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Modeling Inflation Uncertainty and the Effect of Government Bond Rates: A Case Study of Greece

Kalimeris Dimitris
PhD in International European Studies, University of Macedonia, Greece
Adjunct lecturer at the Alexander Technological Educational Institute of Thessaloniki, Greece

Email :dimitris_kal@hotmail.com
Phone. 0030-6974707906

Abstract:
This paper aims to investigate the relationship among inflation, inflation uncertainty and government bond rates in the Greek economy in the last 19 years. The method adopted is the E-GARCH technique in order to capture the conditional variance of inflation shocks, while the VAR method is used with the purpose of examining any signs of granger causality issues. Causality analysis shows a strong relationship between government bonds to inflation, between government bonds and inflation uncertainty, and between inflation and inflation uncertainty. Furthermore, generalized impulse response analysis is implemented which shows a strong causational relationship between government bonds-inflation and government bonds-inflation uncertainty.

Keywords *Inflation, Inflation uncertainty, E-GARCH model, VAR model*
JEL: E31, E29

1. INTRODUCTION AND LITERATURE REVIEW

Inflation uncertainty and its relations with inflation and other macroeconomic variables have been extensively analyzed in the literature. The main reason for such research was provided by the need of a more solid monetary policy framework. Detecting causality among these variables has been proved a very important policy-making tool, with the help of the ever evolving econometric techniques. On the empirical side, a great number of studies focus on the relationship between inflation uncertainty and inflationary shocks. The principle idea that higher inflation levels lead to increased uncertainty for the monetary regulators was captured by Ball (1992). The fact that increased inflation volatility could lead agents to invest more on inflation forecasting was studied by Pourgerami and Maskus (1987).

As far as the methodologies adopted in order to assess the impact of inflation uncertainty, the majority of the studies use is the GARCH method from the ARCH family. Hakan Berument, Nezir Kose, and Afsin Sahin (2010) use the E-GARCH model in order to capture volatility in the conditional mean equation in order to assess the seasonal inflation uncertainties of the USA for the period January 1947 to April 2008. Results show seasonal trends among several months of each year. The same methodology is adopted by Saatcioglu Cem and Korap Levent (2009). They complete their research by adopting also the VAR model in order to capture any signs of granger-causality issues between inflation and inflation uncertainty in the Turkish economy. Caporale Guglielmo Maria, Onorante Luca, and Paesani Paolo (2009) use the AR-GARCH model in their study in combination with the VAR model as well. Other studies that use a model from the ARCH family are the majority of Fountas Stilianos' papers especially from 2006 onwards. The researcher focuses mainly on the inflation volatility and its effects on other variables, such as growth and nominal and real uncertainty.

Apart from its effects on inflation, inflation uncertainty has been researched in relation with private investment. Zelekha Yaron's paper (2010) provides an interesting theoretical foundation and an empirical estimation of private investment in Israel, using Israel's unique data regarding inflation expectations. The research's results show that uncertainty negatively affects private investment in Israel. Furthermore, it appears that uncertainty is the most important factor, next to product, affecting private investment. The present study aims to contribute to the area of variables' combination in examining inflation uncertainty by adding 10-year government bond rates in the equation. The focus will be on one country, Greece, over a timespan of 41 years for inflation data and 19 years for government bonds data. We choose the E-GARCH model since it successfully captures the asymmetric effect of 'good' and 'bad' news on a variable's volatility. This particular model allows for negative coefficients, while when using the standard GARCH model, it is necessary to ensure that all of the estimated coefficients are positive. Therefore, E-GARCH will be used in order to capture conditional volatility inflation estimates as a variable of uncertainty. Using the E-GARCH results we will adopt the VAR approach in order to test for any granger-causalities among inflation, inflation uncertainty and government bond rates. The rest of the current

paper is structured as follows: In the 2nd part we present the data and its nature along with the econometric framework adopted. Special focus is on the econometric tests prior to the E-GARCH analysis in order to detect any signs of stationarity; in the 3rd section we critically present our results from the E-GARCH analysis and we proceed in the use of the VAR method. Our new results here are analytically presented and discussed; in the 4th section we discuss our finds overall and propose new approaches of the research topic.

2. PRLIMINARY DATA AND ECONOMETRIC FRAMEWORK

The data in this study is comprised of yearly observations for inflation rates, which is the harmonized index of consumer prices (HICP) rates and of monthly observations for government bond rates. Inflation rates data is extracted from *The International Macroeconomic Data Set* provided by the United States department - Economic Research Service, and includes data from 1969 through 2020 for real (adjusted for inflation) gross domestic product (GDP), population, real exchange rates, and other variables for the 190 countries and 34 regions. Our dataset of HICP covers the timespan from 1969 to 2009, that is 41 observations. In the processing of the inflation time series, raw data was used in comparison with the differenced logged value of it (Δlog inflation) in order to reach the best (lowest) Schwarz Bayesian Criterion and Akaike Information Criterion.

For government bond rates data from European Central Bank's database has been used and more specifically, the long term interest rates (ten years maturity) for government purposes. In order to have the same time series set for all the three variables, the bond rates series was modified by their yearly average rates. The monthly rates were form January 1993 to August 2011, therefore, after adjusting to the yearly mean values we have 19 observations from 1993 to 2011. In order to construct the proxy variable for inflation uncertainty we use the E-GARCH methodology as proposed by Nelson (1991), which provides us with the possibility of explaining *positive or negative asymmetric information* on the variable. This model has several advantages over the simple ARCH method. Firstly, it allows for negative coefficients, while when using the standard ARCH or GARCH model, it is necessary to ensure that all of the estimated coefficients are positive. Secondly, the tendency for volatility to decline when the variable rises and to rise when the variable falls is called leverage effect. The E-GARCH model allows for the asymmetric effect of good and bad news in the estimation period, unlike other similar models of the ARCH family.

The form of Nelson's E-GARCH model is as follows:

$$\log \sigma_t = \alpha_0 + \alpha_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}^{0,5}} + \lambda_1 \left(\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}^{0,5}} \right| - \mu \right) + \alpha_2 \log(\sigma_{t-1}) \qquad (1)$$

where

σ_t denotes the conditional variance at time t,

σ_{t-1} is the conditional variance at time t-1,

$\mu = E\left(\left| \frac{\varepsilon_t}{h_t} \right| \right)$, where μ's value depends on the density function for the standardized error terms, $\varepsilon_t = \frac{\varepsilon_t}{h_t}$.

More specifically, we have: $\mu = \sqrt{\frac{2}{\pi}}$, with the assumption that

$\varepsilon_t \sim N(0,1)$.

There are some differences between the E-GARCH model provided by the majority of econometric packages and the original Nelson model. Nelson assumes a standard distribution of the ε_t, namely a generalized error distribution (GED), while econometrics software like EVIEWS provides a choice of normal, student's t-distribution or GED. As for the E-GARCH equation, what we are using in this study is a slightly differed version of the above model, which is:

$$\log\left(\sigma_t^2\right) = \omega + \sum_{j=1}^{q} \beta_j \log\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \qquad (2)$$

where the order of the p and the distributional assumption will affect the intercept term ω,

σ_{t-j} and σ_{t-k} are the conditional variance of the previous time period, σ_{t-1},

ε_{t-i} and ε_{t-k} are the conditional variance's error terms of the previous time period ε_{t-1}, and

β_j, α_i and γ_k are coefficients.

The model we apply here is the E-GARCH (1,1) model, following the rule of the lowest Akaike Information criterion (AIC) and Schwarz Baeysian Criterion (SBC), as shown in the results of section 3. The impact of inflation uncertainty will be asymmetric if $\gamma_k \neq 0$. If $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ is positive, the effect of a shock on the log of the conditional variance will be *α+γ*, while if $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ is negative the effect of a shock on the log of the conditional variance will be *α-γ*. Graph 2.a presents the annual trend of the HICP from 1969 to 2009, with 2005 as a base year, and table 2.b presents the descriptive statistic of the variable.

Graph 2.a: inflation raw data (HICP index, 2005=100)

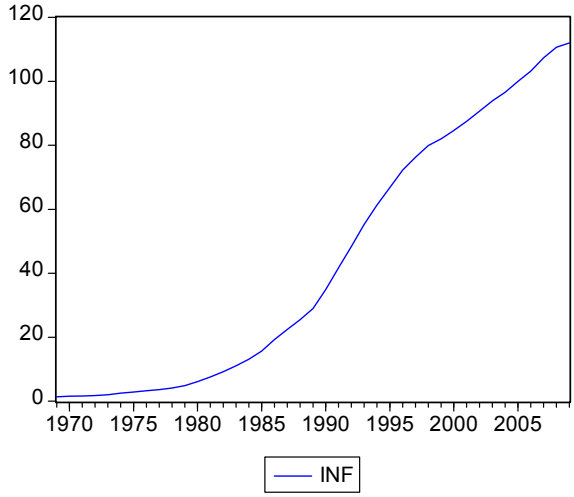


Table 2.b: Descriptive statistics

	Inflation (HICP) 1969-2009
Mean	43.7596
Median	28.9983
Maximum	111.931
Minimum	1.40532
Std. Dev.	39.8449
Skewness	0.3778
Kurtosis	1.5413
Jarque-Bera	4.6104
Probability	0.0997
Sum	1794.143
Sum Sq. Dev.	63504.90
Observations	41

The kurtosis of normally distributed series is 3, while the skewness measure shows the asymmetry of a distribution around its mean. The skewness of a symmetric distribution such as the normal distribution is 0. The combination of a high Jarque-Bera test and a low probability implies that we have to reject the normality assumption.

It is crucial to ensure that our data of inflation and government bond rates are free of stationarity issues, since a non-stationary variable provides unreliable results both for forecasting and causational explanations. After performing standard ADF tests we reached the level of stationarity at the 2nd difference level with a constant at 1% level of significance for inflation, while the same result was obtained by performing the Phillips-Perron test as well. Data of government bonds is stationary at level, as shown below. Results are shown at the following tables 2.c, 2.d, and 2.e:

Table 2.c: Inflation stationariy test results-ADF test

Null Hypothesis: D(INF,2) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=2)

		t-Statistic	***Prob.****
Augmented Dickey-Fuller test statistic		-4.208883	0.0021
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

Table 2.d: inflation stationarity test results-Phillips-Perron test

Null Hypothesis: D(INF,2) has a unit root			
Exogenous: Constant			
Bandwidth: 2 (Newey-West using Bartlett kernel)			
		Adj. t-Stat	***Prob.****
Phillips-Perron test statistic		-4.084702	0.0087
Test critical values:	1% level	-4.004425	
	5% level	-3.098896	
	10% level	-2.690439	

Table 2.e: Government bonds stationariy test results-ADF test

Null Hypothesis: BONDS has a unit root			
Exogenous: None			
Lag Length: 2 (Automatic based on SIC, MAXLAG=2)			
		t-Statistic	***Prob.****
Augmented Dickey-Fuller test statistic		4.244021	0.9999
Test critical values:	1% level	-2.717511	
	5% level	-1.964418	
	10% level	-1.605603	

The number of lag length in the ADF test is 0, while we allowed for a maximum of 2 lags. As for the testing equation we consider a constant term. For the PP test, the Newey-West bandwidths are used. The total number of tests we applied using the ADF and the PP test showed that only at the case of a constant term can the H_0 be reject at 1% level of significance. Government bonds' data is stationary without a trend or intercept. Therefore, we can treat our yearly data as stationary from now on.

3. CONDITIONAL VOLATILITY RESULTS

Using the preliminary data described above we reach the estimated conditional variance and mean equations of the Greek inflation. The estimates of equation 2, using the method of maximum likelihood as well as the quasi-maximum likelihood covariances and standard errors described by Bollerslev and Wooldrige are given in the following table 3.a.

Table 3.a: E-GARCH estimates

Dependent Variable: INF				
Method: ML - ARCH (Marquardt) - Normal distribution				
Sample: 1969 2009				
Included observations: 41				
Bollerslev-Wooldrige robust standard errors & covariance				
Variance backcast: ON				
	Coefficient	***Std. Error***	***z-Statistic***	***Prob.***
C	36.49316	2.715462	13.43902	0.0000
	Variance Equation			
ω	5.689432	2.670722	2.130298	0.0331
α_i	1.946731	0.691795	2.814030	0.0049
γ_k	0.523134	0.416038	1.257420	0.2086
β_j	-0.065957	0.422821	-0.155993	0.8760
R-squared	-0.034089	Mean dependent var		43.75960
Adjusted R-squared	-0.148988	S.D. dependent var		39.84498
S.E. of regression	42.71018	Akaike info criterion		10.05456
Sum squared resid	65669.74	Schwarz criterion		10.26353
Log likelihood	-201.1184	Durbin-Watson stat		0.007069

The sum of the E-GARCH coefficients is 8, meaning that the volatility shocks are quite persistent. This result is often observed in high frequency financial data. For the conditional distribution of the error term ε_t normal Gaussian distribution is assumed. The fact that γ_k is positive denotes that the impact of shocks is asymmetric and the conditional variance of inflation reacts more to past positive shocks than to

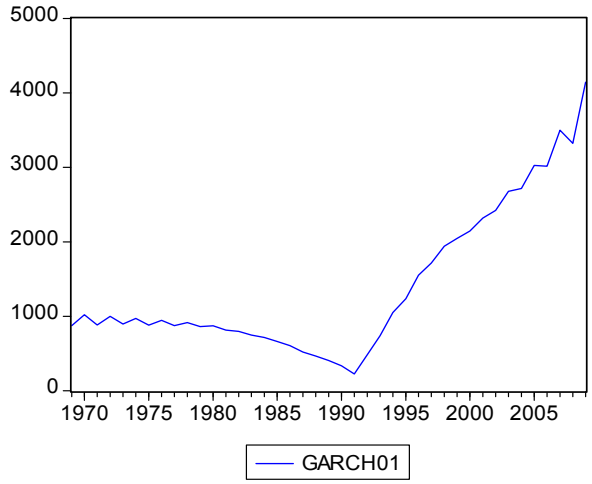
negative innovations of the equal size. A representation of the E-GARCH results is shown in the following equations (3.i-ii):

$$\log\left(\sigma_t^2\right) = \omega + \sum_{j=1}^{q} \beta_j \log\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \qquad (3.i)$$

log egarch=5.6894319-0.0659 $\log\left(\sigma_{t-1}^2\right)$ + 1.9467306 $\left|\frac{\varepsilon_{t-1}}{\sigma t-1}\right|$ + 0.52313448 $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ (3.ii)

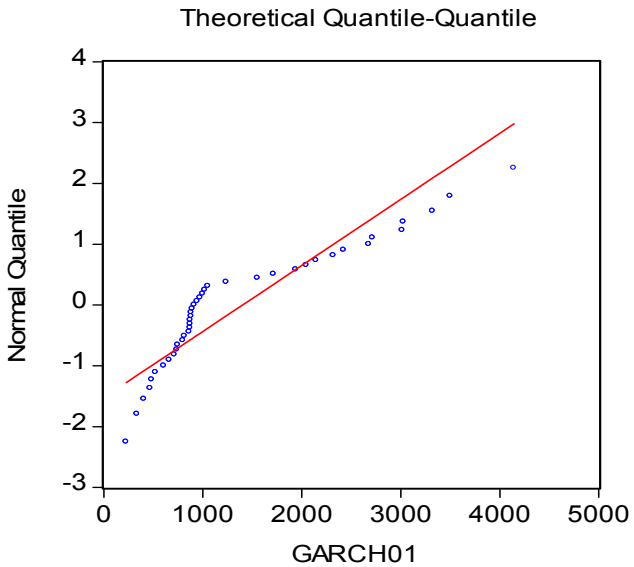
The following graph (3.b) depicts the conditional variance series extraxted from the E-GARCH equation:

Graph 3.b: Conditional variance from E-GARCH equation



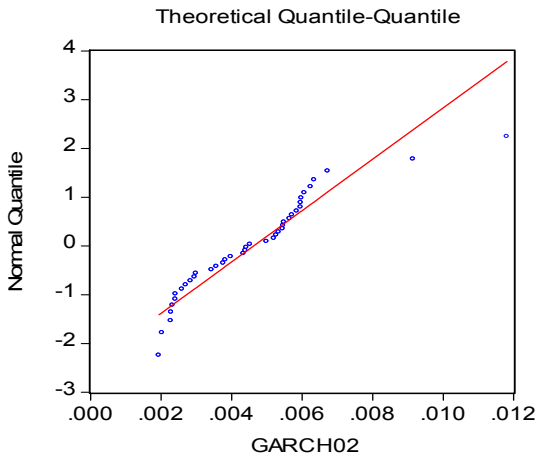
In the following graph (3.c) we depict the quantile-quantile plots in order to examine whether the residuals are normally distributed. In this case the majority of the plots should lie alongside the straight line.

Graph 3.c: Quantile-quantile plot of residuals



By using the Δlog(inflation) E-GARCH conditional variance, with lower AIC and SBC, we depict the next graph 3.d, which show a slightly better fit to the line.

Graph 3.d: Quantile-quantile plot of Δlog(inflation) residuals



The next table 3.e shows the stationary results using the PP test for the conditional variance of equation (2). As shown the series is stationary at 10% level of significance.

Table 3.e: Conditional variance Phillips-Perron test

Null Hypothesis: GARCH has a unit root ***Exogenous:*** Constant ***Bandwidth:*** 2 (Newey-West using Bartlett kernel)				
			Adj. t-Stat	***Prob.****
Phillips-Perron test statistic			2.894135	1.0000
Test critical values:	1% level		-3.605593	
	5% level		-2.936942	
	10% level		-2.606857	
*MacKinnon (1996) one-sided p-values.				
Residual variance (no correction)				29797.44
HAC corrected variance (Bartlett kernel)				31018.73

VAR and granger causality analysis

Moving on to the causational analysis, we applied the VAR methodology as follows: By applying the hypothesis that there are no exogenous variables that affect national debt in our set of variables, we are willing to investigate whether there is any kind of granger-causality among our variables. More specifically, one of the implications of this theorem is that of any two variables, X_t and Y_t, are cointegrated and each one is individually integrated of order 1 (each is individually non-stationary), then either X_t must granger-cause Y_t or the opposite. Not only do we care about any signs of granger-causality, but also about its direction of causality. We have three variables in our model, namely HICP, E-GARCH volatility estimates, and government bond rates; therefore we will end up with a set of three different regressions.

In the simple case of a two-variable model with X_t and Y_t, vector auto-regression is a set of two equations, each of which contains κ lag values of of X_t and Y_t:

$$X_t = a + \sum_{j=1}^{k} \beta_j X_{t-j} + \sum_{j=1}^{k} \gamma_j Y_{t-j} + u_t \qquad (4)$$

and

$$Y_t = a' + \sum_{j=1}^{k} \beta_j Y_{t-j} + \sum_{j=1}^{k} \gamma_j X_{t-j} + u_t \qquad (5)$$

where, X_t and Y_t are column vectors of observations at time t on the two variables,
the u_t*'s* are the stochastic error terms (or *innovations* or *shocks*). In our case, the three sets of vector autoregressions we examine are:

- $hicp_t = \alpha_1 + \beta_1 hicp_{t-1} + \gamma_1 hicp_{t-2} + \delta_1 egarch_{t-1} + \varepsilon_1 egarch_{t-2} + \zeta_1 bonds_{t-1} + \eta_1 bonds_{t-2} + u_t$
- $egarch_t = \alpha_2 + \beta_2 egarch_{t-1} + \gamma_2 egarch_{t-2} + \delta_2 hicp_{t-1} + \varepsilon_2 hicp_{t-2} + \zeta_2 bonds_{t-1} + \eta_2 bonds_{t-2} + u_t$
- $bonds_t = \alpha_3 + \beta_3 bonds_{t-1} + \gamma_3 bonds_{t-2} + \delta_3 egarch_{t-1} + \varepsilon_3 egarch_{t-2} + \zeta_3 hicp_{t-1} + \eta_1 hicp_{t-2} + u_t$

The need for a VEC (Vector Error Correction) model comes when dealing with non-stationary series that are known to be cointegrated. A VEC model has built-in processes in order to restrict the long-run behaviour of the endogenous variables to converge to their cointegrating relationships. In order to test whether there is the need for an error correction, as a confirming test for stationarity, we adopt the following cointegration tests:

Table 3.f: Cointegration tests

Sample (adjusted): 1972 2009
Included observations: 38 after adjustments
Trend assumption: No deterministic trend
Series: INF GARCH01
Lags interval (in first differences): 1 to 2

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	*Eigenvalue*	*Trace Statistic*	*0.05 Critical Value*	*Prob.***
None	0.128327	5.869752	12.32090	0.4521
At most 1	0.016981	0.650818	4.129906	0.4801

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	*Eigenvalue*	*Max-Eigen Statistic*	*0.05 Critical Value*	*Prob.***
None	0.128327	5.218934	11.22480	0.4470
At most 1	0.016981	0.650818	4.129906	0.4801

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

All of our results indicate that there is no sing of cointegration, therefore, it is confirmed that our inflation data and conditional volatility results are stationary. Our VAR analysis among the variables HICP, 10-year government bond rates and conditional variance (E-GARCH) was based on two lag-equations after achieving the lowest AIC and SBC. The final results are the following:

Table 3.g: VAR results

Vector Autoregression Estimates
Sample (adjusted): 1995 2009
Included observations: 15 after adjustments
t-statistics in [ ]

	BONDS	*INFL2*	*GARCH01*
BONDS(-1)	0.303277 [1.28171]	0.148808 [0.62751]	31.01330 [0.90986]
BONDS(-2)	0.445593 [2.49646]	-0.514481 [-2.87610]	-1.889733 [-0.07350]
INFL(-1)	-1.199182 [-4.67993]	1.470904 [5.72779]	-36.01753 [-0.97576]
INFL(-2)	1.161541 [5.69960]	-0.934575 [-4.57585]	28.87240 [0.98349]
GARCH(-1)	0.000819 [0.38994]	-0.001257 [-0.59736]	-0.388900 [-1.28569]
GARCH(-2)	0.001192 [0.49300]	-0.008120 [-3.35052]	1.136644 [3.26287]
C	-2.943894 [-0.10565]	62.66434 [2.24404]	1328.013 [0.33086]
R-squared	0.992813	0.999518	0.996223
Adj. R-squared	0.987422	0.999157	0.993391
Sum sq. resids	1.597932	1.604950	33159.31
S.E. equation	0.446924	0.447905	64.38100
F-statistic	184.1763	2767.027	351.7257
Log likelihood	-4.489027	-4.521897	-79.04179
Akaike AIC	1.531870	1.536253	11.47224
Schwarz SC	1.862294	1.866676	11.80266
Mean dependent	6.884833	83.84298	2519.233
S.D. dependent	3.985006	15.42797	791.9413

By substituting in the VAR equations as described by (4) and (5) we have:

$Bonds_t$ = 0.3032773053*$Bonds_{t-1}$ + 0.4455930308*$Bonds_{t-2}$ - 1.199181803*$Inflation_{t-1}$ + 1.161540587*$Inflation_{t-2}$ + 0.0008187885008*$EGARCH_{t-1}$ + 0.00119220349*$EGARCH_{t-2}$ - 2.943893597

$Inflation_t$ = 0.1488078267*$Bonds_{t-1}$ - 0.514481264*$Bonds_{t-2}$ + 1.470904382*$Inflation_{t-1}$ - 0.9345748688*$Inflation_{t-2}$ - 0.00125708418*$EGARCH_{t-1}$ - 0.008120154829*$EGARCH_{t-2}$ + 62.66434216

$EGARCH_t$ = 31.01329721* $Bonds_{t-1}$ - 1.889732941* $Bonds_{t-2}$ - 36.01753355* $Inflation_{t-1}$ + 28.87239942*$Inflation_{t-2}$ - 0.3888997311* $EGARCH_{t-1}$ + 1.136644134* $EGARCH_{t-2}$ + 1328.012556

The H_0 of the granger causality test is that there is no sign of causality between the variables tested. Since the test follows the F distribution, should the observed F statistics of the test exceed the critical values noted in table 3.f, then there is a sign of granger causality. The granger causality test results are shown in the following table 3.e:

Table 3.e: Pairwise Granger Causality Tests

Sample: 1993 2011

Lags: 2

Null Hypothesis:	***Obs***	***F-Statistic***	***Probability***
Inflation does not Granger Cause Bonds	15	3.33368***	0.07774
Bonds does not Granger Cause Inflation		20.1539*	0.00031
EGARCH does not Granger Cause Bonds	14	5.68008**	0.02538
Bonds does not Granger Cause EGARCH		7.78500*	0.01090
EGARCH does not Granger Cause Inflation	14	2.34046****	0.15190
Inflation does not Granger Cause EGARCH		11.3456*	0.00347

* denotes significance at 1% level, ** denotes significance at 5% level,
*** denotes significance at 10% level, **** denotes significance at 25% level.

Table 3.f: F statistic values for granger causality tests

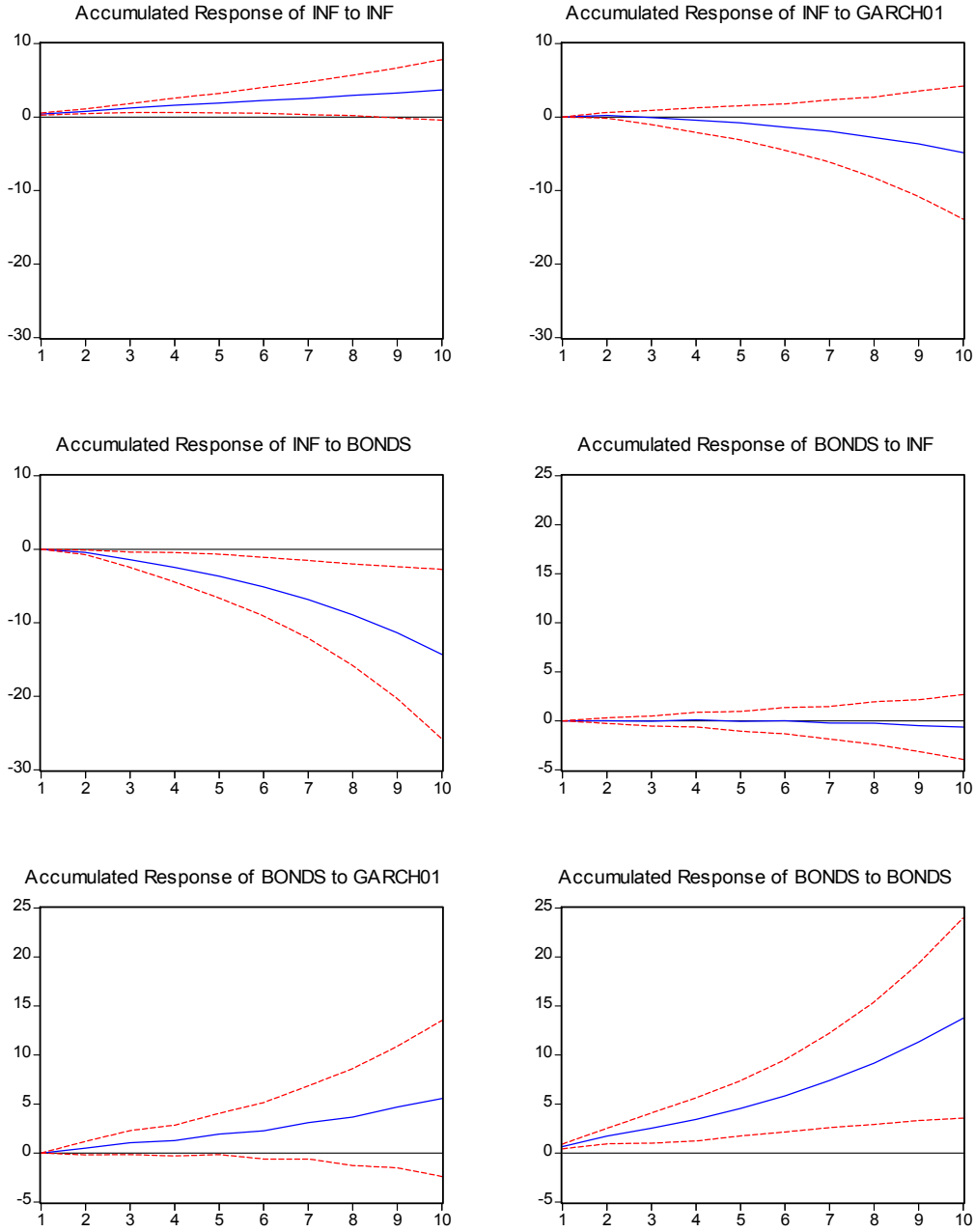
df Numerator (no. of lags)	**df Denominator (n-k) (no. of lags – observations)**	**Levels of significance**			
		25%	10%	5%	1%
2	13	1.55	2.76	3.81	6.70
2	12	1.56	2.81	3.89	6.93

From these results we can see that there is a strong granger-causality of 1% significance directing from government bonds to HICP, from government bonds to inflation uncertainty, and from HICP to inflation uncertainty. The hypothesis that HICP does not granger causes government bonds can be rejected at a 10% level of significance, which is a rather interesting result, especially if we take into account the rising practice and literature regarding inflation-indexed government bonds in order to avoid inflationary effects. To further examine the direction of the relationship among inflation, inflation uncertainty, and government bond rates we apply the Generalized Impulse Response (GIR) analysis as proposed by Koop et al. (1996) for non-linear dynamic equations and developed by Pesaran and Shin (1998) for linear multivariate equations. For the purpose of the analysis we construct an unrestricted VAR (10) system.

What we notice, firstly, is that inflation shows a statistically significant response to its own shocks (top left graph). But when we consider dynamic interactions between inflation and inflation uncertainty (top right graph), we notice a departure from neutrality into negativity after the 5th or 6th period. Therefore, the existence of inflation uncertainty shocks is effective on inflation levels after the 5th time period. The case of interactions between government bonds and inflation levels is slightly different. Shocks in the government bonds' rates seem to have an effect on inflation rather quickly, after the 3rd period (middle left graph). On the contrary, inflation shocks do not seem to seriously affect bond rates, at least not until the 10th period (middle right graph). Finally, inflation uncertainty shocks positively affect government bond rates after the 3rd or 4th period.

Graph 3.e: Accumulated impulse responses

Accumulated Response to Nonfactorized One S.D. Innovations ± 2 S.E.



4. CONCLUDING REMARKS

In this research we tried to implement the E-GARCH model in combination with the VAR approach with the intention of finding any sings of granger causality among inflation, inflation uncertainty and government bond rates in Greece in the period 1993-2011. We included the government bonds variable in order to differentiate this research from the rest of the literature, which mainly focuses on inflation and growth. Our results show that there is a strong bilateral granger-causality of 1% significance directing from government bonds to inflation. Bonds show a strong sign of one-way granger causality to inflation levels and inflation uncertainty of 1% significance, while inflation uncertainty seems to affect government bond rates at a 5% level of significance. Finally, our Generalized Impulse Response analysis shows that inflation levels are the most sensitive to government bond rates' shocks. Inflation uncertainty seems to affect both bonds and inflation in different time periods. A further adjustment of the current research could the comparison of Greece in terms of inflation uncertainty, including the exchange rate levels in a combination with countries outside the euro area, or the creation of a larger sample size in terms of countries and the possible interaction of their inflation uncertainties among each other.

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