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The impact of regime-switching behaviour of price volatility on efficiency of the US sovereign debt market

Omar Masooda, Bora Aktanh, Beata Gavurovád, Bachar Fakhryn, Manuela Tvaronavičienėfa and Raimonda Martinkutė-Kauliënėh

ABSTRACT

This article focuses on the asset price volatility at the stock exchange that result from the regime switching behaviour in the market. This study is devoted to the question about how the asset price volatility affects the US sovereign debt market. The efficient market hypothesis has been a base for the asset pricing. This hypothesis is discussed in this study. The review of the literature reveals nuances of behavioural finance theory, and allows us to better understand the regime switching behaviour in the market. The object of empirical study is the US sovereign debt market. We use the Markov Regime-Switching ARCH (SWARCH) model to analyse data. The results show that there is high volatility regime in both the 2012 and 2017 bonds US market, which significantly affects bond prices.

1. Introduction

The efficient market hypothesis has been the basis of asset pricing since the mid-1960s. According to Malkiel (1962) and Fama (1965), the efficient market hypothesis simply states that the price of any asset should incorporate all available information immediately. So, markets should follow a random walk in the short-term as stated by Malkiel (2003). Though these assumptions do not always reflect the real picture, since market participants in reality are affected by an array of factors, such as obvious structural changes of economy (Akhmadeev & Manakhov, 2015; Dezelus, Ferreira, Pereira, & Vasiliiūnaitė, 2015; Dudzevičiūtė, Mačiulis, & Tvaronavičienė, 2014; Korsakienė & Tvaronavičienė, 2014; Oganisiana, Surikova, & Laizāns, 2015; Praise, 2015; Rezk, Ibrahim, Tvaronavičienė, Sakr, & Piccinetti, 2015; Shatrevich

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The particular question that our research revolves around is: 'Does volatility follow a regime-switching trend in the sovereign debt market?' According to Blanchard and Watson (1982), Evans (1991) and more recently Branch and Evans (2011) and Dajcman (2015), a periodic collapsing bubble can be analysed using a Markov switching model. There are many implementations of the SWARCH model, however the two most relevant ones are Cai (1994) and Hamilton and Susmel (1994). The key to the Cai (1994) model is that the Autoregressive Conditional Heteroskedasticity (ARCH) intercept is regime dependent. We opt to use the SWARCH model proposed by Cai (1994) to establish whether the trend in the price volatility does follow a regime-switching model and hence analyse the trend.

2. The theory of behavioural finance

As stated by De Bondt (2000), one of the perspectives on asset prices is 'the price is right' view proposed by Fama (1970). Another perspective is that any up trend in an asset price must eventually come down, resembling Newton's law of universal gravitation. Newton's perspective is key to understanding the empirical studies of behavioural finance. Some of the issues regarding the pricing of assets cannot be addressed without reference to the behavioural finance theory. Criticism by De Bondt, Muradoglu, Shefrin, and Staikouras (2008) and Kourtidis, Sevic, and Chatzoglou (2011) put against the neoclassical economics model. Particularly, the efficient market hypothesis is that market participants are homo-sapiens and not homo economics. Therefore, there is a requirement to understand the psychology of the market participants in order to address these issues. This led to the alternative theory of behavioural finance being put forward by Statman (2008) and Subrahmanyam (2007) amongst others.

De Bondt et al. (2008) and Kourtidis et al. (2011) argue that there is a necessity to understand the psychology of market participants in order to provide an explanation of market abnormalities, such as asset price bubbles and crashes, and comprehend the efficiency of the financial markets. Kourtidis et al. (2011) stated that the obvious existence of irrational
market participants making random transactions in the market can only be adequately explained by taking account of behavioural factors. As discussed by Barberis and Thaler (2003), the impact on the price from these irrational market participants can be long-lasting and significant. According to Barberis and Thaler (2003), the psychology and the long-lasting impact of irrational market participants form the building blocks of behavioural finance.

According to Kourtidis et al. (2011), traditional financial theories examine how people behave with respect to wealth maximisation, whereas behavioural finance is interested in how people actually behave in a financial environment. As defined by De Bondt et al. (2008) and Statman (2008), behavioural finance is the psychological study of the market participants and their interaction with the financial markets where the market participants may be individual households or organisations. Furthermore, De Bondt et al. (2008) stated that the behavioural finance theory is not necessarily based on the assumption of rational market participants and efficient markets. An important factor in the behavioural finance theory as indicated by Statman (2008), is that market participants are assumed to behave normal in the sense that they act rational but with a limited information set.

The main idea influencing the behavioural finance theory is a number of behavioural factors influences market participants. Kourtidis et al. (2011) state four major behavioural factors in analysing the market participants’ behaviour in the financial market: over-confidence, risk tolerance, social influence and self-monitoring. According to Subrahmanyam (2007) the assumptions and models behind the behavioural finance theory are plausible. He stated that asset prices are influenced by a reference price and the disposition effect. It points toward the existence of a pattern in the trading activity of individual market participants. Another key factor as stated by Statman (2008) is that the disposition hypothesis behind the behavioural finance theory predict that market participants will realise rapid gains but defer losses, are testable.

A key notion in behavioural finance theory is: ‘What is important in market fluctuations are not the events themselves, but the human reactions to those events’ (Lee, Jang, & Indro, 2002, p. 2277).

This lends itself to the overreaction hypothesis as suggested by Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999) and De Bondt (2000). Furthermore, it leads to the existence of bubbles, which causes the asset price to temporary deviate from the fundamental value in the short to medium term as illustrated by Kindleberger and Aliber (2005). Blanchard and Watson (1982), defined a bubble as a price deviation from the fundamental value that is apparently unjustified by the information available at the time. The bubbles in history as illustrated by Kindleberger and Aliber (2005), the first recorded bubble often referred to as the Dutch tulip bubble of the 1630s, the South Sea Company bubble of 1719–1720 and the US stock market bubble of the 1920s which ended with the Wall Street Crash of 29 October 1929.

Brunnermeier (2001) highlights, there is empirical evidence provided by LeRoy and Porter (1981) and Shiller (1979) that prices deviate from their fundamental value more than predicted by the efficient market hypothesis. This evidence would suggest there could be rational deviation from the fundamental value, i.e., rational bubbles. Rational bubbles appear in asset prices:

If market participants are willing to pay more for the stock than they know is justified by the value of the discounted dividend stream because they expect to be able to sell it at an even higher price in the future, making the current high price an equilibrium price. Gurkaynak (2008, p. 166)
As Blanchard and Watson (1982) illustrate the positive/non-correlation between the innovations in the bubbles and asset returns could lead to the bubble increasing the conditional variance in the price. This leads to the possible modelling of bubbles by different econometric models to understand the factors influencing the bubbles. Branch and Evans (2011) hints at feedback effects influencing the bubbles, hinting at the use of the GARCH-m (Engle, Lilien, & Robins, 1987) in understanding these feedback effects. Furthermore, Branch and Evans (2013) stated there is certainly a hint of ARCH and hence GARCH effects influencing the asset price bubble, pointing towards volatility clustering effects. 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 through the use of a Markov process, as suggested by Blanchard and Watson (1982), Evans (1991) and more recently Branch and Evans (2011), using the Markov Switching model (Hamilton, 1988). Moreover, the correlation between the innovations and asset returns points to the use of the ARCH/GARCH models, leading to the use of the SWARCH (Cai, 1994; Hamilton & Susmel, 1994) to model the impact of the bubble on the behaviour of price volatility.

Gurkaynak (2008) explained that there are issues, both theoretically and empirically, underlining the econometrics tests for rational bubbles. As highlighted by Evans (1991), there have been many tests, like Blanchard and Watson (1982), which have found evidence that asset prices deviate from their fundamental values. According to Evans (1991), an alternative test for the bubble hypothesis is to analyse the stationarity properties. Furthermore, the existence of a type of bubble is found by the researcher, which cannot be detected using stationarity analysis. This leads to standard unit root and co-integration tests being unable to distinguish between stationary processes and periodically collapsing bubbles. As West (1987) states previous empirical studies were unable to detect bubbles, due to the tests being too few and not powerful enough. He uses the ARIMA model to analyse the bubbles. He finds that bubbles exist, using the Standard and Poor’s (S&P) 500 index (1871–1980) and the Dow Jones index (1928–1978).

Moreover, Philips, Shi, and Yu (2012) state that there is likelihood of multiple asset pricing bubbles in a long-time series. They test the possible existence of multiple bubbles by generalising the repeated right tailed augmented Dickey Fuller (ADF) test on the S&P 500 index from January 1871 to December 2010, and detected key historical bubbles including the stock market bubble of the 1920s and dotcom bubble of the 1990s.

3. The Markov Regime-Switching ARCH Model

The recent financial and sovereign debt crises have certainly resulted in uplift in the empirical studies of the Markov switching model in the sovereign debt market. Some of the relevant studies are conducted by Georgoutsos and Migiakis (2009, 2010, 2012); Pozzi and Sadaba (2013); and Schuster and Uhrig-Homburg (2012); Yildirim (2015); Marieta (2014). Most of the recent research is around the sovereign debt crisis and financial crisis effect on the eurozone sovereign debt market to a lesser extent. It has been clear that the financial markets sometimes go through alternate periods, characterised by high volatility and others by low volatility as mentioned by Hamilton and Susmel (1994) and Cai (1994). Hamilton (1988) conducted research on monthly short-term interest rates and concluded
the possible presence of regime shifts in ARCH effects could explain the estimates of the ARCH model of Engle et al. (1987). In fact, a common problem in the estimation of ARCH/GARCH is spurious high persistent of volatility across subsamples as stated by Hamilton and Susmel (1994). However, sometimes simple ARCH/GARCH models do not entirely explain volatility; therefore, a combination of the regime-switching capabilities of the MS model with conditional volatility models such as ARCH/GARCH is needed. As noted by Cai (1994), a key factor in the use of SWARCH is the indigenisation of parameter shifts, thus allowing shifts to be determined by the observed data set. Additionally, a key advantage is that it distinguishes between the effects enabling the analysis of their impact on the properties of the observed data set. This lead to several studies by Cai (1994), Hamilton and Susmel (1994) and Hamilton and Lin (1996) to use integrated models generally referred to as SWARCH. As the name suggests the SWARCH model was a combination of MS and ARCH. Gray (1996) introduced a GARCH version of the SWARCH in analysing the regimes switching behaviour of one-month volatility of the US T-Bill yield and found a mean reverting high volatility with low volatility persistence. He also finds the opposite behaviour with a non-mean reverting low volatility state with high volatility persistence. Although the MS-GARCH models seem to produce stronger results than the SWARCH model, yet as discussed by Cai (1994), the intricacy of the estimation in integrating a GARCH with the Markov switching model makes it less feasible in large data sets. Moreover, it can be an advantage for research such as the one influenced by Cai (1994) and Hamilton and Susmel (1994) in highlighting that the high volatility persistence observed in some research is the result of regime switch. On the other hand, the use of a Markov Switching model could overstate the high volatility persistence displayed in a GARCH model.

The literature on the empirical evidence of SWARCH model in sovereign debt market is lesser when compared with other models. Christiansen (2008), conducted research by SWARCH implementation on the yields using the Cai (1994) method. However, Abdymomunov (2013) applied SWARCH using the Hamilton and Susmel (1994) method to study the returns. Furthermore, Christiansen (2008) extended the Cai (1994) implementation of the SWARCH model to a bivariate model in order to estimate the volatilities of US and UK and US and German markets simultaneously. Abdymomunov (2013) extends the Hamilton and Susmel (1994) model to a multivariate SWARCH model to study the impact of financial distress from huge changes in the volatility of key financial variables on the US financial market and found that the joint variables regime-switching model could be a possible indicator of financial distress. As pointed out by Blanchard and Watson (1982) and Branch and Evans (2011, 2013), a possible method of interpreting behavioural finance is using the GARCH family.

Model specification Hamilton (1989) introduced a two-state 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), is illustrated in the following equation:

\[ y_t = \omega_{s_t} + \alpha_{s_t} y_{t-1} + \epsilon_t \]

\[ s_t = \begin{cases} 
1 & \text{if low volatility} \\
2 & \text{if high volatility} 
\end{cases} \]
Although, as Hamilton notes, volatility seem to be following a high-low switching model, and there is a lack of evidence to the SWGARCH (i.e., Switching GARCH) models. Due to issues regarding the complexity (see Cai, 1994; Guidolin, 2012), and the high persistency in the volatility (see Guidolin, 2012); we follow Christiansen (2008) and Abdymomunov (2013) in using a SWARCH model instead of a SWGARCH, with the ARCH model of Engle (1982) to derive the volatility. The following equation uses a single lag ARCH model as proposed by Engle (1982):

\[ h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 \]

where \( h_t = \sigma_t^2 \)

The simplicity of the SWARCH model is that it is a combination of the Hamilton (1989) Markov Switching model and ARCH model of Engle (1982). We use the SWARCH model of Cai (1994) to interpret 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. The SWARCH model is stated below:

\[ h_t = \omega_0 + \omega_1 s_t + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \]

\[ s_t = \begin{cases} 
1 & \text{if low volatility} \\
2 & \text{if high volatility} 
\end{cases} \]

The key to the Cai (1994) SWARCH model is the ARCH intercept. By analysing the ARCH intercept for each of the regimes, we could get an idea of the volatility in each regime.

4. Empirical evidence

In order to provide empirical evidence on the impact of behaviour of price volatility on the US sovereign debt market, 10-year notes are observed from 1 July 2002 to 31 December 2011 and from 1 July 2007 to 31 March 2013. We use the daily 10-year sovereign debt, maturing in 2012, end-of-day bid prices for US obtained from Bloomberg. 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 US bonds maturing in 2017. We follow the norm by defining our week as Monday to Friday. We substitute all missing observations with the last known price in order to make the observed data uniformed. The observed data sample is taken from 1 July 2007 to 31 March 2013 which makes a total of 1500 daily observations for the US sovereign debt market. Table 1 shows the 2012 and 2017 bonds with their reference numbers, issued and maturity dates.

The summary statistics, i.e., the mean, median, maximum/minimum values and standard deviation for the said bond data is presented in the Table 2.

<table>
<thead>
<tr>
<th>Bond</th>
<th>Reference Number</th>
<th>Download Date</th>
<th>Issue Date</th>
<th>Maturity Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>9128277L0</td>
<td>16/07/2012</td>
<td>15/02/2002</td>
<td>15/02/2012</td>
</tr>
<tr>
<td>2017</td>
<td>912828GH7</td>
<td>08/04/2013</td>
<td>15/02/2007</td>
<td>15/02/2017</td>
</tr>
</tbody>
</table>

Table 2. Summary statistics.

<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>105.3247</td>
<td>104.3031</td>
<td>107.6985</td>
<td>105.1213</td>
<td>112.1776</td>
<td>107.7516</td>
<td>115.2112</td>
</tr>
<tr>
<td>Median</td>
<td>105.6094</td>
<td>104.4844</td>
<td>108.6172</td>
<td>105.4219</td>
<td>112.8281</td>
<td>107.5938</td>
<td>116.2344</td>
</tr>
<tr>
<td>Maximum</td>
<td>114.5156</td>
<td>114.5156</td>
<td>112.7344</td>
<td>109.0156</td>
<td>120.1719</td>
<td>120.1719</td>
<td>119.6875</td>
</tr>
<tr>
<td>Minimum</td>
<td>98.26563</td>
<td>98.26563</td>
<td>99.20313</td>
<td>100.5625</td>
<td>95.70313</td>
<td>95.70313</td>
<td>107.7500</td>
</tr>
<tr>
<td>S.D.</td>
<td>3.277713</td>
<td>3.186893</td>
<td>2.976343</td>
<td>2.371351</td>
<td>5.464889</td>
<td>5.042972</td>
<td>3.206333</td>
</tr>
</tbody>
</table>

In order to test the stationarity of the data we use the ADF test of stationarity as proposed by Dickey and Fuller (1979, 1981). The key to understanding the ADF tests is in the test statistics, which must be lower than the test critical value at the chosen confidence level, which in our case is the 5% level. Under most circumstances, the prices are likely to be non-stationary at level order difference; hence, the prices tend to be differentiated to first and in some cases second order.

Table 3 illustrates results from the ADF test of stationarity in the prices of the observed US 2012 and 2017 government bonds. The results show that the observed data is stationary at the first order level.

As illustrated by Appendix 1, the observed data does not follow the normal distribution. The Jarque-Bera statistics point to a variation from the normal distribution for both price data sets. However, both price variance data sets do vary from the normal distribution by a significant amount as illustrated by the Jarque-Bera statistics. The Jarque-Bera statistics hint at the use of a different distribution model, e.g., t-student or Generalised Error.

Appendix 2 hints at the existence of structural breaks in both price data sets. The significant of these statistics is that both hints at the existence of five breaks in the prices of the sovereign debts. This has an effect on the estimation and the statistics. As illustrated by Appendix 3, due to existence of structural breaks, we need to use a special test for stationarity. The Lumsdaine-Papell test highlights two structural breaks and the stationarity statistics which seem to be hinting at the acceptance at the level order for both data sets.

A key rule for the efficient market hypothesis is that markets should follow the random walk model. Appendix 4 highlights the variance ratio test for both price data sets, the statistics seem to be suggesting a rejection of the random walk for all data sets and sub-data sets. This is important because it means that the prices do not follow the weak form efficient market hypothesis, hence there is a need to use the behavioural finance theory to explain the prices of the sovereign debt market. The forthcoming set of table and figures (Table 4, Figure 1 and Figure 2) depict the SWARCH statistics and graphical representation of the US 2012 and 2017 bonds, along with the high volatility regime for both 2012 and 2017 US bonds respectively.

The evidence from above mentioned table and figures certainly points towards the existence of a regime-switching behaviour influencing the pattern of price volatility in the US sovereign debt market. The figures illustrate the extent to which the sovereign debt market in general is highly volatile within the 2012 bonds. The 2012 bonds were associated with a period of changing market environment in the global financial market. While, the 2017 bonds are associated with a highly volatile period in the global financial market mainly due to the financial and consequent sovereign debt crises. Although, this in itself is interesting, mostly due to the differing impact on the observed market of each crisis; however, another influencing factor is the different impact from on the run and maturity effects on the financial and sovereign debt crises respectively. The extended observed period allows us to analyse the full impact of the sovereign debt crisis which may have influenced the

### Table 3. 2012 and 2017 price ADF unit root test statistics.

<table>
<thead>
<tr>
<th>ADF Test</th>
<th>Critical Value 5% Level</th>
<th>Level Order</th>
<th>1st Order</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>-2.866437</td>
<td>1.263962</td>
<td>-24.65435</td>
</tr>
<tr>
<td>2017</td>
<td>-2.863265</td>
<td>-2.772514</td>
<td>-31.16835</td>
</tr>
</tbody>
</table>

SWARCH model. With the US market approaching 1.0, it seems to be indicating that the US market was highly volatile throughout the observed period.

The persistence of the high volatility regime during the early stages of the US market observations was the result of a flight from the 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 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 limitations with the estimation of the SWARCH model, we had to limit our observed data set to 1 October 2012, which meant the full impact of the US fiscal cliff, and debt-ceiling crises on the US market was not captured.

5. Discussion and conclusion

The US market seems to be dictated by individual pattern of volatility. A relevant factor in our research is that the SWARCH model seems to be picking on the changing environment for the observed market. Since the US market was affected by a number of different factors.

The later stages of observed period were associated with the financial and sovereign debt crises, yet it was also governed by several 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. The quality and liquidity factors of the US market helps make it the benchmark market for both the dollar and euro currencies. This makes them prime markets for flights to safety during crises or extreme events. Another influencing factor in the US market is that the Basel II regulations to hold sovereign debt on their balance sheets as capital are a requirement of many financial institutions. Hence, many of these organisations choose to hold the US sovereign debt depending on their home currency.

Certainly, the SWARCH model seems to point to a regime-switching behaviour in the price volatility of the US sovereign debt market. In general, the high volatility regime in both the 2012 and 2017 bonds governed the SWARCH model. A relevant factor in our research is that SWARCH model seems to be picking up on the changing environment for the observed market.

Theory dictates that when bonds approaches maturity the price approaches the par value, this generally leads to low volatility, as the market participants tend to hold these bonds until they mature. In contrast, when the bond is issued, it is said to be on the run until another similar bond is issued. Theoretically, the expectation is these on the run sovereign debts are benchmark bonds, which means they are seen as liquid assets and to a certain extent risk free. This makes them very volatile since they have a high volume of trading at the initial stage. Another important issue is the policies of the governments and central banks during the resulting recession in the aftermath of the financial crisis (Alshubiri, 2015; Novickyté & Pedroja, 2015). Essentially, this links to the fiscal stimulus policies which increase and quantitative easing policies, which decrease the supply in the sovereign debt market, thus distorting the markets from their true value.

The events during the last few years led to a fast changing and highly volatile market environment, increasing uncertainty in the global financial market. Our empirical evidence highlights the fact that the fast-changing market environment had a big impact on the observed sovereign debt market. The evidence seems to suggest that the behaviour of price volatility changed significantly in the aftermath of both the financial and sovereign debt crises. As illustrated by the SWARCH graphs of the 2012 bonds, the pre-crisis period is evidence of how external events could change the market environment. In general, the observed market witnessed a flight to safety from other markets, which pushed the prices higher as market participants sought more liquidity and risk-free assets, obviously reflected
in the behaviour of price volatility during the financial crisis period in both 2012 and 2017 bonds.

Although the sovereign debt crisis did affect the US market in the form of the fiscal cliff and debt ceiling crises, the true impact was not felt until the later stages of the sovereign debt crisis. In general, the market environment can be an influential factor on the market participants in the global financial market. However, in a fast changing and highly volatile market environment, the interesting factor is the behaviour of market participants. Our empirical evidence seems to be suggesting that market participants tend to overreact or underreact to information and events depending on the general market environment. In general, market participants tend to overreact during a crisis period and underreact during a bubble period. The US market was suffering from the fiscal cliff and debt ceiling crises. A key factor is the assumption that the US government would not risk the consequences; another influencing factor is the crisis in the eurozone overshadowed the US crises. Of course, the crises did eventually have an effect on the US market with the closure of the US government; however, this was outside of our observations.

During the financial crisis, a possible explanation is available as to why the US market did not suffer from any negative effect on the price volatility. The Federal Reserve was implementing a huge quantitative easing policy, which distorted the market to a certain extent. An influencing behavioural factor is that during a crisis, market participants are highly reactive; this is the crucial factor influencing the market responses to the policy communication by many influential politicians.

In concluding, it is hard to capture the impact from the behaviour of volatility in a dynamic and highly volatile environment using one model. While this is true for any market, not just the sovereign debt market, yet the possible distortion of the sovereign debt market by factors other than market participants. Hence, the price may not be determined by the reaction of the market participants to information or news, it could be determined by supply side players, like the central banks and governments implementing extenuating policies such as quantitative easing or fiscal stimulus. In truth, these are rare and need special environmental circumstances like the recent financial crisis and following deep recession. Interestingly, it is these distortions that could provide one possible explanation to the efficiency of the market during the highly volatile environment of the financial and sovereign debt crises. However, another explanation is the idea of the overreaction/underreaction state whereby the market efficiency is determined by the reaction of the market participants cancelling each other out during any period. Essentially, this means that market participants reactions to information is a key factor whether the market is efficient or not.

On the whole, our findings seem to be hinting at many factors during a crisis, which determine the market efficiency and the behaviour of price volatility. However, the key factor is the market environment, which is backed by the results from the SWARCH models, since as hinted by Cai (1994) and Hamilton and Susmel (1994) financial markets go through alternate periods characterised by high and low volatility. Certainly, the past empirical evidence seems to hint at a link between the general market environment and the regime switches in high and low volatility. Our results are pointing to the fact that it is these volatility switches being linked with the changes in the general market environment with respect to each market.

There were some developments which influenced the sovereign debt market. These developments could have implications on our research, especially on the efficiency and behaviour
of volatility in our observed markets. Therefore, it will be interesting to widen our research to the impact of these developments, i.e., the shutdown and near default of the US government as discussed by Nippani and Smith (2014). The problem regarding the debt-ceiling crisis was that both sides of the US federal government could not agree to a compromise plan to raise the debt ceiling before the next payment was due which could have resulted in them defaulting. Hence, the US federal government effectively ran out of money and had to shut down from 1 October 2013 to 13 October 2013. The crisis saw the credit rating and hence price of US sovereign debt fall sharply to below 100 at one point. Importantly the price has since recovered. We suspect that mainly due to the overreaction/underreaction steady state the market could be efficient at present. However, in the immediate aftermath of the crisis we suspect that the market is likely to have suffered from overreaction making the market inefficient.

**Disclosure statement**

No potential conflict of interest was reported by the authors.

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**References**


Appendix

1. Test for normality.

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<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Skewness</td>
<td>0.006672</td>
<td>-0.682903</td>
<td>3.640635</td>
<td>4.599066</td>
</tr>
<tr>
<td>Kurtosis</td>
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2. Test for structural breaks.

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4. Variance ratio test of the random walk model.

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