i.d, but the main problem of this method is that this assumption eliminates the time dependence of variables. In this regard, Hiemstra and Jones (1994) modify the previous test to allow data autocorrelation in their nonlinear Granger causality test. However, Diks and Pachenko (2005) detected that the probability to reject the null hypothesis in the Hiemstra and Jones (1994) test tends to one when the sample increases. All these nonlinear Granger causality tests are carried out on the residuals of VAR models. This is because when applying the causality test on the VAR residuals, the linear dependence is filtered and then can check whether there is any nonlinear dependence remaining in the data series.

[3] Highly developed countries like France, Germany or the USA

Nonlinear Granger causality tests have been used to examine the presence of Granger causal links of nonlinear nature between many economic and financial time series like oil and precious metals in Bildirici and Turkmen (2015) and USA inflation and commodities in Kyrtsou and Labys (2006). However, to the best of our knowledge, no study has addressed so far the analysis of the existence of nonlinear Granger causal relationships between interest rate changes and stock returns.

Another interesting aspect is whether asymmetric effects exist in the financial environment. In this regard, Hatemi-J (2012) argued "there are reasons for the existence of asymmetric causal effects that need to be taken into account but usually are neglected in the literature". It is broadly recognized that positive and negative shocks may have different impacts on financial markets. Economic agents may react differently to positive and negative shocks even if the absolute magnitude of shocks is the same. This is because market participants tend to react more to negative news than to the positive ones as is indicated in Chen and Chan (1989) or in Lobo (2000). Another reason could be the existence of the asymmetric information phenomenon. One example about asymmetric information in financial markets could occur in a financial transaction, where one of the two parties involved has more information than the other and will have the ability to make a more informed decision. Since the pioneer works of Akerlof (1970) and Stiglitz (1974), it is widely agreed that there is asymmetric information in financial markets. Several papers have studied the presence of asymmetric relationships between interest rate movements and stock market returns like Chen and Chan (1989), where they found that stock returns of banks appeared to be more responsive to rising interest rates, or Lobo (2000), where they show an overreaction in the wake of bad news (interest rate rises).

Another interesting methodology applied in this study is the NARDL model, which permits testing about the existence of asymmetric cointegration in a single equation framework and provides robust empirical results even for small sample sizes. It has been recently used by Shahzad et al. (2017) and Nusair (2016). The first study focuses on the possible asymmetric relationship between 5-year Credit Default Swaps (CDS) index spread at the USA industry level and a set of macroeconomic and financial variables. They find significant asymmetries in the linkage between ten US industry CDS spreads and a set of major macroeconomic and financial variables, arguing about the importance of considering the asymmetries in that context. Similarly, in the second study, Nusair (2016) uses the NARDL approach to examine the relationship between changes in oil prices and Gross Domestic Product (GDP) in Gulf Cooperation Council (GCC) countries.[4] This author also finds relevant asymmetric relationship between variables as a positive

[4] This cooperation council is a regional intergovernmental political and economic union consisting of all Arab states of the Persian Gulf, except for Iraq. Its member states are Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates. This area has some of the fastest growing economies in the world, mostly due to a boom in oil and natural gas revenues coupled with a building and investment boom backed by decades of saved petroleum revenues.

change are statistically significant in all countries while in negative case, only in two countries have been found a significant relationship. It means, positive changes rise the GDP in producing countries while in buyer countries these price increases may trigger in a recession like in 1970's. Instead, negative changes do not affect the GDP in producing countries, generally.

3 Data

The dataset used in this study consists of two variables for each country. The first variable corresponds to yields on 10-year government bonds. The second one is the main broad stock market index. This study has been carried out for nine developed countries, namely France, Germany, Greece, Ireland, Italy, Portugal, Spain, the United Kingdom (UK) and the United States of America (USA). This selection includes some countries in the periphery of the Eurozone such as Portugal, Spain, Greece, Italy or Ireland; some countries belonging to the core of the Eurozone, such as France and Germany; one European country (the UK), which is not in the Eurozone and finally, the USA, which is usually employed as a benchmark.

The sample period covers from January 1999 to March 2017. This period allows us to study the relationship between interest rate fluctuations and stock returns considering some major economic events like the recent global financial crisis and the subsequent European sovereign debt crisis. The frequency used is weekly, according to many authors like Flannery and James (1984), Olugbode et al. (2014) or Shamsuddin (2014), weekly frequency is preferred over daily and monthly frequencies since daily data is more contaminated by noise, and compared to monthly data, a larger number of weekly observations are available to reach more reliable results.[5]

Data series[6] have been extracted from Thomson Financial DataStream. The stock market indices considered are the IBEX35 (Spain), CAC40 (France), DAX (Germany), PSI20 (Portugal), FTSE-MIB (Italy), FTSE100 (the UK), ATHEX (Greece), ISEQ20 (Ireland) and S&P500 (the US). Regarding the interest rates, we have chosen the yields on 10-year government bonds because they have become increasingly popular in the literature on the interest rate-stock market link as we can see in Azadeh et al. (2016); Ballester et al. (2011), Kuenen (2005) or Elyasiani and Mansur (1998), and is supported by the following arguments. Firstly, 10-year interest rates are used as a proxy to measure the cost of financing for the government of each country. Besides, they are supposed to contain market expectations about future economic situation. Secondly, long- term bonds are often seen as the closest maturity substitutes to stock. Finally, it is worth noting

[5]Total number of observations are 951. However, it is important to point out that Greece data are available from April of 1999, having therefore 938 observations.

[6]In the A appendix can be found the variables evolution over time.

that long-term government bond yields have a great impact on investments decisions to portfolio managers and determine the cost of firms financing.

Table 1 presents the main descriptive statistics of stock market indices and 10-year government bond yields for the entire sample period (from January 1999 to March 2017). As can be seen, 10-year government bond yields show big differences in their means depending on the country considered. In particular, countries in the periphery of the Eurozone such as Portugal, Italy, Ireland, Greece and Spain (often denominated PIIGS) have higher mean bond yields than other European countries like France or Germany. Series are clearly not normal as the Jarque and Bera test rejects the null hypothesis of normality at the 1% significance level in all case because of the series have asymmetry or kurtosis.

Table 1: Descriptive stats: Series in levels

	Mean	Median	Max	Min	Std.Dev	Skewness	Kurtosis	JB
Panel A: Stock market indices								
ATHEX	12236.42	11210.70	31970.20	1170.70	8342.92	0.36	1.89	68.67***
CAC40	4308.06	4266.19	6796.79	2403.04	890.87	0.50	2.72	42.83***
DAX	6585.21	6246.92	12231.34	2202.96	2227.71	0.54	2.64	51.74***
FTSE100	5680.64	5860.04	7382.90	3287.04	877.93	-0.52	2.36	59.72***
FTSEMIB	27226.16	24403.98	48810.40	12506.74	9257.24	0.48	2.07	71.25***
IBEX35	9810.36	9707.60	15890.50	5364.50	2090.81	0.60	3.32	60.39***
ISEQ20	813.32	796.87	1572.42	292.01	271.52	0.38	2.72	26.44***
PSI20	7754.95	7417.50	14776.92	4335.24	2358.33	0.73	2.61	89.41***
S&P500	1385.18	1307.40	2395.96	712.87	365.44	0.84	2.92	111.36***
Panel B: 10-year government Bond yields								
France	3.38	3.66	5.83	0.10	1.41	-0.64	2.55	72.56***
Germany	3.11	3.49	5.65	-0.22	1.56	-0.52	2.10	74.85***
Greece	7.90	5.70	46.69	3.23	6.12	2.98	13.21	5458.36***
Ireland	4.29	4.25	13.52	0.33	1.99	0.59	4.92	202.11***
Italy	4.14	4.31	7.22	1.08	1.20	-0.81	3.38	109.30***
Portugal	5.03	4.42	15.38	1.43	2.21	2.02	7.37	1404.60***
Spain	4.10	4.19	7.44	0.97	1.25	-0.68	3.10	74.01***
UK	3.74	4.25	5.80	0.63	1.32	-0.58	1.98	93.93***
US	3.69	3.83	6.73	1.37	1.32	0.10	2.03	38.74***

Note: The table 1 presents the main descriptive statistics of weekly stock market indices and 10-year government bond yields over the sample under study (from January 1999 to March 2017).As usual, *,**,*** indicating “statistical significance” at 10%, 5% and 1% levels, respectively

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As a preliminary analysis, we check if the data series are stationary or they have a unit roots. If they had a unit root, the results of all standard estimation techniques could be invalid and any conclusion could be misleading. Thus, we will be forced to differentiate them unless they are cointegrated.[7]

[7] It means, a linear combination of two variables are stationary although they do not and would signify they share a long-term tendency.

To do that, we use the well-known Augmented Dickey-Fuller (1979,1981) test (ADF hereafter).

A unit root can be tested using the ADF test as follows

$$y_t = \beta + \delta_t + \rho y_{t-1} + \sum \phi_t \Delta y_{t-1} + \epsilon_t \tag{1}$$

Table 2: Results of unit root tests

Series	**Levels**		**Differences**	
	t-stadistic	p-value	t-stadistic	p-value
Panel A: Stock market indices				
ATHEX	-1.41	(0.58)	-32.47	(0.00)***
CAC40	-1.82	(0.37)	-36.4	(0.00)***
DAX	-0.3	(0.92)	-34.17	(0.00)***
FTSE100	-1.66	(0.45)	-12.82	(0.00)***
FTSEMIB	-1.43	(0.57)	-15.47	(0.00)***
IBEX35	-2	(0.29)	-12.38	(0.00)***
ISEQ20	-2.03	(0.28)	-4.64	(0.00)***
PSI20	-1.77	(0.40)	-16.63	(0.00)***
SP500	0.35	(0.98)	-12.42	(0.00)***
Panel B: 10-year government bond yields				
France	-0.46	(0.9)	-31.42	(0.00)***
Germany	-0.21	(0.94)	-31.36	(0.00)***
Greece	-1.91	(0.33)	-8.73	(0.00)***
Ireland	-1.03	(0.74)	-21.95	(0.00)***
Italy	-0.87	(0.8)	-10.79	(0.00)***
Portugal	-2.3	(0.17)	-5.15	(0.00)***
Spain	-0.9	(0.79)	-10.79	(0.00)***
UK	-0.42	(0.9)	-32.95	(0.00)***
USA	-1.42	(0.57)	-31.61	(0.00)***

Note: This table shows the t-statistic and p-value for the ADF test with the aim to know if the series have a unit root. It is applied to levels and first differences of stock market indices and 10-year government bond yields. As usual, *,**,*** indicate “statistical significance” at 10%, 5% and 1% levels, respectively.

Table 2 reports the results of the ADF unit root test. As can be seen, in all countries the 10-year government bond yields and stock market indices are non-stationary in levels, but stationary in differences. This result implies that all the original series have a unit root, that is, are one order integrated, I(1).

4 Methodology

This section describes briefly the different econometric techniques that are used in this study to examine the relationship between interest rate changes and stock market returns. Our selection tries to get a complete and robust conclusion about the relationship between movements in interest rates and stock returns. We are going to start with the linear and nonlinear Granger causality relationships, after which we will tackle the possible existence of asymmetric relationship using the NARDL model. This structure is defined to start from the most common techniques to most current ones.

The concept of causality in the sense of Granger was created by the Economy Nobel winner Clive W.J. Granger in 1969. This causality type refers to the fact that the past of one variable, z , can contribute to do better predictions of another variable, y, than only using past values of y.

The lack of Granger causality is given by the following expression

$$E(y_t/y_{t-1}, y_{t-2}, ...; z_{t-1}, z_{t-2}, ...) = E(y_t/y_{t-1}, y_{t-2}, ...) \qquad (2)$$

This expression shows that the incorporation of the past values of z in the first part of equality does not improve the forecast of variable y. In this case, the past values of z would do not add relevance information to y values prediction and, therefore, there would be not causality in the Granger sense.

The Granger causality test is technically carried out by testing the significance to the block of the lags of the potential causal variable using generally the Wald test. This test does not consider if the predictions improve using past values of another variable as it seems in the definition of the granger causality. Following the standard practice, a VAR model is utilized to examine the presence of linear Granger causality relationships between both variables. There is one equation for each variable we want to explain. In our case, we would have two equations for each country. The independent variables are lags of the two variables involved in the model specification.

It is important to notice that it is equally efficient to estimate one equation by one using OLS or all the equations together considering the innovation correlation matrix. One of the most relevant things to do is finding the optimal lag number to use in the model as too many lags add complexity to the estimation of the model and, too little lags may not get non-auto correlated residuals in the model estimation. Consistent estimations is the minimum we have to guarantee when we create a model. In a VAR model specification, we get it as long as we obtain non- auto correlated and stationary residuals. We have chosen the optimum lag starting with 1 lag and checking if residuals were lack of autocorrelation using the Ljung- Box test and simple autocorrelation function. If they do not, we add one lag to the model until the n-lag model produces non-auto correlated residuals.

The model specification used to test the presence of linear Granger causality has the following structure

$$\Delta y_t = \mu_t + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + B x_t + \epsilon_t \tag{3}$$

with

$$\Pi = \sum_{i=1}^{p} A_i - I_k = -\Phi(1), \Gamma_i = -\sum_{j=i+1}^{p} A_j, i = 1, 2, ..., p-1 \tag{4}$$

The Πy_{t-1} term is known as a error correction term and is very important for the cointegration analysis. It has to be noticed Johansen cointregration test is carried out within the framework of an error correction mechanism.

If variable dependent y_t has some unit root, then $|\Phi(1)| = 0$ and $\Pi = -\Phi(1)$ will be a singular matrix. There are three possible cases when studying Π matrix :

1. $Rank(\Pi) = 0$. This means $\Pi = 0_{kxk}$ and vector y_t variables are not cointegrated. In that case, error correction model (ECM) is equal to first differences VAR model which expression is :

$$\Delta y_t = \mu_t + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + ... + \Gamma_{p-1} \Delta y_{t-p+1} + \epsilon_t \tag{5}$$

2. $Rank(\Pi) = k$. This means $|\Phi(1)| \neq 0$ and y_t does not have unit roots, it is, all variables in vector y_t are I(0). ECM model is not required, is used VAR model directly

$$y_t = \mu_t + \Gamma_1 y_{t-1} + \Gamma_2 y_{t-2} + ... + \Gamma_p y_{t-p} + \epsilon_t \tag{6}$$

3. $0 < Rank(\Pi) = m < k$. In that case, $\Pi = \alpha\beta'$,where α and $\beta$are kxm matrices with rank(α) = rank(β)= m. ECM models turns into

$$\Delta y_t = \mu_t + \alpha\beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + ... + \Gamma_{p-1} \Delta y_{t-p+1} + \epsilon_t \tag{7}$$

In last case, variables of vector y_t are cointegrated. There would be m independent lineal cointegration vectors given by lineal combinations existing in $w = \beta' y_t$.

The Johansen approach focuses on studying the Π rank of long-term multipliers. In fact, it consists in estimating VAR model using maximum likelihood and analyze the Π

matrix rank. He suggests two test statistics to run: the trace statistics and the eigenvalue statistics. The Johansen cointegration test proceeds sequentially, the results obtained from the both statistics might be a little bit different but there is no reason to prefer one of them.

In the case that the presence of cointegration is rejected, a VAR model in first differences must be used to investigate the existence of linear Granger causality relationships. The general expression of a first difference VAR model would be like

$$\Delta y_{1,t} = \beta_{10} + \beta_{11}\Delta y_{1,t-1} + \beta_{12}\Delta y_{2,t-1} + ... + \beta_{1n}\Delta y_{n,t-1} + u_{1t} \quad (8)$$

$$\Delta y_{2,t} = \beta_{20} + \beta_{21}\Delta y_{1,t-1} + \beta_{22}\Delta y_{2,t-1} + ... + \beta_{2n}\Delta y_{n,t-1} + u_{2t} \quad (9)$$

Where $\Delta y_{1,t}$ and $\Delta y_{2,t}$ are both first differences variables at time t. Similarly, $\Delta y_{n,t-1}$ show the first differences value of variable y_n in at t-1 time. The betas measure the impact of one lag variable of another and finally, $u_{n,t}$ represents the error terms of variable n at time t.

Once we have the VAR model estimated we can check the linear Granger causality relationships may exist in the nine countries. To do that, we apply the Granger test which test if the parameters related to another variable are statiscally significant. This test is carried out with a Wald test where $\beta_{12} = 0$ would be the null hypothesis to test if y_2 cause y_1 in last VAR model example. If the optimal lag number were greater than one, all the coeficients would be tested.

Until now, we have focused on the linear Granger causal linkages. We could think that doing this we are studying completely the possible relationship that may exist between the variables. However, anything guarantees the relationship is linear as more and more studies are considering the possible presence of nonlinear relationships. Moreover, in the Introduction section we have seen this linear relationship assumption is less assumed nowadays. Furthermore, if we were wrong and only linear relationship exists, we would not find nonlinear relationship and could we keep with the results of linear ones but not without previously trying to detect the possible nonlinear linkage. For that reason we are going to check if this relationship could be nonlinear.

There are many nonlinear Granger causality tests such as Baek and Brock (1992) or Hiemstra and Jones (1994). The most common one used by practitioners in economic and finance is the Hiemstra and Jones (1994) even said by Pachenko. Nevertheless, we apply the nonlinear Granger causality test developed by Diks and Pachenko (2006)[8] as it improves the early test, not only because it has the more flexibility by considering no i.i.d series, which had already been introduced by Hiemstra and Jones (1994), but also

[8] For space reasons, we have not included the technical details of the Diks and Pachenko methodology. However, a complete and profound explanation of this method may be found in the Diks and Pachenko (2006) paper called "A new statistic and practical guidelines for nonparametric Granger causality testing"

solving the problem Hiemstra and Jones (1994) test had with the sample. That is, the greater sample is, higher probability to reject the null hypothesis the test has. Although further details can be explained in his study, we want to explain the basics. The Diks and Pachenko (2006) test is a extension of Hiemstra and Jones (1994) test, which uses correlation integrals to measure the discrepancy between an equality of conditional independence whose Baek and Brock (1992) test uses in the first nonlinear Granger created. Pachenko show that equality not always happens and is the reason that Hiemstra and Jones test tends to reject the null hypothesis when the sample increases. This test is applied on the VAR residuals, following the idea of all Granger nonlinear test developers that any relationship could remain in residuals after testing the linear relationship should be nonlinear as linear relationship would be in VAR estimated coefficients.

It is important to carry out nonlinear methods because, as we mentioned previously, interest rates affect market stock returns in two ways, first through the discount rate of the stock and second by altering the cost of financing of firms, hence impacting expected future cash flows and stock prices. According with that, the relationship between interest rate changes and stock market returns does not have to be necessarily linear because financial markets are often more complex than linear relationships as financial economies are connected each other and one shock is rapidly transmitted to other markets. To take into account this possible nonlinearity, it is necessary to use more sophisticated techniques to gain a better insight into the real linkage between financial variables. Otherwise, we would be assuming the relationship is necessarily linear when we do not have any certainty.

Similarly, it is also critical to consider the possibility that the relationship between interest rate changes and stock market returns could be of asymmetric nature. This asymmetric effect can be found when positive interest rate shocks do not have the same effect on stock returns than negative interest rate shocks. Moreover, it seems reasonable to think that economic agents may react differently to positive and negative news in financial markets. In our field of study an example could be when negative change in interest rate could affect more to stock market than a positive one.

The existence of this financial markets asymmetry has been argued by many authors such as Hatemi-J (2012), Bildirici and Turkmen (2005), Stiglitz (1974) or Akerlof (1970). Furthermore, the asymmetric relationship in interest rate and stock returns are specifically studied by these authors Chen and Chan (1989), Kalu (2017) or Lobo (2000). They support this asymmetric effect with several reasons. For instance, Chen and Chan (1989) says when interest rate rises could exacerbate the maturity mismatch between assets and liabilities trigging in a negative impact of financial institutions stock returns. However, when interest rate drops the stock returns may not increase as expected due to the existence of asset refinancing and/or interest rate rigidity found in some types of deposit accounts(e.g pass-book savings and NOW[9] accounts)

[9]An interest-earning bank account with which the customer is permitted to write drafts against money

In order to test the presence of asymmetry in long-run relationships among a set of variables, the NARDL model can be used. The NARDL approach is an asymmetric extension of the linear autoregressive distributed lag (ARDL) cointegration model proposed by Pesaran et al. (2001). The linear ARDL approach does not consider the possibility that negative and positive variations of the explanatory variables have different effect on the dependent variable. The NARDL model not only allows us to detect the existence of asymmetric effects that independent variables may have on the dependent variable, but also permits testing for cointegration in a single equation framework. Moreover, this model presents some advantages, which have been previously explained, over other cointegration techniques used frequently, such as its flexibility regarding the order of integration of the variables involved, the possibility of testing for hidden cointegration, avoiding to omit any relationship which is not visible in a conventional linear setting and a better performance in small samples.

To facilitate the interpretation of the NARDL model, we first present the expression of the linear (ARDL) model given by

$$\Delta y_t = \mu + \rho y_{t-1} + \theta x_{t-1} + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-j} + \sum_{j=0}^{q-1} \pi_j \Delta x_{t-j} + \epsilon_t \quad (10)$$

where Δ represents the first difference operator, y_t is the dependent variable in period t, μ denotes the intercept, x is a kx1 vector of regressors, and ρ and θ denote the long-run coefficients. Furthermore, α_j and π_j are the short-run coefficients, p and q represent the optimal lags for the dependent variable and the independent variables, respectively, and finally, ϵ_j the error term at time t.

However, the ARDL approach does not consider the possible asymmetric link among the variables. In other words, it assumes implicitly than positive and negative variations of the explanatory variables have the same effect on the dependent variable. We think this is not the correct approach to study the relationship between interest rate changes and stock returns as there may be asymmetric links between these variables.

We are going to use the nonlinear version of ARDL which allows asymmetric relationships. According to Shin et al. (2014) the NARDL model is built around the following asymmetric long-run equilibrium relationship

$$y_t = \beta^+ x_t^+ + \beta^- x_t^- + u_t \quad (11)$$

where we can observe that the equilibrium relationship between y and x is divided into positive ($\beta^+ x_t^+$) and negative ($\beta^- x_t^-$) effects, plus the error term (u_t) representing possible deviations from the long-equilibrium.

held on deposit. Also known as a "NOW account".

As shown in equation (11), the effect of the variable x can be decomposed into two parts, positive and negative

$$x_t = x_0 + x_t^+ + x_t^- \tag{12}$$

where x_0 represents the random initial value and $x_t^+ + x_t^-$ denote partial sum processes which acumulate positive and negative changes, respectively, and are defined as

$$x_t^+ = \sum_{j=1}^{t} \Delta x_j^+ = \sum_{j=1}^{t} max(\Delta x_j, 0) \tag{13}$$

$$x_t^- = \sum_{j=1}^{t} \Delta x_j^- = \sum_{j=1}^{t} min(\Delta x_j, 0) \tag{14}$$

Combining equation (11) with the linear ARDL(p,q) model, as we specified previously in equation (10), we obtain the asymmetric error correction model which takes the following expression

$$\Delta y_t = \mu + \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta x_{t-j}^+ + \pi_j^- \Delta x_{t-j}^-) + \epsilon_t \tag{15}$$

As mentioned above, the NARDL approach allows using a combination of variables I(0) and I(1) without any problem. However, it is important we have checked the integration order of variables in previous steps as the NARDL model is not valid for variables that are I(2).

The NARDL model to be estimated in the framework of our study takes the following form:

$$\begin{aligned} \Delta SMI_{k,t} = \mu + \rho SMI_{k,t} + \theta_1^+ IR_{k,t-1}^+ + \theta_1^- IR_{k,t-1}^- + \sum_{j=1}^{p-1} \alpha_j \Delta SMI_{k,t-j} \\ + \sum_{j=0}^{q-1} \pi_j^+ \Delta IR_{k,t-j}^+ + \sum_{j=0}^{q-1} \pi_j^- \Delta IR_{k,t-j}^- + \epsilon_t \end{aligned} \tag{16}$$

where $SMI_{k,t}$ stands for the stock market index of country k in period t, $IR_{k,t}$ is the long-term interest rate of country k in period t, ΔIR^+ and ΔIR^- are the partial sums of positive and negative changes in the long-interest rate, respectively.

The empirical implementation of the NARDL model implies several steps. The first step is the estimation of equation (16) by OLS. The second step consists of testing the presence of cointegration relationships using a bounds testing approach. This can be done using two different tests.[10] The first one is the F-statistic, introduced by Pesaran et al. (2001) and denoted by F_{PSS}, which tests the null hypothesis of no cointegration ($\rho = \theta^+ = \theta^- = 0$) against the alternative hypothesis of cointegration ($\rho \neq \theta^+ \neq \theta^- \neq 0$). The second one is the t-statistic, proposed by Banerjee et al. (1998) and denoted by t_{BDM}, which tests the null hypothesis of $\theta = 0$ against the alternative hypothesis of $\theta < 0$. The third step involves testing for long-run symmetry ($\theta^+ = \theta^-$) using the standard Wald test. In the fourth step, the asymmetric cummulative dynamic multipliers effect on y_t of a unit change in x_t^+ and x_t^- can be obtained, respectively, as follows

$$m_h^+ = \sum_{j=0}^{h} \frac{\delta y_{t+j}}{\delta x_t^+}, \qquad m_h^- = \sum_{j=0}^{h} \frac{\delta y_{t+j}}{\delta x_t^-}, h = 0, 1, 2... \tag{17}$$

Note that as $h \to \infty$, then $m_h^+ \to \beta^+$ and $m_h^- \to \beta^-$, where β^+ and β^- are calculated as $\beta^+ = -\theta^+/\rho$ and $\beta^- = -\theta^-/\rho$, respectively.

[10] Note that if both test do not match their results, authors like Shahzad et al. (2017) consider F-statistic.

5 Empirical results

This section presents the results from the different time series methods previously discussed. Firstly, the results of the Johansen cointegration test between 10-year sovereign bond yields and stock market indices are reported in Table 3. [11]

Table 3: Cointegration analysis: Johansen test

Trace statistic

	H0:No of CE(s)	**Eigenvalue**	**Trace Statistic**	**Critical Value(5%)**	**Prob**
France	None	0.007	8.280	15.495	0.436
	At most 1	0.002	1.505	3.841	0.220
Germany	None	0.011	10.077	15.495	0.275
	At most 1	0,000	0.002	3.841	0.966
Greece	None	0.009	9.054	15.495	0.360
	At most 1	0.001	0.874	3.841	0.350
Ireland	None	0.007	7.151	15.495	0.560
	At most 1	0.001	0.735	3.841	0.391
Italy	None	0.006	7.234	15.495	0.551
	At most 1	0.002	1.898	3.841	0.168
Portugal	None	0.006	7.982	15.495	0.467
	At most 1	0.002	2.256	3.841	0.133
Spain	None	0.007	9.146	15.495	0.352
	At most 1	0.002	2.349	3.841	0.125
UK	None	0.011	11.193	15.495	0.200
	At most 1	0.001	0.760	3.841	0.384
USA	None	0.007	6.461	15.495	0.641
	At most 1	0.000	0.001	3.841	0.969

Note: This table shows the results of the Johansen cointegration test (Trace statistic) to detect the existence of cointegration relationships between the 10-year government bond yields and stock market indices in each country.As usual, *,**,*** indicate "statistical significance" at 10%, 5% and 1% levels, respectively.

The results of the Johansen cointegration procedure show clearly that the null hypothesis of no cointegration cannot be rejected at the usual significance levels for any country. This implies that there is not long-run equilibrium relationships between 10-year government bond yields and stock market indices. Therefore, long-term interest rates and stock indices do not share a common stochastic trend during the entire sample period.

[11] We have shown the test results considering the trace statistic option test.

According to this, the existence of linear Granger causality relationships must be examined using a VAR model in first differences in order to get stationary residuals, which is one of the two requirements for reaching consistent estimations.

The next step is the analysis of the presence of linear Granger causality relationships through the estimation of a difference VAR model [12] for each country. To do that, we apply the standard linear Granger causality test, which tests if the parameters associated to another variable are statistically significant at the usual levels.

Table 4 reports the p-values obtained by testing the two possible directions, from interest rates to stock returns and vice versa, of linear Granger causality relationships for each country.

Table 4: Linear Granger Causality results

Relations	**Linear Causality**
IRC France ⇒ rCAC40	(0.20)
rCAC40 ⇒ IRC France	(0.03)**
IRC Germany ⇒ rDAX	(0.24)
rDAX ⇒ IRC Germany	(0.01)***
IRC Greece ⇒ rATHEX	(0.06)*
rATHEX ⇒ IRC Greece	(0.92)
IRC Ireland ⇒ rISEQ20	(0.21)
rISEQ20 ⇒ IRC Ireland	(0.04)**
IRC Italy ⇒ rFTSE-MIB	(0.03)**
rFTSE-MIB ⇒ IRC Italy	(0.19)
IRC Portugal ⇒ rPSI20	(0.74)
rPSI20 ⇒ IRC Portugal	(0.47)
IRC Spain ⇒ rIBEX35	(0.18)
rIBEX35 ⇒ IRC Spain	(0.10)*
IRC UK ⇒ rFTSE100	(0.11)
rFTSE100 ⇒ IRC UK	(0.00)***
IRC USA ⇒ rSP500	(0.27)
rSP500 ⇒ IRC USA	(0.72)

Note: This table contains the p-values obtained by estimating the presence of linear Granger causality relationship between interest rate changes and stock market returns for the two possible directions in each country under study. "IRC" represents interest rate changes and "rIndex" is the stock market return for each country.As usual, *,**,*** indicate "statistical significance" at 10%, 5% and 1% levels, respectively.

[12] Linear Granger causality has been carried out using Eviews and Matlab packages.

The results reveal interesting conclusions about the existence of linear Granger causality relationships. It is shown that there are more causal linkages from stock market indices to 10-year sovereign bond yields than the opposite. In particular, significant linear Granger causal links from the stock market to long-term interest rates are found for France, Germany, Spain, Ireland and the UK. A possible explanation for this finding is that the forward-looking nature of the stock market causes stock prices to anticipate the behavior of the general economy, so that the stock market incorporates information on future economic prospects before than long-term interest rates. This leads to the emergence of linear causal relationships from the stock market to 10-year government bond yields. Nevertheless, there are less significant Granger causal relationships from long-term interest rates to stock market returns as they have been only found for Italy and Greece. This result indicates that in these two countries 10-year sovereign bond yields have a significant influence on the performance of the domestic stock market. This finding may be related to the fact that Greece and Italy are two of the countries most severely impacted by the European sovereign debt crisis since the end of 2009. Thus, the strong rises in the risk premium of the 10-year sovereign debt experienced in this context may have had a significant influence on the stock market performance in these two countries. The USA and Portugal are the only countries where significant linear Granger causal linkages are not found in any direction.

Nevertheless, we want also to study the presence of linear Granger causality relationships using the literal definition of Granger causality[13], that is, seeing whether the forecast of one variable is improved by using the past behavior of the other variable. To do that, we use the partial autocorrelation function to determine the optimal lag number of the autoregressive (AR) process of the variables. Once done this, we estimate the AR(p) model and we compare its forecast with the VAR(n) prediction, both done out-of sample [14] to be able to compare with real data values. The results are presented graphically in the appendix B. However, graphically it is difficult to see what process commits less error. Therefore, we utilize two error measures to identify what model leads to a larger error in the prediction. The measures used are the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) whose expressions are as follows

[13] In this case, this analysis has been done in Matlab package.

[14] A true out-of-sample analysis would be to estimate the model based on data up to and including today, construct a forecast of tomorrow's value Y_{T+1}, wait until tomorrow, record the forecast error $e_{T+1} = Y_{T+1} - \widehat{Y_{T+1,T}}$, re-estimate the model, make a new forecast of Y_{T+2}, and so forth. At the end of this exercise, one would have a sample of forecast errors vector which would be truly out-of-sample and would give a very realistic picture of the model's performance. Since this procedure is very time-consuming, people often resort to "pseudo", or "simulated", out-of-sample analysis, which means to mimic the procedure described in the last paragraph, using some historical date $T_0 < T$, rather than today's date T, as a starting point. The resulting forecasting errors vector will lenght of $T - T_0$ and will be used to get an estimate of the model's out-of-sample forecasting ability.

$$RMSE = \sqrt{\frac{1}{h}\sum_{k=T}^{T+h} (\widehat{r_k - r_k})^2} \tag{18}$$

$$MAE = \sum_{k=T}^{T+h} |r_k - r_k| \tag{19}$$

Table 5 shows the two aggregated error measures calculated in the prediction of the two variables considered with a difference VAR(q) model, which includes the past values of the another variable, and with an AR(p), which only takes into account the past values of the own variable.

Table 5: RMSE and MAR measures error for both predictions.

France	AR(p)	VAR(q)	Germany	AR(p)	VAR(q)	Greece	AR(p)	VAR(q)
RMSE	74.87	69.86	RMSE	196.55	187,54	RMSE	97.51	105.87
MAE	1336.31	1248.03	MAE	3438.96	3411.66	MAE	1733.73	1796.60
Ireland	AR(p)	VAR(q)	Italy	AR(p)	VAR(q)	Portugal	AR(p)	VAR(q)
RMSE	18.68	18.74	RMSE	485.03	497.73	RMSE	88.22	89.66
MAE	331.36	326.9	MAE	8263.84	8618.78	RMSE	1555.80	1651.36
Spain	AR(p)	VAR(q)	UK	AR(p)	VAR(q)	USA	AR(p)	VAR(q)
RMSE	197.88	199.58	RMSE	3646.86	3536.53	RMSE	30.34	30.28
MAE	3688.23	3658.97	MAE	78718.90	78631.19	MAE	553.31	560.94

Note: The table contains the two error measures explained before to compare the error committed by AR(p) and VAR(q) models. Each model has commited two errors in forecasting both variables. Then we would have VAR error for interest rate prediction and VAR error for stock market returns prediction, and the same to the AR process. Nevertheless, we have aggregated the two errors of each process in only one number to facilitate the comparison.As usual, *,**,*** indicate "statistical significance" at 10%, 5% and 1% levels, respectively.

Accordingly, we could think there is a linear Granger relationship in a given country when the two error measures tell us that the VAR(q) model commits less error than the AR(p) process as this would mean that the lags of one variable add relevant information to forecast another variable. Comparing both methods of testing linear Granger causality we can see that the results obtained using prediction errors are largely consistent with those of the standard Granger causality test above carried out. Considering the table information, significant linear Granger causality is found in countries such as France, Germany or the UK. These three countries results would support the two strongest linear causal linkages found with the previous Granger causality test (Germany and the UK). In the French case, a significant causal link was also found with the causality test at the conventional significance levels, 10% and 5%, but not at the 1% level as in the two above mentioned countries. On the contrary, for Portugal the prediction errors are lower by using a AR(p) process than with the VAR model having a match with the previous test results where significant Granger causality was not found. However, the results for the rest of countries are not so conclusive with regard to the existence of linear causal linkages. For example, in the Spanish case, one error measure supports the VAR model and another measure supports the opposite model, so that the presence of linear causality relationships is not clear as the previous linear Granger causality test also told us with a p-value of 0.10. In other countries like Ireland and the USA, the errors measures does not add any information as divergent effect also happens and we would have to keep with Granger test information having relationship in Ireland and not in the USA.

A singular result is found for Italy and Greece where, according to the standard linear Granger causality test, there was significant causal linkages, but considering the two error measures, it seems that there is not Granger causality. As we do not know what causality tool is more powerful and the prediction have been done with an **out of sample** method, it is difficult to make a categorical statement on the presence of linear Granger causality in these two countries, at least, with the information we have. However, prediction error method may be used to contrast linear Granger test results and give more powerful conclusions to the ones previously obtained.

Nevertheless, it is important to remember we are not stay here and we are going to test also the possible existence of nonlinear Granger causality[15] between interest rate changes and stock market returns. Residuals of the VAR model in differences above estimated are required because the nonlinear Granger causality test of `Diks and Panchenko (2005)` is, by construction, applied on the residual series. Table 6 presents the p-values of the nonlinear Granger causality test for the two possible directions, that is, from interest rates changes to stock market returns and vice versa.

[15]This study has been carried out using Matlab and Eviews software to obtain residuals of difference VAR model and then the nonlinear Granger causality test developed by Diks and Pachenko (2005) has been applied.

Table 6: Nonlinear Granger Causality results

Relations	**Nonlinear Causality**
IRC France ⇒ rCAC40	(0.58)
rCAC40 ⇒ IRC France	(0.08)*
IRC Germany ⇒ rDAX	(0.35)
rDAX ⇒ IRC Germany	(0.12)
IRC Greece ⇒ rATHEX	(0.01)***
rATHEX ⇒ IRC Greece	(0.00)***
IRC Ireland ⇒ rISEQ20	(0.33)
rISEQ20 ⇒ IRC Ireland	(0.06)*
IRC Italy ⇒ rFTSE-MIB	(0.03)**
rFTSE-MIB ⇒ IRC Italy	(0.07)*
IRC Portugal ⇒ rPSI20	(0.02)**
rPSI20 ⇒ IRC Portugal	(0.17)
IRC Spain ⇒ rIBEX35	(0.40)
rIBEX35 ⇒ IRC Spain	(0.19)
IRC UK ⇒ rFTSE100	(0.11)
rFTSE100 ⇒ IRC UK	(0.09)*
IRC USA ⇒ rSP500	(0.23)
rSP500 ⇒ IRC USA	(0.39)

Note: This table reports the p-values of the nonlinear Granger causality test proposed by `Diks and Pachenko(2005)` test applied to difference VAR residuals in each country.As usual, *,**,*** indicate "statistical significance" at 10%, 5% and 1% levels, respectively.

The results of the nonlinear Granger causality analysis tell us several important things. On the one hand, the two countries with the most meaningful linear Granger causal links (Germany and the UK) show poor evidence of significant nonlinear Granger causality relationships. In particular, there is no significant nonlinear Granger causal linkages in any direction for Germany. For the UK there is only nonlinear Granger causality at the 10% level from the stock market to 10-year government bond yields. This implies that in both countries the causality relationships between long-term interest rates and stock market would be predominantly linear. On the other hand, we can see a significant bidirectional nonlinear causal link in Greece at the 1% significance level. A similar bidirectional nonlinear causality relationship is also found in Italy, although with a lower significance level. It could signify the causal linkages between 10-year sovereign bond yields and stock returns in Greece and Italy are specially complex and strong compared to other European countries, so that a little change in one of the two variables, regardless of which variable shock occurs, would affect a lot to the other. This effect would be mainly nonlinear in Greece and both linear and nonlinear in Italy. The reason that these two countries have significant linear and nonlinear Granger causality relationships could be the great impact of the European sovereign debt on both countries. It is also found a weak nonlinear Granger relationship in Ireland, from stock market to 10-year bond yields, and in France from interest rate to stock market. Notice also than in Spain, the Granger causality is strictly linear as it was shown previously. Finally, we can find a significant nonlinear causal linkage in Portugal from 10-year bond yields to stock market where previously was not found, telling us the causality relationship seems to be only nonlinear. It would be important to note that equal than linear Granger test approach, the USA, cannot reject the null hypothesis of not existence of nonlinear Granger causality relationship. It may sense in this country, knowing the past value of another does not have importance to predict the value of variable, that is, connection between 10-year government bond yields and stock market returns, would not exist in Granger terms.

Having established with the ADF unit root test previously conducted that none of the variables is integrated of order 2, we proceed to estimate the NARDL model.[16]The first step is to test for the presence of a nonlinear long-run relationship between changes in 10-year government bonds and stock returns. This can be done by using either the F-test of Pesaran et al. (2001) or the t_{BDM}-statistic of Banerjee et al. (1998). The results are displayed in Table 7. The F-test takes into account the stationarity properties of the variables. Specificially, Pesaran et al. (2001) compute bounds for the critical values at any significance level. The bounds procedure works as follows. Firstly, there are a pair of bounds for any significance level, a lower and an upper. The lower bound assumes that all variables we are using are $I(0)$, whereas the upper one assumes that all the variables are $I(1)$. If the F statistic is higher than the upper bound critical value, the null hypothesis of no cointegration is rejected at the significance level we are considering the bounds values. Instead, if the F statistic is below the lower bound, then the null hypothesis cannot be rejected, indicating the lack of cointegration at that confidence level. In the special case that the statistic falls between the two bounds, the inference remains inconclusive and other cointegration test like Johansen must be used. Instead, t_{BDM} statistic takes into account the critical value, according to Table 1 in Banerjee et al. (1998), and reject the null hypothesis when the t-statistic , in absolute value, is bigger than the critical value.[17]

[16]The NARDL model has been estimated using Eviews econometric software.

[17]The critical upper and lower bounds for the F-statistic and the critical values for t-statistic are shown in C appendix.

Table 7: Test for cointegration in the NARDL model in all countries.

Countries	**NARDL Model**	
	$FPSS_{Nonlinear}$	t_{BDM}
France	4.13	-2.32
Germany	3.51	-2.64
Greece	4.15*	-2.89*
Ireland	2.39	-2.63
Italy	4.32*	-2.99*
Portugal	2.49	-1.90
Spain	2.93	-2.25
UK	3.55	-2.55
USA	3.19	-2.37

Note: This table shows the results of the bounds testing procedure for cointegration in the NARDL models for the nine countries chosen. The $FPSS_{Nonlinear}$ and t_{BDM} denote the F-statistic and t-statistic proposed by Pesaran et al. (2001) and Banerjee et al. (1998), respectively, for testing the null hypothesis of no cointegration in the NARDL model. The critical values for these statistics have been obtained from Pesaran et al. (2001) for the F-statistic and Banerjee et al. (1998) for the t-statistic. As usual, *, ** and *** indicate "statistical significance" at 10%, 5% and 1% levels, respectively.

Using both statistic critical values, we can see that there is no cointegration for most countries at any significance level because the F-statistic is less than the upper bound and we cannot reject the null hypothesis of no cointegration, which indicates that the variables are not affected by each other in the long-run. Moreover, the t-statistic reject the null hypothesis in the same countries and match the cointegration results with F-statistic. It is worth to notice that there are countries where the F-statistic is not also less than the lower bound, which signify the rejection of null hypothesis, but when it is between the two bounds we would have to use another cointegration test and we already have the Johansen results where all countries were lack of cointegration. This means that it would not make sense to study the possible long-run asymmetrical relationship over a long term in these countries as long-run relationship does not exist, according with both tests used. Greece and Italy are the only countries where we can reject the null hypothesis of no cointegration at the 10% significance level. This implies that a long-run relationship exists for these two countries, although not very strong as we only could reject the null hypothesis at 10% of significance level. It is worth to notice that the results of the NARDL model are very similar to those of the nonlinear Granger causality test above performed as the two only countries where long term relationship has been found are the countries where strongest nonlinear Granger causality is observed.

Next, we proceed to test for asymmetry in the long-run relationship for Greece and Italy to see if the long-run relationship for these countries is significantly asymmetric. We should find asymmetric effects when positive and negative shocks are not the same for the dependent variable. The null hypothesis to be tested consists of $\theta^{+} = \theta^{-}$, that is, long-run symmetry. Table 8 contains the Wald statistics for the test of long-run symmetry between 10-year government bond yields and stock market returns in the framework of the NARDL model. Furthermore, in this table are also reported the estimated long-run coefficients associated with positive and negative changes of the independent variable for both countries.

Table 8: Wald tests for long-run asymmetry

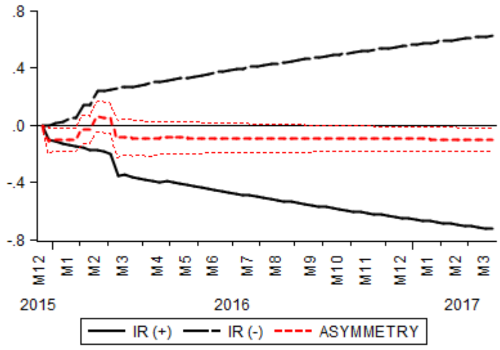
	Long-run asymmetries		
		Long-run asymmetric effects	
Country	$W_{LR}(IR)$	Positive	Negative
Greece	6.570 (0.011)**	L_{IR}^{+} = -1.302 (0.008)***	L_{IR}^{-} = -1.178 (0.024)**
Italy	6.747 (0.010)***	L_{IR}^{+} = -0.756 (0.010)***	L_{IR}^{-} = -0.661 (0.017)**

Note: This table reports the Wald statistics of the long-run symmetry tests in the long-run relationship between 10-year sovereign bond yields and stock market indices for each country. Firstly, $W_{LR}(IR)$ denotes Wald statistics for the long-run symmetry, which test the null hypothesis of $IR(\theta^{+}) = IR(\theta^{-})$. Secondly, L_{IR}^{+} and L_{IR}^{-} are the estimated long-run coefficients associated with the positive and negative changes of the variable IR , defined by $\hat{L_{IR}} = -\hat{\theta}/\hat{\rho}$. As usual, *, **and *** indicate "statistical significance" at 10%, 5% and 1% levels, respectively.

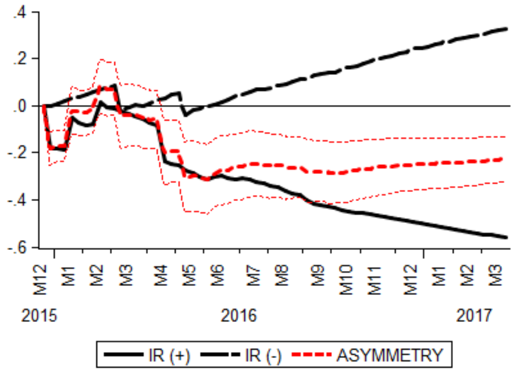
The results of the Wald tests indicate the existence of long-run asymmetric effects for Greece and Italy. It would add power to our main asymmetric relationships conclusions as different methods lead to similar conclusions. This asymmetric effect implies that the stock market index does not react equal in the long-term to positive and negative shocks in 10-year sovereign bond yields. Finding this result in these two peripheral European countries means that this type of countries may have been affected by asymmetric effects in the long-run with more probability than a central European country as in these countries seems to not exist this type of relationship. This finding implies that in Italy and Greece, stock market investors react differently when the interest rate variation is positive or negative. It would have to take into account for investors and hedgers as previously it has been usually accepted one shock causes the same impact on financial markets regardless it was positive or negative. However, it may be not happening in all financial market countries and they should take care about the interest rate sign movement to prevent the stock market reaction, as it could be not equal if is positive or negative movement. Other countries would do not have asymmetric effects in the long-term because there are not long-run relationships between 10-year government bond yields and stock market indices. We could say, in our study, according with the NARDL model that, when long-run relationship exists, it is asymmetrical in nature.

In the right part of Table 8 we find the estimated long-run coefficients associated with rises and falls in 10-year government bond yields, $IR(\theta^+)$ and $IR(\theta^-)$, which capture the relationship between 10-year interest rates and stock market indices in the long-run. It is worth noting that the long-run coefficients are statistically significant and negative, implying an inverse relationship in the long-run between both variables. This finding is consistent with the argument that rises in long-term interest rates would imply a fall in stock market returns and is empirically supported by many authors like Amarasinghe (2015), Eita (2014) or Ferrer et al. (2010). Furthermore, it can be observed that the long-run effect of increases in the interest rate is more pronounced (in absolute value) than the effect of interest rate decreases for both countries.

The last step of the NARDL model consists of calculating the cumulative dynamic multipliers effect on ΔSMI_t of a unit change in IR^+ and IR^-. Figure 1 plots the cumulative dynamic multipliers obtained according to equation (17). These multipliers show the pattern of adjustment of stock market returns to its new long-run equilibrium following a positive or negative unitary shock in the 10-year sovereign bond yield. The dynamic multipliers are estimated based on the best-fitted NARDL model chosen by applying general-to-specific criterion. The positive (continuous black line) and negative (dashed black line) change curves describe the adjustment of stock market returns to positive and negative 10-year government bond yield shocks at a given forecast horizon. The asymmetry line (broken red line) reflects the difference between the positive and negative effect of multipliers to shocks in the 10-year interest rate. It is also shown the upper and lower confidence bands (dotted red lines) showing the 95% confidence values to provide a measure of statistical significance of asymmetry. If the zero line is between the lower and upper bands, the asymmetric effects are not significant at 5% of confidence level. Several interesting results emerge from the dynamic multiplier analysis. Firstly, the graphs in the appendix confirm the existence of an inverse relationship between interest rate and stock market indices in the long-run equilibrium as we can see negative 10-year interest rate shocks having a positive effect, and the opposite for positive 10-year interest rate shocks. Secondly, we can observe some patterns that are present in both countries. The effect of a shock is stronger in the long-run equilibrium because can be observed in the first steps the effect is nearer to zero. Furthermore, the positive shocks effect is higher than the negatives as it can be better appreciated in the long-run. However, in Italy case, we observe ups and downs at the first periods of time while in Greece the effect is more stable. To continue, we can observe, graphically, significant asymmetric effects in Italy in the long-run equilibrium whereas in Greece, according to the graphic, it seems to exist a little asymmetry in some periods but is not seen as clearly as Italy. This would be the reason why Wald test of symmetry is rejected but being so close to the critical value.



(a) Greece



(b) Italy

Figure 1: Dynamic multipliers for the interest rate - stock market indices in Greece and Italy

Having found only two cases out nine of asymmetric effects between interest rate changes and stock market returns could tell us that maybe the asymmetry in the interest rate-stock market relationship is not as important as we thought previously at least for this sample period, frequency and data used. The empirical evidence seems to support the idea of no asymmetric relationship between 10-year interest rate changes and stock market returns for most countries. However, it is worth mentioning that there are countries where exist and we would be careful. The existence of a long-run asymmetric association between changes in 10-year sovereign bond yields and stock returns in Greece and Italy shows the importance of taking asymmetry into account when studying the relationship between interest rate fluctuations and stock returns in these two countries. This conclusion means that a shock in 10-year interest rates would cause the same magnitude effect in stock market returns in most European countries as well as in the UK and USA, regardless the sign of it. It would be contrarian about other conclusions reached by Chen and Chan (1989) or Lobo (2000). However, it is important to note that we have used different methodologies to those employed by these authors.

5.1 Robustness analysis

In this subsection, we assess the robustness of our results using a special sample like the global financial crisis sub-period that includes the global financial crisis and the subsequent European sovereign debt crisis (from September 2008 to September 2012) [18]) in order to examine whether the nature of the relationship between 10-year government bond yields and stock returns is substantially altered during this sub-period, which is characterized by major turbulences in financial markets. We also use threshold regressions, which consist in using one external variable to see if it could encourage the existence of a change in the sign and magnitude of the relationship between our two variables.

In a global crisis context, we should expect that markets and economic agents are nervous and scared. According to Kuenen (2005), "in crisis periods all assets tend to become riskier, also government bonds". The uncertainty rises and nobody trusts in what can happen next day. This uncertainty situation could cause variables to be more closely connected and the interactions between financial markets may be stronger as shown in Kuenen (2005), where in recession periods the correlation between stock prices and bond yields is more pronounced because of flight-to quality effects. To check whether the interest rate-stock market link is affected by this uncertainty scenario, we use the NARDL model as it allows to detect the possible asymmetric nonlinearity and long-run relationships in a more comprehensive way. The NARDL approach is estimated following the steps than in the analysis for the full sample. We present similar statistics results for this special subsample data. To begin, Table 9 reports the F and t statistics tests to detect the existence of a long-run relationship between yields on 10-year sovereign bonds and stock returns.

[18] Note that with this sample the Greece data problem is solved as there were less observations at the beginning of the all sample.

Table 9: Bounds test for cointegration in the NARDL during the global financial crisis sub-period.

Countries	NARDL Model	
	$FPSS_{Nonlinear}$	t_{BDM}
France	1.80	-0.64
Germany	6.13**	-3.13*
Greece	4.62*	-2.66
Ireland	6.37***	-4.3***
Italy	9.6***	-5.25***
Portugal	3.36	-1.55
Spain	1.81	-2.27
UK	5.42**	-3.79**
USA	13.65***	-5.98***

Note: This table shows the F- and t-statistics, respectively, of null hypothesis of no cointegration in the subsample. The critical values for F-statistic are in appendix C. As usual, *, **and *** indicate "statistical significance" at 10%, 5% and 1% levels, respectively.

Considering the information provided by Table 9, the cointegration relationships seem to be clearly different from those obtained in the analysis for the entire sample period. The results show six significant long-run relationships, at conventional significance levels, for Germany, Greece, Ireland, Italy, the UK and the USA. Comparing with the results for the whole sample, we can see that there are long-run relationships not only for two Eurozone peripheral countries like Italy or Greece, but also in Ireland and some more developed countries such as Germany, the UK or the USA. This increase of cointegration relationships is consistent with the argument that the degree of linkage among financial markets tends to rise during periods of financial turmoil. The next step consists in checking if these long-run relationships are asymmetric as we have done in the previous analysis. Table 10 contains the results of the Wald tests for long-run asymmetry and the long-run coefficients that measure the effect of positive and negative changes in 10-year government bond yields are also reported.

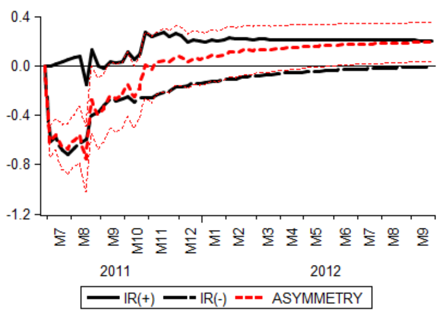
Table 10: Wald tests for long-run asymmetry

	Long-run asymmetries		
		Long-run asymmetric effects	
Countries	$W_{LR}(IR)$	Positive	Negative
Germany	13.51 (0.00)***	L_{IR}^{+} = 0.25 (0.06)*	L_{IR}^{-} = 0.03 (0.01)***
Greece	0.02 (0.89)	L_{IR}^{+} = -0.95 (0.01)***	L_{IR}^{-} = -0.98 (0.09)*
Ireland	9.23 (0.00)***	L_{IR}^{+} = -0.23 (0.02)**	L_{IR}^{-} = -0.32 (0.01)***
Italy	0.02 (0.88)	L_{IR}^{+} = -0.63 (0.00)***	L_{IR}^{-} = -0.62 (0.01)***
UK	44.12 (0.00)***	L_{IR}^{+} = 0.49 (0.00)***	L_{IR}^{-} = 0.28 (0.00)***
USA	231.97 (0.00)***	L_{IR}^{+} = 0.37 (0.00)***	L_{IR}^{-} = 0.18 (0.00)***

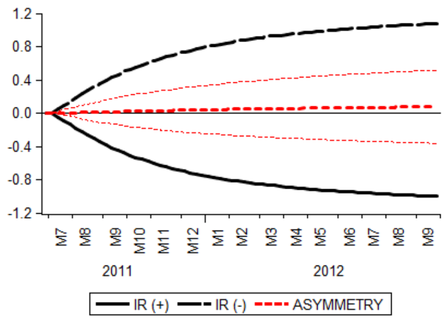
Note: This table reports the Wald statistics of the long-run symmetry tests in the long-run relationship between 10-year sovereign bond yields and stock market indices for each country in the global financial crisis sub-sample. Firstly, $W_{LR}(IR)$ denotes Wald statistics for the long-run symmetry, which test the null hypothesis of $IR(\theta^{+}) = IR(\theta^{-})$. Secondly, L_{IR}^{+} and L_{IR}^{-} are the estimated long-run coefficients associated with the positive and negative changes of the variable IR , defined by $\hat{L_{IR}} = -\hat{\theta}/\hat{\rho}$. As usual, *, **and *** indicate "statistical significance" at 10%, 5% and 1% levels, respectively.

The Wald test results indicate that most of the long-run relationships found are asymmetric. Only Greece and Italy would have symmetry effects between 10-year bond yields and the stock market. We can divide the results obtained into two different groups. Firstly, we have the peripheral European countries, such as Italy, Greece and Ireland, where an inverse relationship with the stock market is observed for both interest rate falls and interest rate rises and it is not clear which one is higher. It seems that Greece and Italy have lost the asymmetric effects they had in the full sample analysis. It would imply that during this period of financial turmoil, the stock market of these two countries would be affected similarly by rises and downs of interest rate. This would signify, investors react equally to a shock in interest rate in these countries, regardless is positive or negative, because of the general uncertainty in global financial markets. However, the Irish case is different because, being a peripheral European country, it has asymmetric long-run relationship what would sense investors react differently to positive and negative interest rate shocks. Secondly, we have the most developed countries like Germany, the UK and the USA. All of them seem to have an asymmetric relationship in the long-term, the effect is in both cases positive and also, the magnitude of positive shocks is bigger than that of negative 10-year interest rate shocks, what would sense the stock market rises more when interest rate grow up than when it falls. A possible explanation for this result is that increases of long-term government bond yields in these countries are interpreted by market participants as a sign of strength in the respective economies, which has a positive effect on the stock markets.

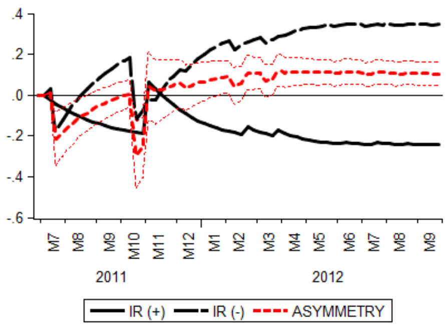
The last step is to represent the dynamic multipliers, which are depicted in Figure 2. The dynamic multipliers reflect the adjustment pattern of the stock market to positive and negative shocks to 10-year interest rates. On the one hand, the results are heterogeneous across countries. It is difficult to establish a general pattern because each country is differently affected by interest rate shocks. In general, graphics show the inverse relationship between yields on 10-year sovereign bonds and the stock market. However, the most developed countries under study (Germany, the UK and the USA) exhibit a positive relationship between 10-year bond yields and stock market. It implies that when 10-year bond yield rises, we should expect stock market does the same instead of falling as other countries do. This finding may be explained by the fact that rises in long-term interest rates in these countries are perceived as indicating better economic prospects in the future, which influences positively on the stock market. On the other hand, while Greece graphic confirms the lack of asymmetric effects, Italy seems to have certain asymmetric effects, although the test does not reject the null hypothesis of symmetry. This would signify we cannot reach an accurate conclusion for this country as graphic and test do not match. Positive shocks in 10-year sovereign bond yields seem to have a greater impact on the stock market in Germany, the UK, the USA and Italy in the long-run, otherwise in other countries looks like could be the same but is difficult to appreciate visually. One interesting thing we can observe is the change between positive effect and negative effect have the shocks in Ireland where negative shock starts to be negative and finally is positive.



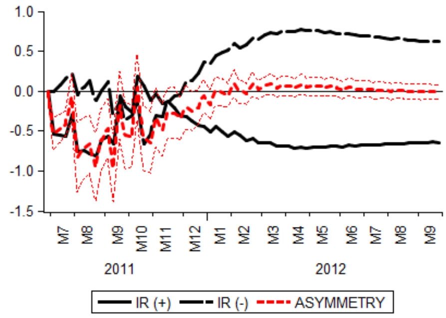
(a) Germany



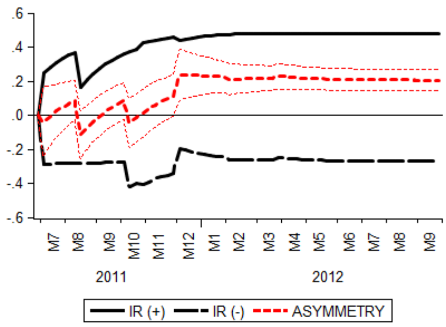
(b) Greece



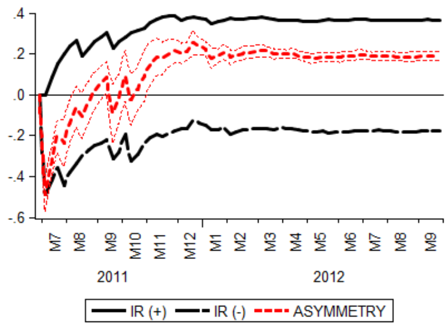
(c) Ireland



(d) Italy



(e) The UK



(f) The USA

Figure 2: Dynamic multipliers for the interest rate - stock market indices in subsample analysis

Regarding to the differences obtained when using the two samples, we could think there are two different regimes where the relationship in both regimes are very different. In this regard, we use a threshold regression method to detect if some exogenous variable is the cause that of the interest rate-stock market relationship changes. To carry out the threshold regressions we have chosen the conditional volatility of the stock index return as the variable that could change the relationship under study. We think that the volatility of the stock market could produce investment reactions unleashing changes in the interest rate-stock market link. This is because volatility affects investment risk and profitability and, hence, investment decisions. The aim of this methodology is to contrast whether there is a value of conditional volatility, our z variable, that can divide the full sample into two subsamples and find statistically different estimates. The algorithm tries different possible values of z, to test if there is regime change we should compare with a F test the residuals obtained in the two models; general and restrictive one. In our case, restrictive model would be when regime change does not exist, implying the coefficients estimations are equal in both models. In Appendix D we have shown the graphical behavior to the sum of squares of residuals in the general model considering the existence of regime change. In the nine countries the F test takes high values and we can reject the null hypothesis of existence of two regimes in our sample considering the volatility of stock market returns as a variable z. These results would told us we should not expect shifts in the relationship between our two variables due to changes in stock market volatility.

6 Conclusions

This paper investigates the linkage between changes in 10-year government bond yields and stock returns for nine developed countries over the period 1999-2017 using linear and nonlinear Granger causality tests and the NARDL model developed by `Shin et al. (2014)`. The linear Granger causality test tries to detect if past values of one variable, z, add relevant information in forecasting another one variable, y, than only using the past values of y. Furthermore, the nonlinear Granger causality test of `Diks and Pachenko (2006)`, which uses the VAR model residuals to test if after extracting linear relationship could remain some linkage between these variables, is also applied. The NARDL approach examines the existence of long-run relationships between yields on 10-year sovereign bonds and stock market indices, taking also into account the presence of asymmetries in such a linkage. It emerges as a helpful tool to see if 10-year interest rates and the stock market are connected differently depending on the sign of shocks of long-term interest rates.

Several interesting results arise from this analysis. On the one hand, significant linear Granger causality relationships are found for seven countries, namely France, Germany, Greece, Ireland, Italy, Spain and the UK. Most of these causal links go from the stock market returns to 10-year interest rate changes, consistent with the forward-looking nature of the stock market, that is, the stock market is able to anticipate the general economic prospects before the government bond market. However, there are only two countries where linear Granger relationship was not found and these are Portugal and the USA. On the other hand, less countries exhibit a significant nonlinear Granger causality relationship between long-term interest rates and the stock market, but some relevant results also appear like the Portuguese case, where there is not a linear causal link, but it seems to have a nonlinear one from interest rate changes to the stock market. It would sense the linkage in that country may be completely nonlinear in Granger sense. Moreover, the two strongest bidirectional causality relationships are found in Italy and Greece, two countries of the European periphery particularly damaged by the European sovereign debt crisis since late 2009. Other nonlinear connections less strong are also found in France, Ireland or the UK. These countries have the relationship from stock market to interest rate as also be found in nonlinear case. This implies that the causal linkage is a combination of linear and nonlinear but only in one direction. These results mean that most Granger causality relationships found are linear but there are also nonlinear ones and in some cases, only exists in nonlinear nature. Thus, we should consider the possibility of nonlinear relationship in studying the relationship between interest rate changes and stock market returns as this could lead us to reach biased conclusions.

The results of the NARDL approach are broadly consistent with those of the nonlinear Granger causality analysis as the only two countries where asymmetric linkage has been found are Greece and Italy, being both countries those who show a most important nonlinear Granger causal link. This methodology also shows that in both countries 10-year interest rate rises have a higher impact on stock market returns than interest rate falls, in line with the argument of Lobo (2000), according to which stock prices overreact with bad news (interest rate rises). This finding suggests that ignoring the asymmetry in modeling the relationship between 10-year government bond yields and the stock market may lead to spurious conclusions for some countries.

Summarizing, we could finish the study remarking the most important conclusions. Firstly, we have found that a significant linkage between yields on 10-year sovereign bonds and the stock market exists for most countries. This relationship is heterogeneous among countries as in some countries we detected linear Granger causality, in others nonlinear one and finally, two countries show a connection of asymmetrical nature. However, the strongest nonlinear link matches with long-run asymmetrical relationships found. These results warn us that relationship between these two variables would should not be considered as only linear one. Secondly, we have analyzed this findings in extreme economic situations and we have observed the asymmetrical relationship tends to increase as the countries with this nature relationship has been doubled, without making a distinction between more or less developed.

The results presented in this study could be particularly relevant for investors and portfolio managers in order to design improved investment strategies in both financial markets considering that the nature of the relationship between interest rate 10-year government bond yields and stock market may change under different conditions in both sovereign bond and stock markets. In this regard, it has been shown the asymmetric relationship tends to increase during periods of financial turmoil. Furthermore, our results may assist policy makers to make the most appropriate decisions in each country to preserve financial stability, especially in financial crisis.

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Appendix A Serial graphics

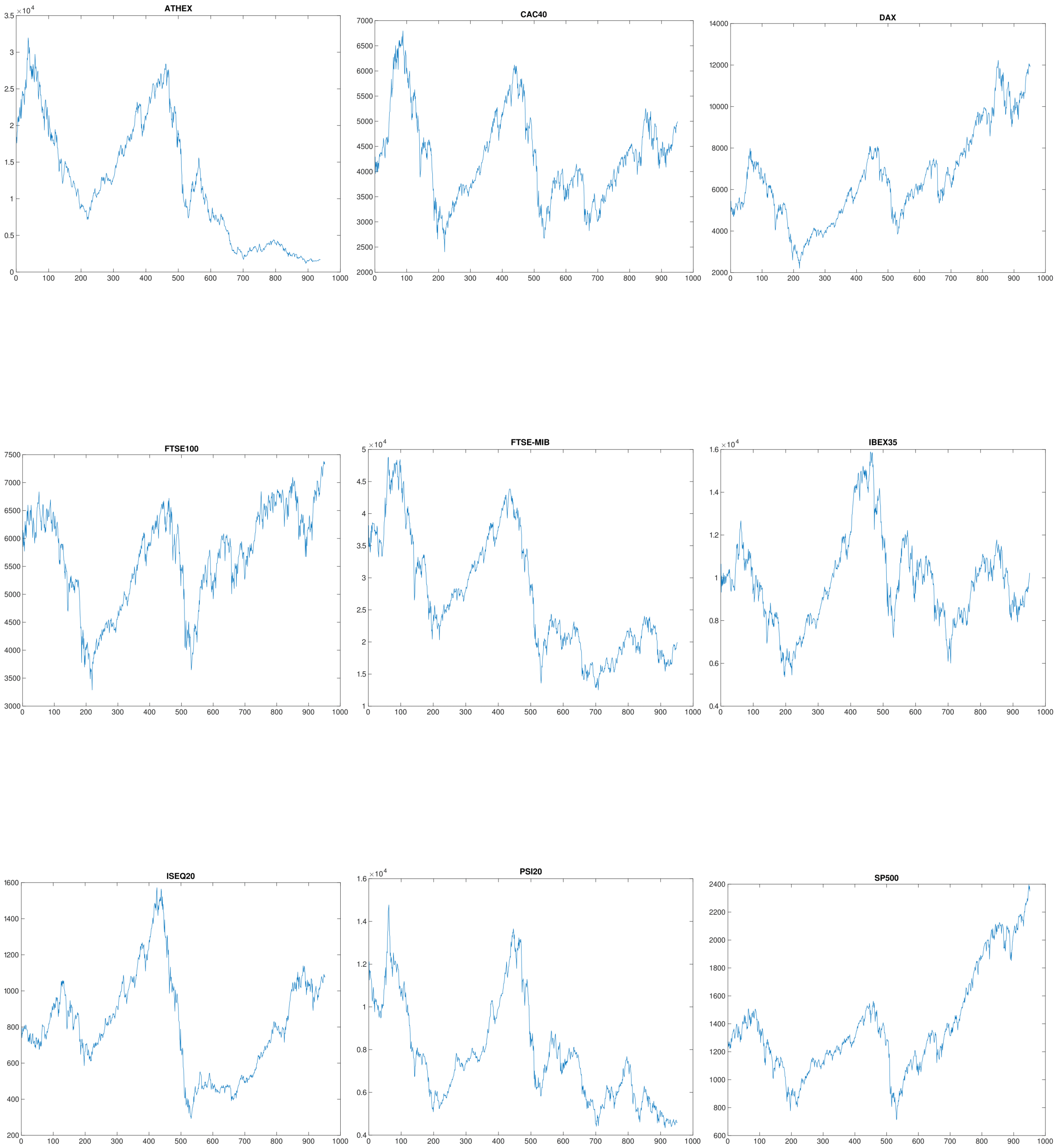


Figure 3: Serial graphics - Indices

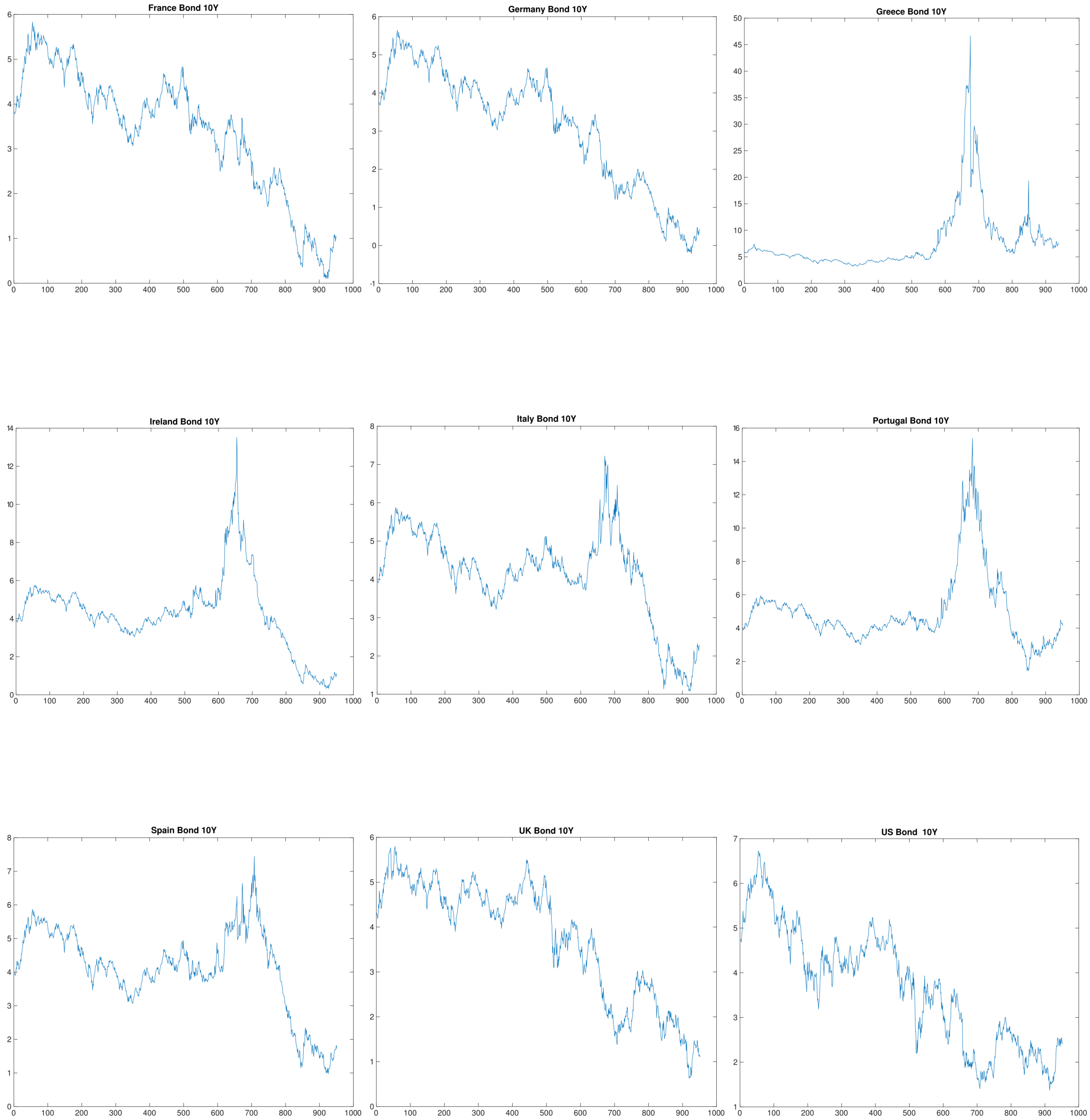
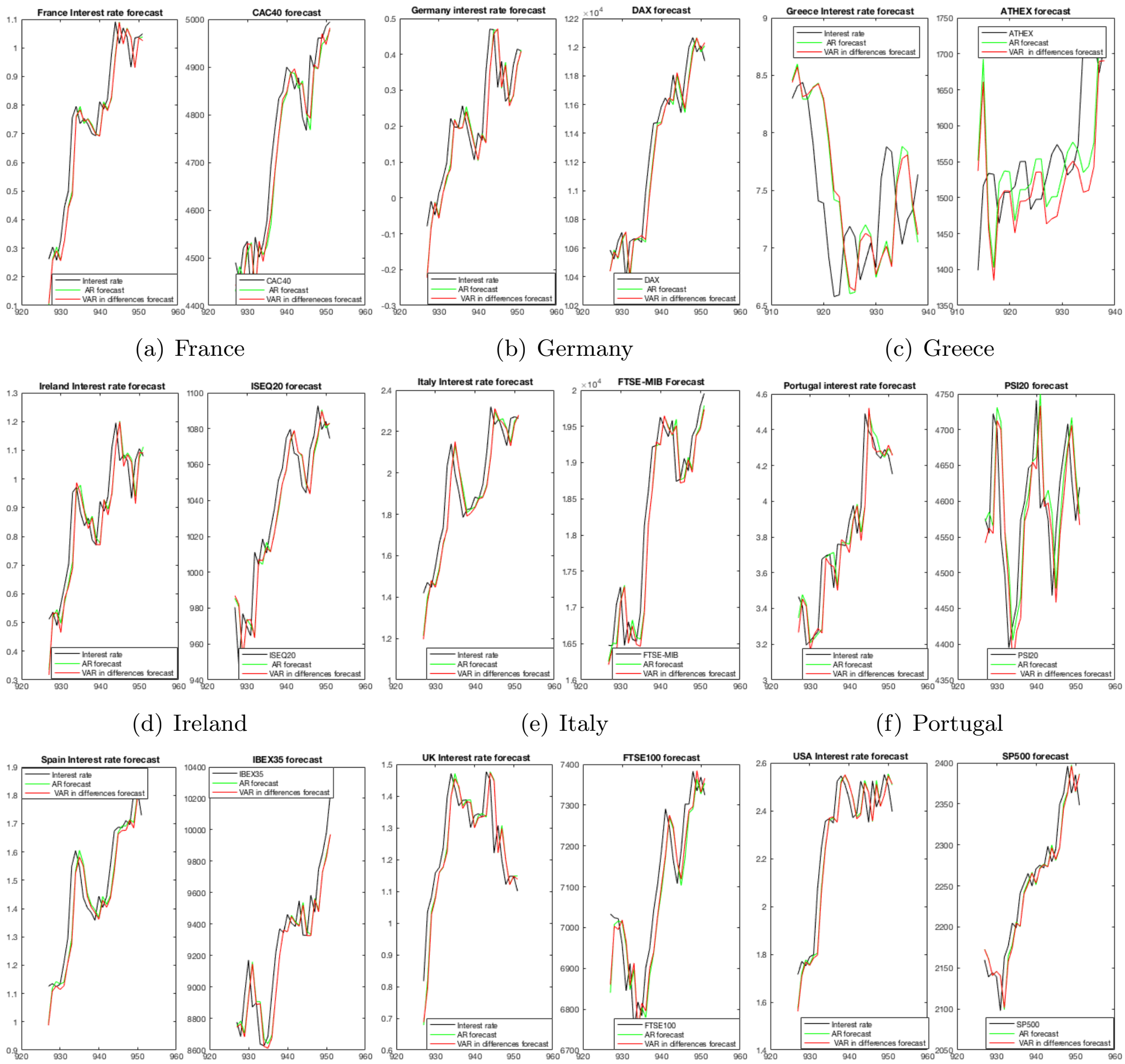


Figure 4: Serial graphics - 10Y Government yields

Appendix B AR(p) vs VAR(q) forecasts



(a) France (b) Germany (c) Greece

(d) Ireland (e) Italy (f) Portugal

(g) Spain (h) UK (i) USA

Figure 5: AR(p) vs VAR(q) forecasts

Appendix C Critical values for NARDL cointegration analysis

Table 11: Critical values for lower and upper bounds ($FPSS_{Nonlinear}$)

Significance	Lower bound - I(0)	Upper bound - I(1)
10%	3.17	4.14
5%	3.79	4.85
1%	5.15	6.36

Table 12: Critical values for t_{BDM} test

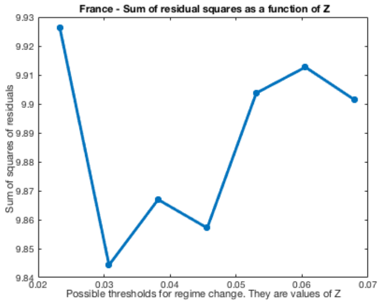
Significance	0.01	0.05	0.10
Critical values	3.78	3.19	2.89

In subsample, the F critical values are the same and for t_{BDM} test we have next table:

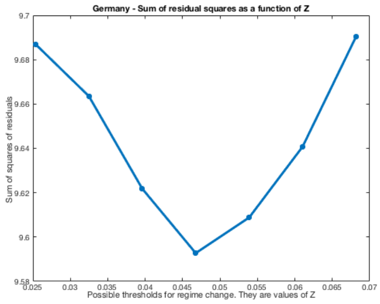
Table 13: Critical values for t_{BDM} test

Significance	0.01	0.05	0.10
Critical values	3.92	3.27	2.94

Appendix D Threshold graphics

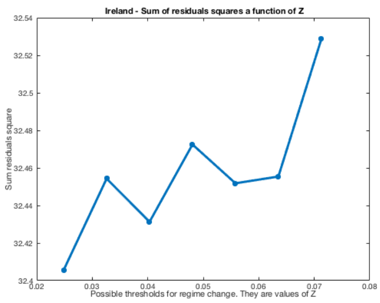


(a) France

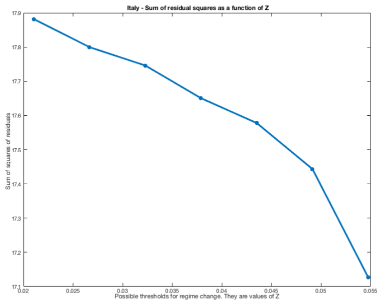


(b) Germany

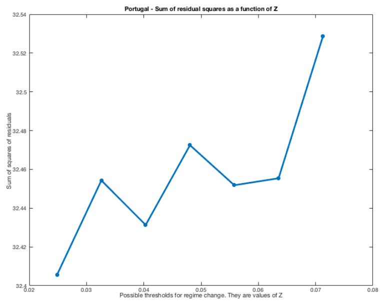
(c) Greece



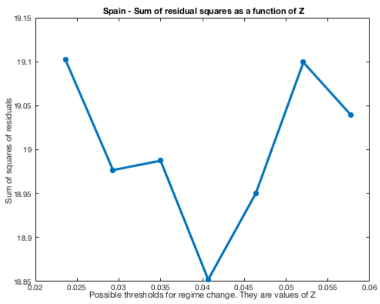
(d) Ireland



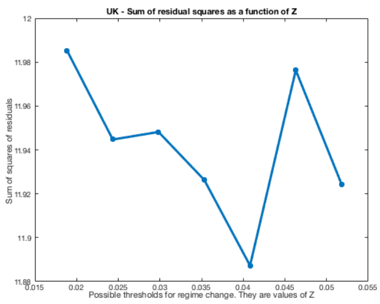
(e) Italy



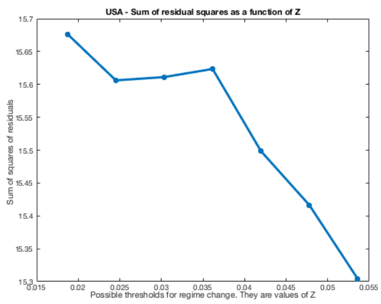
(f) Portugal



(g) Spain



(h) UK



(i) USA

Figure 6: Sum of squares of residuals in threshold regressions