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A Regime Switching Explanation of the Reactions of Market Participant during the Crisis

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Abstract. Empirical evidence suggest that markets are too volatile to be efficient, essentially this means the influencing factor in the pricing of assets is the reaction of market participants to the information or events, rather than the actual information. Hence in order to understand the pricing of assets, there is a need to include the behavioural finance theory. An influencing observation during the recent financial and sovereign debt crises as well as the pre-crisis period is that market participants seem to be reacting to the general financial environment. We use the SWARCH model of Cai (1994) to analyse the reaction of market participants in six key sovereign debt markets (i.e. US, German, Greek, Italian, Spanish and Portuguese) in a fast changing and highly volatile environment. In general, the evidence seems to be pointing at a change in the reaction of the market participants reflecting the underlying fast changing and highly volatile environment.
Keywords. Overreaction/Underreaction Hypothesis, Regime Switching, SWARCH, Sovereign Debt Market, Crises.
JEL. C13, C58, D53, D81, G01, G02, G15, H63.

1. Introduction

A criticism often put against the efficient market hypothesis is that market participants are homo-sapiens and not homo economics (De Bondt et al., 2008 and Kourtidis et al., 2011). Hence, in order to address this criticism there is a requirement to understand the psychology of the market participants. This led to the alternative theory of behavioural finance advocated by Statman (2008) and Subrahmanyam (2007) amongst others. A key notion in the behavioural finance theory as Bernard Baruch states:

> *"What is important in market fluctuations are not the events themselves, but the human reactions to those events"* as quoted by Lee et al. (2002, p. 2277).

As illustrated in Fakhry & Richter (2015) and Fakhry et al. (2016), one of the issues is the price tend to deviate from the fundamental value. As with the comment from Bernard Baruch, the key to understanding this deviation is the market participants' reactions. This lends itself to the overreaction / underreaction hypothesis as suggested by Barberis et al. (1998) and De Bondt (2000).

However, on some occasions there can be the appearance of multiple bubbles occurring over a short duration. This periodic collapse in a bubble can be analysed thru the use of a Markov process as alluded by Blanchard & Watson (1982), Evans (1991) and recently Branch & Evans (2011); this can be modelled by the use of the Markov Switching models (Hamilton, 1988). A related issue raised by Fakhry & Richter (2015) and Fakhry et al. (2016) is the reaction of the market participants seem to depend on the general market environment. Hence, we proposed using the SWARCH model of Cai (1994) to explain the reaction of the market participants during the recent financial and sovereign debt crisis as well as the pre-crisis period.

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As we are analysing the possibility of using a regime-switching model to explain the overreaction and underreaction hypothesis, we start this paper with two short reviews of the overreaction//underreaction hypothesis and Markov regime switching ARCH models. The next section gives the methodology of the SWRCH model used. Section 5 and 6 presents the data and empirical results. Finally, section 6 concludes.

2. The Overreaction / Underreaction Hypothesis

A key assumption of the efficient market hypothesis is that current prices should fully reflect all information on the asset as hinted by Fama (1965) and Malkiel (1962). There is an issue with this statement in that the current price reflects the sentiment of the market participants with respect to the information as suggested by De Bondt (2000) and Daniel et al. (1998) among others. Therein lays the key to understanding the overreaction / underreaction hypothesis (as hinted by Barberis et al., 1998; Daniel et al., 1998; Hong & Stein, 1999 and De Bondt, 2000); since market participants have different perspectives on how to interpret the new information, therefore the price could deviate from the fundamental value. Essentially, as hinted by De Bondt (2000), the overreaction hypothesis states that sometimes market participants tend to disproportionately react to information (fundamental and news) causing a temporarily and dramatic deviation from the fundamental value. Usually the price does revert to the fundamental value within a short period as market participants digest the information.

In essence, according to De Bondt (2000), most overreactions are due to errors in market participants' forecasts. A common issue is that market participants are often upbeat during bull markets and gloomy during bear markets, this is reflected in their perspectives of the asset price. Another issue is the problem of overestimation of the information on the asset during the issuance or initial public offering stage by the agents. According to Barberis et al. (1998), a key factor in the overreaction hypothesis is that a sequence of good or bad news can lead to an overreaction by market participants assuming the continuation of the trend. Daniel et al. (1998) suggest there is a differentiation based on whether the information is public or private. Thus meaning market participant are overconfident in their private information leading to an overreaction in the market. Whilst in general they tend to underreact to public information. Moreover, as discussed in Barberis et al. (1998) the evidence seems to be pointing at some market participants' conservative attitude to updating the model incurring the underreaction hypothesis.

However, as Hong & Stein (1999) highlight it is essential to analyse the interaction between heterogeneous market participants. They analyse two types of bounded rational market participants: momentum traders and news watchers to illustrate the effects on one another both types have. The results seem to be suggesting that when news watchers pick up new information, in general they underreact. This is mainly due to the gradual diffusing of information and the assumption that they do not observe prices. When short run momentum traders enter the market, seeing a chance to profit, instead of pushing the price back towards the fundamental value, they cause an overreaction to the news. While in the short run market participants could make a profit, in the long-run they make losses due to the price exceeding the long run equilibrium price. According to Hong & Stein (1999), the inclusion of well-informed fully rational arbitrageurs does not eliminate the effects of other less informed and rational market participants. Thus meaning the overreaction continues to have an impact on the price.

Recent empirical evidence has painted a mixed picture for the overreaction/underreaction hypothesis. Spyrou et al. (2007) find a split between large and small capitalization stocks in the London Stock Exchange. Large capitalization stocks were consistent with the efficient market hypothesis, while medium to small capitalization stocks seem to underreact to news shocks for many days. This underreaction is unexplained by risk factors or any other known effect.

A relevant factor raised by Fakhry & Richter (2015) and Fakhry et al. (2016) regarding the efficient market hypothesis is that during some highly volatile periods some markets seem to be rejecting the null hypothesis of the market being too volatile to be efficient. As hinted by Kirchler (2009), the underreaction / overreaction hypothesis provides one possible explanation, which suggests that market participants' reaction leads to overvaluation or undervaluation during bulls or bears market respectively. Hence, a highly volatile period with instances of both a bear and bull market would give the impression of an efficient market.

However, contrary to Spyrou et al. (2007), Lobe & Rieks (2011) find significant evidence of short-term overreaction in the Frankfurt stock exchange is not limited to small capitalization stocks. The explanation seems to be in the anomalies and stock characteristics. However, transaction costs and unpredictable markets mean that market participants may not be able to exploit these effects. This means that due to the unforeseeable direction of the reaction and the existence of transaction costs prohibiting the implementation of consistent profit making strategies, they conclude the evidence seem to be suggesting no violation of the efficient market hypothesis.

3. A Review of the Markov Regime-Switching ARCH Models

As stated by Hamilton (1989) the basis of a number of previous researches studying the relationship between the business cycle and GNP is the assumption of the observed data following a linear stationary process. However, as a number of studies have proved the assumption of linearity and stationary in key macroeconomic datasets is weak. Hence, in an article on non-stationary time series and the business cycle, Hamilton (1989) introduced a regime-switching model based on autoregression using a discrete-state Markov process.

Conversely, it has long been acknowledged financial markets sometimes go thru alternate periods, characterized by high and low volatilities as noted by Hamilton & Susmel (1994) and Cai (1994) amongst others and highlighted by Fakhry & Richter (2015) and Fakhry et al. (2016). In researching monthly short-term interest rates, Hamilton (1988) concludes the possible present of regime shifts in ARCH effects could explain the estimates of the ARCH-m of Engle et al. (1987). In fact, a common problem in the estimation of ARCH/GARCH is spuriously high persistent of volatility across subsamples as noted by Hamilton & Susmel (1994). Diebold (1986) and Lamoureux & Lastrapes (1990) argue that structural changes in the observed dataset could be the reason for a high estimate of the ARCH/GARCH parameter, which leads to high persistent.

Thus meaning that sometimes, simple ARCH/GARCH models do not entirely explain volatility, there is a need to combine the regime-switching capabilities of the Markov switching model with conditional volatility models such as ARCH/GARCH. As noted by Cai (1994), a key factor in the use of SWARCH is the endogenisation of parameter shifts, thus allowing shifts to be determined by the observed dataset. Additionally, a key advantage is that it distinguishes between the effects enabling the analysis of their impact on the properties of the observed dataset. This led to a number of integrated models generally called SWARCH, i.e. Cai (1994), Hamilton & Susmel (1994) and Hamilton & Lin (1996).

Although the models of Cai (1994) and Hamilton & Susmel (1994) are based on SWARCH implementation, they adopt different methods of implementation. Cai (1994) models the shifts in the asymptotic long-run variance of the SWARCH process. Thus in this model the intercept of the conditional variance is allowed to change in response to the discrete shifts in the regimes. Whereas Hamilton & Susmel (1994) model the shifts in the dynamic process of the conditional variance, this means that the basis of the regime shifts are the changes in the scales of the conditional variance.

The literature on the empirical evident of the SWARCH in the sovereign debt market is not a huge one in comparison with other models. Although the Markov switching and GARCH models separately have been the focus of attention since the financial and sovereign debt crises, yet there is a drought in the empirical evident of the SWARCH model. We find a two way split in the evident with a group, such as Christiansen (2008), researching the yields and the second group such as Abdymomunov (2013) studying the returns. The significant of these two papers is that they also use different SWARCH implementations whereas Christiansen (2008) uses the Cai (1994) method; Abdymomunov (2013) uses the Hamilton & Susmel (1994) method.

In a research on the relationship between the volatility on the short rate of the US and UK and the US and Germany, Christiansen (2008) extended the Cai (1994) implementation of the SWARCH model to a bivariate model in order to estimate both volatilities, i.e. US and UK and US and Germany, simultaneously. The research used the weekly 1-month Eurodollar, Libor and Euromark[1] for the US, UK and Germany respectively; observed from January 1975 to December 2004 obtained from the Federal Reserve and Datastream. They found the inclusion of the level effect and regime switching in the model seems to be rendering the ARCH effect in the conditional volatility insignificant. In addition, the regime switching occurs in the level or constant in the ARCH model specification. Moreover, they find evident suggesting that neither a state dependant level nor volatility have an advantage over the other. The results seem to be indicating a mixed picture with each country short rate model conforming two different models with respect to the two states. However, there is a difference in the models each country conforms with respect to the states. There seem to be no evident of contagion between the US and Germany and US and UK. However, in general they did fund some evident of Granger causality. Essentially, this is suggesting that the ECB in particular can exert some influence on the Eurozone short rate volatility.

In contrast, Abdymomunov (2013) extends the Hamilton & Susmel (1994) model to a multivariate SWARCH model; in a study on the impact of financial stress from abrupt and large changes in the volatility of key financial variables on the US financial. They use transformed weekly TED spreads, value-weighted NYSE returns and capital-weighted CDS from a number of banks as the financial variables obtained from various places such as Bloomberg and the FRED database of the Federal Reserve Bank of St Louis observed over the period 6 December 2000 to 29 September 2010. However, the CDS data was observed between 10 November 2004 and 29 September 2010. They find strong evident of the high volatility state in the joint variables mimicking times of financial stress such as the terrorist attacks of 11 September 2001, subprime crises and credit crunch in August 2007 and the Lehman Brothers bankruptcy in September 2008. The results seem to

[1] After the introduction of the Euro, the rate used was Eurocurrency

suggest that a possible indicator of financial stress could be the joint variables regime-switching model.

4. Model Specifications for Markov Switching ARCH

The main aim of this paper is to analyse the overreaction/underreaction by using the SWARCH model. The SWARCH model is basically a combination of the Markov switching model of Hamilton (1989) and the ARCH model of Engle (1982). Hamilton (1989) derived the MS(s)-AR (k) model from a combination of two or more first order autoregression models, each with a different intercept to highlight the change in the observed data at a certain time. However, as indicated by Hamilton (2008) the problem with that was priori knowledge of abrupt changes in the observed data. Hence, Hamilton (1989) introduced a multiple-state (i.e. two-state in this case) Markov chain with a system of probabilities attached to each state to model the changes in the observed data regime. The Markov Switching model as derived by Hamilton (1989), illustrated in equation 1.

$$y_t = \omega_{s_t} + a_1 y_{t-1} + \varepsilon_t$$
$$s_t = \begin{cases} = 1 \; if \; low \; regime \\ = 2 \; if \; high \; regime \end{cases} \tag{1}$$

As previously stated, the literature and empirical evident on the Markov switching model in the sovereign debt market in the last few years have been strong, see (Georgoutsos & Migiakis, 2012, and Pozzi & Sadaba, 2013). Given the evidence of regime switching in the volatility of sovereign debt prices over the past few years, hence a volatility-switching model would help in identifying the reaction of market participants. However, due to issues regarding the complexity, see (Cai, 1994) and (Guidolin, 2012), and the exaggerated high persistency in the volatility, see (Guidolin, 2012); we follow Christiansen (2008) and Abdymomunov (2013) in using a SWARCH model instead of a SWGRACH (i.e. Switching GARCH). In effect using the ARCH model of Engle (1982) to derive the volatility. Equation 2 uses a single lag ARCH model as proposed by Engle (1982).

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 \; where \; h_t = \sigma_t^2 \tag{2}$$

The simplest method to estimate the integrated heteroskedasticity and switching effects in the volatility is by the use of a SWARCH model such as Hamilton & Susmel (1994) and Cai (1994). We opt for the Cai (1994) implementation mainly due to initial tests with our observed data raising a few estimation issues with respect to the Hamilton & Susmel (1994) implementation. In combining the Markov switching model as in equation 1 with the ARCH model in equation 2, it is easy to see how Cai (1994) integrated the two models. The Cai's model is derived from the two equations, illustrated by equations 3 and 4, with the first equation being the integrated model and the second being the regime-switching probabilities. Analysing equation 3 closely reveals the beautiful simplicity in the construction of the model. Yet the model is powerful in its ability to model the regime switching in the volatility of the underlining observed dataset and complicated to estimate. The simplicity of the model is that it is a combination of the Hamilton (1989) Markov Switching model in equation 1 and ARCH model of Engle (1982) in equation 2 whereby the autoregression model in equation 1 is substituted by the conditional heteroskedasticity model as derived by equation 2.

However, since Cai (1994) uses a two-lagged ARCH model, this implies that the SWARCH model follows equation 3

$$h_t = \omega_0 + \omega_1 s_t + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \quad (3)$$

$$s_t = \begin{cases} 0 \; if \; low \; volatility \\ 1 \; if \; high \; volatility \end{cases}$$

$$P(s_t = i|\widetilde{\varsigma_T}) = \sum_{j=1}^{M=2} P(s_t = i, s_{t+1} = j|\widetilde{\varsigma_T}) \quad (4)$$

$$Pr_s = \frac{1}{1+Exp(\theta_{m,n})} \quad (5)$$

In the Cai (1994) model, the intercept for the low volatility regime is ω_0 and the high volatility regime calculated by multiplying ω_0 with the coefficient of the ARCH. Since the SWARCH model was originally proposed to highlight the issue of spuriously high persistence in the volatility of other models due to regime switching.

In a two-regime Markov switching model, we calculate the expected probabilities by using $\theta_{1,1}$ and $\theta_{1,2}$ logistic indices. Equation 5 illustrates the calculation; a key factor is that we substitute $\theta_{1,1}$ and $\theta_{1,2}$ into $\theta_{n,m}$ for the low and high regimes' probabilities respectively. We opt for the smoothing effect to calculate the probabilities. This gives a more accurate figure of each probability, but requires extensive computing, due to the complex estimation method involving the entire history of filtered and predicted probabilities, see Hamilton (1994).

5. Data Description

As illustrated by Table 1, we use the daily 10-year sovereign debt, maturing in 20120F[2], end of day bid prices for Germany, Greece, Italy, Portugal, Spain and US obtained from Bloomberg. Importantly, the reference numbers are ISIN for all the markets, except the US which uses CRSPID. In order to capture the price volatility during the sovereign debt crisis without the maturity effect, we extend our data to obtain a second group of sovereign bonds for the above-mentioned countries with the exception of Greece maturing in 2017 as illustrated in

Table **2**. We follow the norm by defining our week as Monday to Friday. In order to make the observed data uniformed across all six observed datasets, we substitute all missing observations with the last known price.

Table 1. *The 10-Year Sovereign Debt Prices Data with maturity in 2012*

	Reference Number	*Download Date*	*Issue Date*	*Maturity Date*
German	DE0001135192	16/07/2012	02/01/2002	31/12/2011
Greece	GR0124018525	17/12/2012	17/01/2002	18/05/2012
Italy	IT0003190912	16/07/2012	01/08/2001	01/02/2012
Portugal	PTOTEKOE0003	16/07/2012	12/06/2002	15/06/2012
Spain	ES0000012791	17/12/2012	14/05/2002	30/07/2012
US	9128277L0	16/07/2012	15/02/2002	15/02/2012

[2] The exception is the German which matures at the end of 2011

Mainly due to the last issue date, that of Portugal, and first maturity date, that of Germany, our observed sample is from 1st July 2002 to 30th December 2011. Thus meaning our sample has a uniformed total of 2,480 daily observations for each sovereign debt market.

Table 2. *The 10-Year Sovereign Debt Prices Data with maturity in 2017*

	Reference Number	*Download Date*	*Issue Date*	*Maturity Date*
German	DE0001135317	08/04/2013	17/11/2006	04/01/2017
Italy	IT0004164775	08/04/2013	01/08/2006	01/02/2017
Portugal	PTOTELOE0010	08/04/2013	18/06/2007	16/10/2017
Spain	ES00000120J8	08/04/2013	23/01/2007	31/01/2017
US	912828GH7	08/04/2013	15/02/2007	15/02/2017

In our second observed sample, we follow the same concept as before by using the Portuguese issue date to set the start. This means our observed sample is from 1st July 2007 to 31st March 2013, a total of 1,500 daily observations for each sovereign debt market.

6. Empirical Evidence

We use the Cai (1994) variant of the SWARCH model as indicated earlier to analyse the regime-switching behaviour of volatility in the sovereign debt market. We derive a single lagged two states SWARCH to model the switching conditional variance of the first order-differentiated price.

In estimating our SWARCH model, we use the maximum likelihood with normal distribution. With the exception of the US and German 2017 datasets, we use the BHHH method. However, due to errors in the estimations of these two datasets, we opted to use the BFGS method. Due to errors with the estimations, we used various sample periods.

Table 3. *SWARCH Statistics of the 2012 Bond*

	US	*Germany*	*Greece*	*Italy*	*Portugal*	*Spain*
Mean Eq. M	-1.58E-2 (1.06E-3)	-1.33E-2 (1.60E-3)	4.93E-3 (4.82E-3)	-9.22E-3 (2.19E-3)	2.38E-3 (4.22E-3)	-7.25E-3 (3.50E-3)
Variance Eq. ω_0	5.01E-4 (4.15E-5)	8.29E-4 (1.31E-4)	3.74E-2 (1.96E-3)	4.21E-3 (3.24E-4)	3.64E-2 (1.79E-3)	9.20E-3 (8.39E-4)
$\omega_{s=1}$	0.293810 (0.02157)	0.253356 (0.0355)	0.335285 (0.04391)	0.158109 (0.03212)	0.033347 (0.02050)	0.085378 (0.02609)
$\omega_{s=2}$	0.314870 (0.029868)	0.092030 (0.02164)	0.105865 (0.0227)	0.092066 (0.02193)	-0.002624 (0.00115)	0.113403 (0.02237)
α	166.03853 (13.7276)	48.809924 (7.38853)	43.495632 (9.50358)	11.191042 (0.85112)	10.619878 (1.04933)	6.523605 (0.55092)
$\theta_{(1.1)}$	7.018339 (1.06231)	4.815815 (0.67957)	4.380112 (0.27218)	4.840678 (0.45375)	3.846200 (0.27491)	4.530508 (0.42917)

	US	*Germany*	*Greece*	*Italy*	*Portugal*	*Spain*
$\theta_{(1.2)}$	-7.752714 (0.59254)	-5.930005 (0.60767)	-1.846393 (0.31131)	-5.598055 (0.45617)	-2.164589 (0.31478)	-5.352082 (0.44011)
$Pr_{s=1}$	8.95E-4	8.04E-3	1.24E-2	7.84E-3	2.09E-2	1.07E-2
$Pr_{s=2}$	0.99957	0.99735	0.8637	0.99631	0.89702	0.99528
Log Likelihood	187.0060	1097.174	-530.0750	837.6236	-91.3807	362.2630

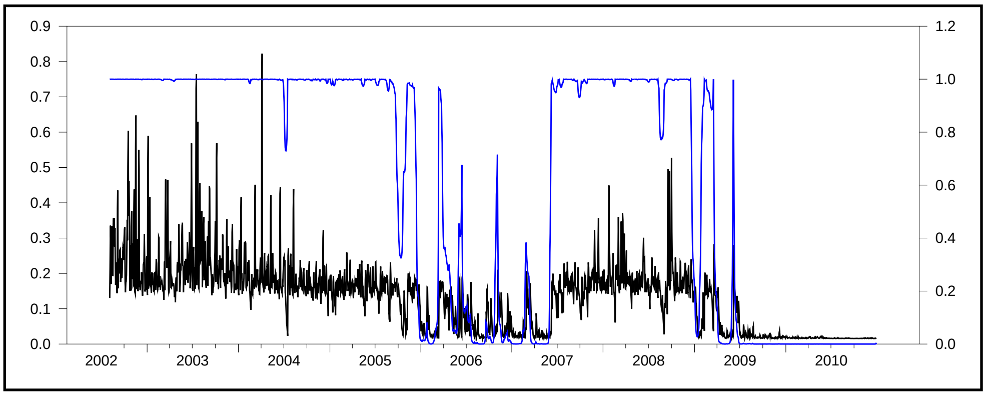

Figure 1. *US 2012 High Volatility Regime*

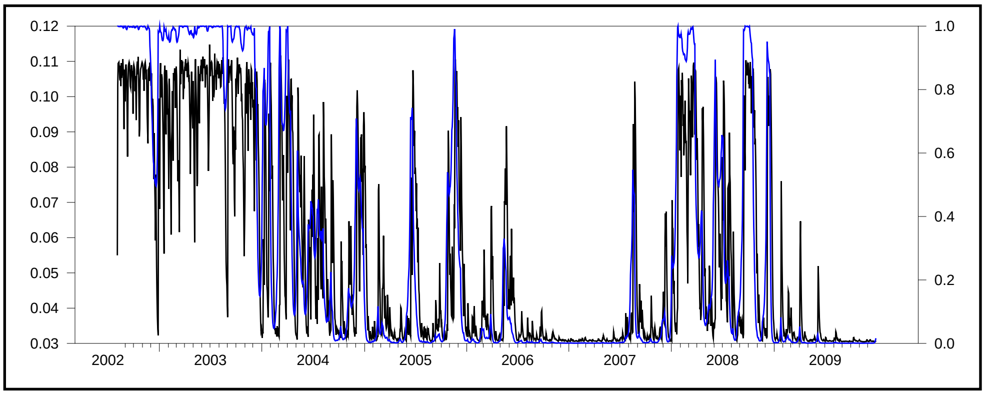

Figure 2: *German 2012 High Volatility Regime*

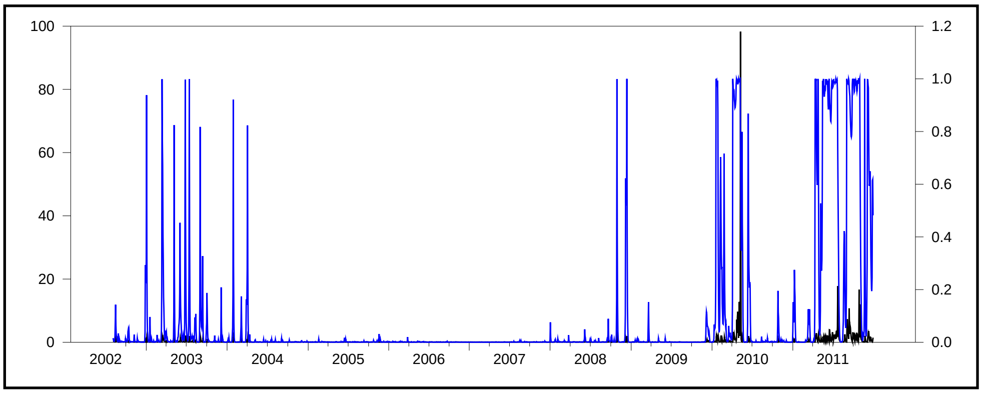

Figure 3: *Greek 2012 High Volatility Regime*

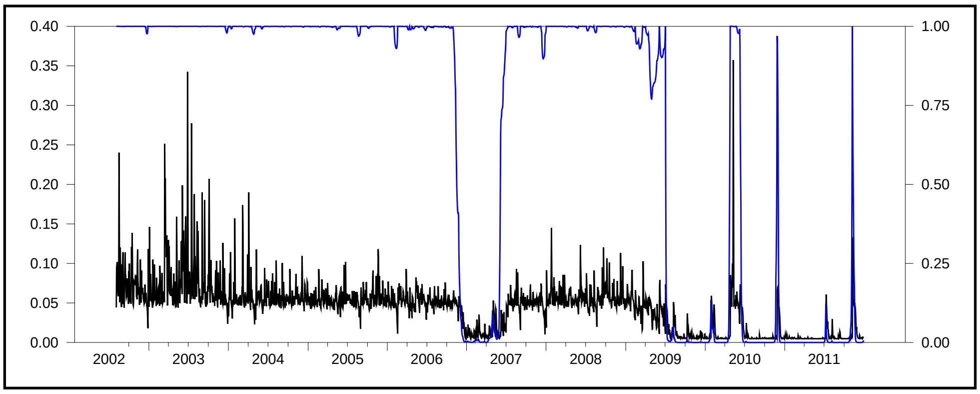

Figure 4: *Italian 2012 High Volatility Regime*

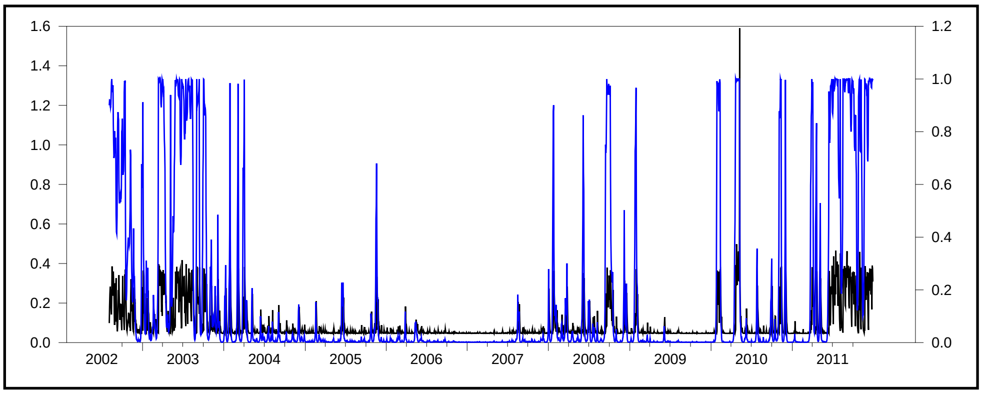

Figure 5: *Portuguese 2012 High Volatility Regime*

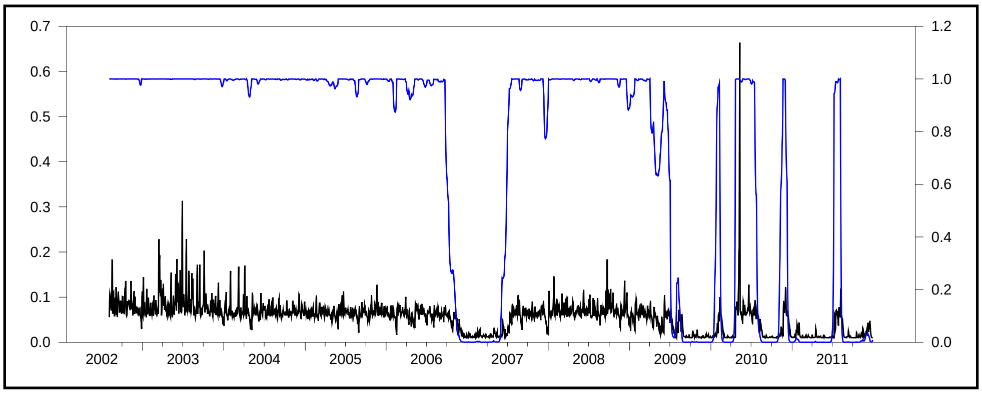

Figure 6: *Spanish 2012 High Volatility Regime*

In essence, the 2012 bonds were associated with a period of changing market environment in the global financial market. Of course the later stages of the period were associated with the financial and sovereign debt crises, yet it was also governed by a number of events which changed the market environment during the earlier stages such as the asset price bubble and accountancy issues leading to the bankruptcy of Enron and WorldCom. However, two events, which had an influential impact during the early stages, were the introduction of the euro and the terrorist attacks of 11 September 2001 leading to a number of wars. Although these two events occurred before the observed period, yet the persistency in their aftermath had a big impact on the behaviour of market participant.

The evidence from figures 1 to 6 certainly points towards the existence of a regime-switching behaviour influencing the pattern of price volatility in the sovereign debt market. While the figures illustrate the extent to which the sovereign debt market in general is highly volatile, further illustrated by analysing the probabilities of the high volatility regime in table 3, in essence regime 2. Surprisingly for our observed markets, this is highly significant with a minimum probability of 0.8637 as observed by the Greek market, backed by the probability for the low volatility regime, which is regime 1, with a maximum probability of 0.0209 for the Portuguese market. This would suggest it is more likely that the next regime will be highly volatile. With the exception of the Greek and Portuguese markets, the probabilities are in the high 0.90s, which are hinting at the other observed markets being more volatile. Notably the Greek and Portuguese markets also point to a significant probability of a high volatility regime.

In general, the ARCH intercepts seem to be hinting at a three way split in the markets. This is consistent with previous observation of the behaviour of volatility in the sovereign debt market, see Fakhry & Richter (2015) and Fakhry et al. (2016). The ARCH intercepts in both regimes for the Italian and Spanish markets seem to be hinting at very low levels of volatility, understandable as the high volatility did not impact the two markets until the later stages as illustrated by figures 4 and 6. Both these figures also illustrate that the highly volatile period of the early 2000s did not really influence the volatility levels. Arguably, the financial crisis did not affect the Spanish market until later on and the Italian market remained unaffected.

The US and German markets seem to be portraying a more volatile market than the other observed markets. However, as illustrated by figures 1 and 2, at the highest level their volatilities are below the Greek and Portuguese markets. A counter argument is during some spells the level of volatility for the German and especially the US markets seem to be higher than the Greek and Portuguese markets. A possible explanation is the quality and liquidity factors of the US and German markets making them the benchmark markets for both the dollar and euro currencies. This makes them prime markets for flights to safety during crises or extreme events i.e. Knightian uncertainty. Another influencing factor with respect to both markets is the requirement of the Basel II regulations to hold sovereign debt on their balance sheets as capital. Hence, many of these organizations choose to hold either US or German sovereign debt depending on their "home" currency.

The Greek and to a lesser extent Portuguese markets were in the "eye of the hurricane" during the sovereign debt crisis, hence the high levels of volatility, as illustrated by figures 3 and 5, which had an impact on the regime 2 ARCH intercepts. However, as the figures also illustrates there are long periods of low volatility in both the Greek and Portuguese markets. An influencing factor is that both these markets are not liquid and more importantly are not large markets. Hence, as illustrated by the figures, during "normal" market environment these markets do not have a high number of transactions, which gives the appearance of stable markets.

In essence, the 2017 bonds are associated with a highly volatile period in the global financial market mainly due to the financial and ensuing sovereign debt crises. Although, this in itself is interesting, mainly due to the differing impact on the observed markets of each crisis; however, as hinted previously, another influencing factor is the different impact from the on the run and maturity effects on the financial and sovereign debt crises respectively. The final factor is the extended observed period; therefore, allowing us to analyse the full impact of the sovereign debt crisis. These factors may have had an effect on the SWARCH model.

Table 4. *SWARCH Statistics of the 2017 Bond*

	US	*Germany*	*Italy*	*Portugal*	*Spain*
Mean Eq. μ	-7.64E-4 (6.83E-3)	1.18E-2 (7.39E-3)	5.38E-3 (8.20E-3)	-1.46E-2 (1.15E-2)	-1.68E-3 (8.93E-3)
Variance Eq. ω_0	1.95E-2 (2.02E-3)	2.88E-2 (7.77E-3)	6.68E-2 (3.95E-3)	1.34E-1 (9.01E-3)	1.04E-1 (4.93E-3)
$\omega_{s=1}$	0.135506 (3.18E-2)	0.0897424 (4.07E-2)	0.0063287 (1.69E-2)	0.014309 (3.30E-2)	0.076919 (3.42E-2)
$\omega_{s=2}$	0.071336 (3.46E-2)	-0.0269799 (4.62E-3)	0.0710576 (3.13E-2)	0.096304 (3.28E-2)	-0.006101 (5.47E-4)
α	12.987887 (1.250402)	4.5921499 (0.839103)	10.1028920 (1.137037)	16.841144 (2.236902)	7.764033 (0.977439)
$\theta_{(1.1)}$	6.571102 (1.492712)	3.2786740 (0.393502)	3.7757628 (0.274308)	3.331685 (0.257237)	4.512419 (0.402756)
$\theta_{(1.2)}$	-7.203025 (1.235778)	-4.0878472 (0.570678)	-2.2659541 (0.283508)	-1.738651 (0.351140)	-2.670022 (0.382444)
$Pr_{s=1}$	1.40E-3	3.63E-2	2.24E-2	3.45E-2	1.09E-2
$Pr_{s=2}$	0.99926	0.98350	0.90602	0.85052	0.93523
Log Likelihood	-761.8270	-352.5236	-590.8467	-1242.7689	-749.8844

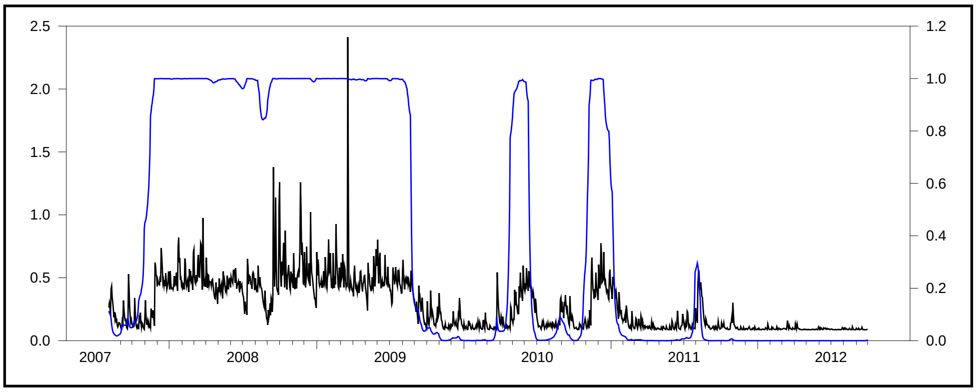

Figure 7: *US 2017 High Volatility Regime*

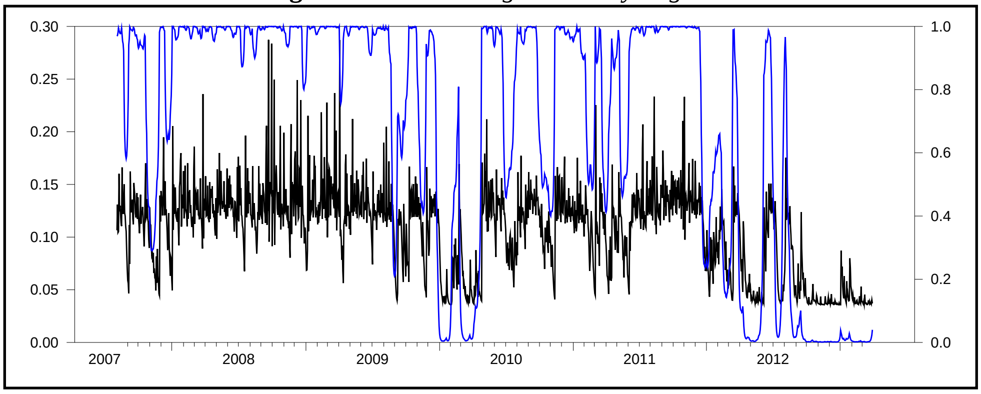

Figure 8: *German 2017 High Volatility Regime*

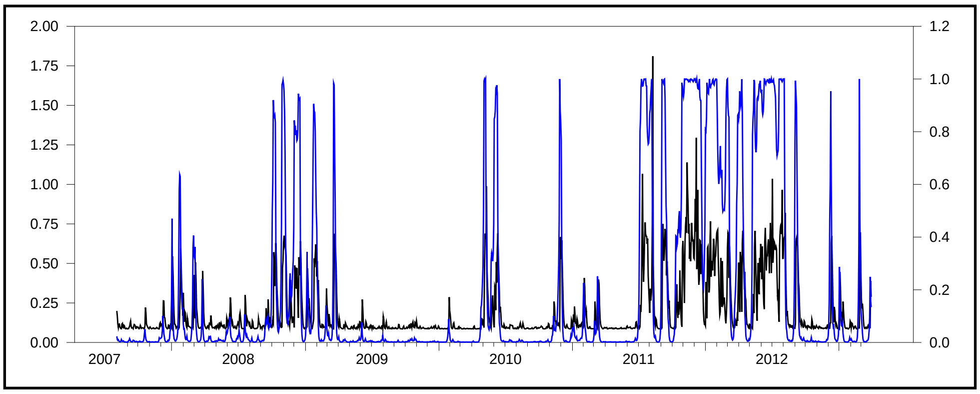

Figure 9: *Italian 2017 High Volatility Regime*

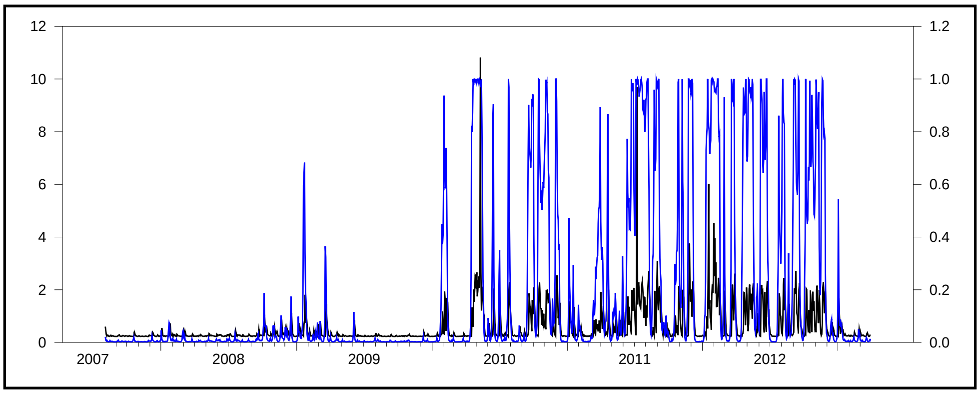

Figure 10: *Portuguese 2017 High Volatility Regime*

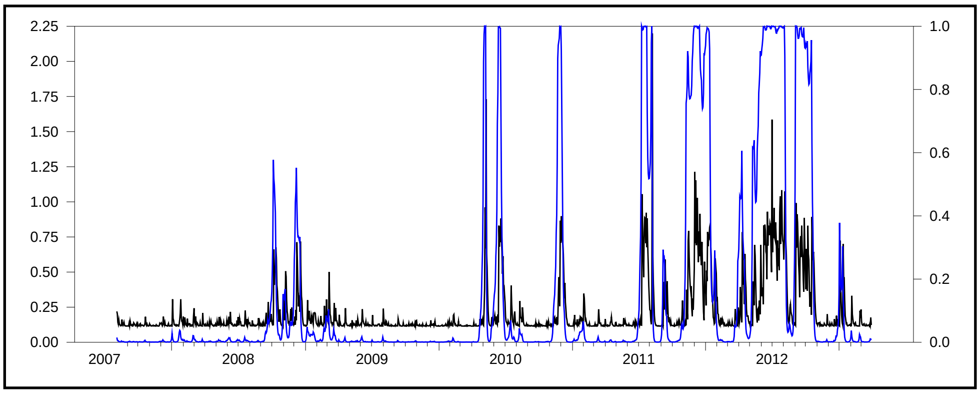

Figure 11: *Spanish 2017 High Volatility Regime*

The evidence from table 4 is pointing at a mixed picture with respect to the probabilities. The high probability of regime 2 suggests that there is a significant probability of a highly volatile regime throughout our observed markets. With the exception of the Portuguese market, the observed markets are hinting at a significant probability of above 0.9 that the next regime is highly volatile. With the US and German markets approaching 1.0, this seem to be indicating that the US and German markets were highly volatile throughout the observed period, although the probabilities of both the Italian and Spanish markets were also significantly high.

Like the probabilities, the ARCH intercept for regimes 1 and 2, points at a rather mixed picture in terms of the level of volatility in the observed markets. As illustrated by figures 7 to 11, it would seem that the German market had the lowest level of volatility in both regimes. An influencing factor is that both crises did not really affect the German economy or financial market, despite the downgrading of the German sovereign debt ratings. However, the evidence from figure 8 seems to suggest that the market was highly volatile and backed by the high probability of regime 2 as hinted earlier. A possible explanation is the status of the German market as the benchmark market for the Eurozone; hence, the persistency of the high volatility regime is the result of flights to safety during both crises. Similarly, the persistency of the high volatility regime in the US market during the early stages was the result of a flight from financial assets to the US market during the financial crisis. Since the financial crisis had its origin in the US; hence, these flights to safety as illustrated by figure 7 significantly affected the US market. However, the timings of the two hikes in volatility during the sovereign debt crisis period seem to be hinting at the Eurozone sovereign debt crisis, hence a plausible explanation is that the US market was at the centre of a flight from the euro to the US dollar. It must be remembered that due to problems with the estimation of the SWARCH model, we had to limit our observed dataset to 1st October 2012, which meant the full impact of the US fiscal cliff and debt-ceiling crises on the US market was not captured.

To a certain extent figures 9 to 11 seem to be hinting at the limited impact of the financial crisis on the IPS markets. Although there is some evidence of high volatility regimes during the financial crisis period, yet this evidence seems to be telling. Certainly, the evidence seems to be pointing at jumps rather than changes in the volatility regime effecting these markets during the financial crisis, especially around the period of the Lehman Brothers bankruptcy. This seems to be hinting at a period of reactive behaviour by the market participants to events during the financial crisis period. However, during the sovereign debt crisis, the regime changes became increasingly persistence and frequent. An interesting factor is the lag between the Greek deficit revision and the reaction of the market participants leading to contagion in the IPS markets.

7. Conclusion

In this paper, we used the SWARCH model volatility regime switching proposed by Cai (1994) to analyse the reaction of the market participants in a fast changing and highly volatile environment. In order to overcome the "on the run" and maturity effects, we used two group of government bonds: the 2012 bonds and 2017 bonds. We used the prices of the GIPS plus US and German markets. The aim was to analyse the changing reaction of the market participants during the pre-crisis period and the financial and sovereign debt crises.

In summarising, the SWARCH model seems to point to a regime-switching behaviour in the price volatility of the sovereign debt market. In general, the high volatility regime in both the 2012 and 2017 bonds governed the SWARCH model. The SWARCH model also seems to highlight an interesting factor in the 2012 bonds, the observed markets seem to be generally divided into three groups depending on the pattern of the volatility and regimes: the US/German, Greek/Portuguese and Italian/Spanish markets. Another factor observed in the patterns of volatility in the 2017 bonds is that the IPS markets do follow a similar pattern of volatility while the US and German markets seem to be dictated by individual patterns of volatility. A relevant factor in our research is that the SWARCH model seems to be identifying the changing environment for each of the observed markets. Since each of the markets was effected by a number of different factors.

In concluding, the evidence does hint at the changing environment effecting the market participants' reactions. Thus indicating an overreaction/underreaction during both crises in the sovereign debt market. However, there was evidence of underreaction during the pre-crisis asset bubble and to a certain extent the financial crisis, since the macroeconomic indicators were indicating the worsening underlying economic condition in the observed markets.

A big issue is that market participants also react to policy makers; the problem is that during both crises the policy makers were also reacting to events. At the heart of both crises there was confusions bought on by mixed political communications. These two issues illustrate a genuine lack of ideas and agreement by the policy makers leading to an overreaction. Another issue is both crises were highlighted by incomplete or asymmetrical information. The sad thing was that the spillover effect that followed the initial crises was a consequent of the overreaction to the indecision of the policy makers.

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