ISCTE Business School
Instituto Universitário de Lisboa

DOES CONTAGION REALLY MATTER
Real role of Greece in the Sovereign Bond Crisis

Zongyuan Li

Dissertation submitted as partial requirement for the conferral of

Master in Finance

Supervisor:

Prof. António Manuel Rodrigues Guerra Barbosa, ISCTE Business School, Department of Finance

September 2015

Resumo: Este trabalho tem por objectivo identificar a eventual existência e a magnitude da influência do mercado de dívida pública Grega nos mercados de dívida pública de outros países da União Económica e Monetária (UEM) durante o período da Crise das Dívidas Soberanas. Em primeiro lugar, foram analisados os coeficientes de correlação dínamica entre as variações dos riscos de cauda das obrigações a 5 anos Gregas e as obrigações a 5 anos de outros três países da UEM (Itália, Espanha e França) usando o modelo Dynamic Conditional Correlation (DCC). Os resultados indicam a existência de um efeito de contágio nas correlações, embora as correlações tendam a diminuir, quando o risco de cauda das obrigações Gregas aumenta. Em segundo lugar, tentou-se distinguir entre interdependência e contágio entre as obrigações Gregas e as obrigações de outros países da UEM. Os resultados apontam para a existência de contágio nas obrigações de todos os países da UEM no dia seguinte à ocorrência de um evento de crédito nas obrigações Gregas, mesmo após a exclusão de efeitos de interdependência entre os mercados. No entanto, este efeito de contágio tendeu a desaparecer durante o período da Crisa das Dívidas Soberanas, especialmente para os países mais estáveis (Áustria, Bélgica, França, Alemanha e Holanda).

Abstract: The main purpose of this article is to identify the existence and extent of the influences of the Greek sovereign bond market on other European Economic and Monetary Union (EMU) countries' sovereign bond markets during the Sovereign Bond Crisis. First, we analyze the dynamic correlation coefficients between the percentage changes of the tail risks of Greek 5 year sovereign bonds and the 5 year sovereign bonds of other three EMU countries (Italy, Spain and France) using the Dynamic Conditional Correlation (DCC) model. We find volatility spillover exists between Greece and other EMU countries, but the overall correlation coefficients decrease, with the increasing tail risks of Greek sovereign bonds. Second, we distinguish between interdependence and shift contagion, and find that there were statistically significant shift contagions in all of the EMU sovereign bonds on the day after the Greek credit events, even after excluding the effects of interdependence, between 2006 and 2011. However, we also find that the statistically significant shift contagions in the short term disappeared during the Sovereign Bond Crisis, especially in stable countries (Austria, Belgium, France, Germany and Netherlands).

Key words: Value at Risk, Sovereign bond Crisis, contagion, volatility spillover

JEL Classification: C52, F30, G15

Contents

1. Introduction

The European Sovereign Bond Crisis in 2010 was, to some degree, triggered by the Subprime Crisis started in late 2007. And the Subprime Crisis forced regulators, investors, and rating agencies to reevaluate the risk of the traditional "risk-free" and "low risk" financial securities, among the sovereign bonds of the European Economic and Monetary Union countries.

Most European countries were seriously affected by the Sovereign Bond Crisis, in particular Greece, Ireland, Italy, Portugal and Spain (GIIPS). These countries, with huge stocks of sovereign debt, rampant budget deficits and stagnated economies, began, one by one, to lose the trust of investors in the bond market once the latter realized that not all Euro-denominated bonds were alike. This meant that GIIPS countries faced major difficulties to secure new funds in the bond market and soaring yield rates. Eventually, some of these countries lost the ability to issue new debt at sustainable interest rates, forcing them to secure their financing needs through a rescue plan by the European Union (EU), the European Central Bank (ECB) and International Monetary Fund (IMF), jointly known as the "Troika". In return, the rescued countries had to cut down the government expenditure and make structure reforms in order to create the conditions to return to a path of economic growth, thus reconstructing the confidence of financial markets. Not surprisingly, the difficulties spilled to the private sector, which also faced major difficulties in seeking funds from the banking sector and from the global financial market, and soaring interest rates. Furthermore, the big cuts in the government expenditure in the rescued countries and everywhere else in the EU, resulted in unemployment and recession, which put even more pressure on the government budgets, fueling a vicious circle of austerity, unemployment and recession that eventually spread across almost all countries in the EU.

This transmission of financial difficulties across regions is a typical symptom in recent large financial crisis. It was the case in the US stock market crash of 1987 (Black Monday), the speculative attacks on currencies in European Exchange Rate Mechanism between 1992 and 1993, the Asian financial crisis of 1997, the dot-com Bubble of 2001, the Subprime Crisis between 2007 and 2008 and the European Sovereign Bond Crisis of 2010.

When it comes to EMU sovereign bond market, the existence of risk contagion is well documented in the literature. Even before the Subprime and Sovereign Bond Crisis, Clare and

Lekkos (2000) and Skintzi and Refenes (2006) showed the evidence of volatility spillover among the European sovereign bonds.

Following the Sovereign Bond Crisis, this topic gathers renewed interest. Missio and Watzaka (2011), Contancio (2012), Mink and Haan (2012), Kalbaska and Gatkowski (2012), Audige (2013), Buchholz and Tonzer (2013), Gunduz and Kayay (2013), and Elkhaldi, Chebbi and Naoui (2013) all tried to identify the contagion of the Sovereign Bond Crisis from different perspectives and to point out the root cause for the contagion.

Missio and Watzaka (2011) found that there is a positive correlation between Greek sovereign Credit default swaps (CDS) spreads (the differences between Greek sovereign CDSs and German sovereign CDSs) and those of the rest European countries', Kalbaska and Gatkowski (2012) revealed that there is a significant effect from the CDS spreads of debt of GIIPS to the CDS spreads of France, Germany and the UK between 2005 and 2010. Audige (2013) highlighted the contagion effects from Greece to Ireland and Portugal in 2010.

Most of the previous articles focus on CDS, since, in theory, CDS should reflect the market expectation of the default risk. However, CDS is not the best choice to objectively estimate the tail risks. Before 2008, all of the CDS transactions had to be done in the over-the-counter (OTC) market, and dealers did not need to publish market information. Only after November of 2008, because of the intense pressure by regulators, did the Depository Trust & Cleaning Corporation, which accounted for around 90% of the CDS market, start to release their CDS trades data on a weekly basis. In contrast, investors could easily access to the daily date of interest rates of sovereign bond market. All in all, the CDS market was neither transparent nor standardized before the Subprime Crisis. But more worryingly, it is questionable whether the CDS contracts were fairly priced, as the American International Group (AIG) episode demonstrated. AIG, the biggest CDS issuer during the Subprime Crisis, would go bankrupt due to the abrupt eruption of liquidity crisis caused by a sudden increase of collateral requirement of their CDS positions, if it could not receive the $182.3 billion bailout from the Treasury and the Federal Reserve Bank of New York.

In contrast, Value at Risk (VaR) is the generally accepted method to measure market risks, especially for financial institutions. It is the only acceptable internal market risk valuation model in BASEL III, and it even comes to be a worldwide standard model to quantify the market risk in financial institutes[1]. For example, the EU had already applied the Capital Requirements Directive IV package to implement BASEL III agreement on January 1st, 2014, and the EU will also add some new provisions between 2014 and 2019. In the US, the Federal Reserve announced in 2011 that it would implement BASEL III rules.

Besides, VaR is also a widely used measure when analyzing the risk contagion and co-movements of systematic risks. For example, Reboredo and Ugolini (2014) tested the difference between co-movements of the systematic risks of European sovereign bonds before and after the Sovereign Bond Crisis by a CoVaR model; Polanski and Stoja (2014) analyzed the co-dependence of extreme events in Foreign Exchange markets by a Multidimensional Value at Risk model. Also, VaR is a popular measure to identify the credit events in previous articles. Nevertheless, no one, to the best of our knowledge, has analyzed the relation between the VaR of different sovereign bonds, thus we would like to fill in this blank.

In this paper, we estimate the market risk of each European sovereign bond market with $\mathrm{VaR}_{j,1,99\%}$, which is the loss that security j will not excess within 1 day, at 99% confidence level.[2] Since VaR is the basis of the whole analysis, our first step is to review the prevailing VaR models and find the most appropriate model to estimate VaR of EMU sovereign bonds. In section 3, we put several VaR models through a battery of tests and choose the most appropriate model to estimate the VaR of the EMU sovereign bonds with a punishment scorecard based on those tests.

After completing the estimations of the VaR of each sovereign bond, we use a Dynamic Conditional Correlation (DCC) model to analyze daily dynamic correlation coefficients between the percentage changes of VaR of Greek sovereign bonds and other sovereign bonds. The DCC model was first introduced by Engle (2002) as a simplified extension of traditional multivariate GARCH model, and then became the main methodology to identify risk spillover effects among

[1] Relation between Value at Risk and the Capital Requirement in BASEL III
$\mathrm{c_t} = \max\{\mathrm{VaR}_{t-1,10,99\%}; \mathrm{m_c} \times \mathrm{VaR_{avg}}\} + \max\{\mathrm{sVaR}_{t-1,10,99\%}; \mathrm{m_s} \times \mathrm{sVaR_{avg}}\}$
where $\mathrm{c_t}$ is the capital requirement at time t; $\mathrm{VaR}_{t-1,10,99\%}$ is the Value at Risk at time t-1, at the confidence level 99%, and period 10 days. $\mathrm{VaR_{avg}}$ is the mean of last 60 days VaR at the confidence level 99% and period 10 days; $\mathrm{sVaR_{avg}}$ is the stressed Value at Risk at time t-1, at the confidence level 99%, and period 10 days. $\mathrm{sVaR_{avg}}$ is the mean of last 60 stressed VaR at the confidence level 99% and period 10 days; $\mathrm{m_c}$ and $\mathrm{m_s}$ are the multiplication factors decided by supervisory authorities basing on the quality of VaR system, with a minimal value 3.
[2] Even though there is not a general scaling rule for all kinds of distributions. The scaling rule in BASEL III is straight forward: $\mathrm{VaR}_{j,t,1,99\%} = \sqrt{10}\mathrm{VaR}_{j,t,10,99\%}$ Thus, $\mathrm{VaR}_{j,t,1,99\%}$ is closely related to the daily capital requirement.

countries. For instance, the DCC model was used by Missio and Watzaka (2011), and Elkhaldi, Chebbi and Naoui (2013) to analyze the pattern of risk spillover effects between EMU countries during the Sovereign Bond Crisis.

In section 4, we apply the DCC model to estimate daily correlation coefficients and test how the VaR of Greek sovereign bonds influence the correlation coefficients between the percentage changes in the VaR of Greece and other countries (France, Italy, and Spain). We find, in general, that the correlation coefficients between percentage changes in the VaR of Greek and another countries' sovereign bond tend to decrease, when the VaR of Greek sovereign bonds increase. And most of those decreases are statistically significant even though there are sporadic reversals.

Contagion, however, is commonly defined as an increment in cross-market linkages after a credit event in one country. But analysis based on the DCC model cannot test whether contagion exists after Greek credit events. Besides, the DCC model cannot help us distinguish "true" contagion from interdependence during crises. Kaminsky and Reinhart (2000) conceptually distinguished international financial crisis transmission through fundamentals-based channels and "true" contagion. After that, Forbes and Rigobon (2001, 2002) drew a distinction between contagion and interdependence and found that the evidence of contagion during 1987 U.S. stock market crash, 1994 Mexican Peso Devaluation, 1997 Asian Financial Crisis disappeared after adjusting heteroscedasticity bias.

As mentioned above, we need to identify and test the existence of "real" contagions in other EMU countries, following a credit event in Greek sovereign bonds. Hence, in Section 5, we regress the percentage changes of VaR of other EMU countries on global financial factors, country specific factors and also credit events of Greek sovereign bond market.

As Sy (2004) suggested, to be more comprehensive, credit events should be defined as distressed debt events rather than just defaults, since sovereign bonds can avoid default by bilateral or multilateral support. In this paper, we consider credit events as the extreme events in the lower tail of the sovereign bond's profit and loss distribution, measured by $\mathrm{VaR}_{j,99\%}$.

Since global factors capture the interdependence caused by global financial market and country-specific factors capture the influences of local substitutive markets, the coefficients of the Greek credit events indicators should reflect the extent of the shift contagions in other EMU sovereign bonds, given the condition that there is a Greek credit event. In the end, we find that "real" contagions exist in all of other EMU countries' (Austrian, Belgian, French, German, Italian, Dutch, Portuguese and Spanish) sovereign bonds before the Sovereign Bond Crisis. But the shift contagion disappears in the short term, especially in the stable countries (Austria, Belgium, France, Germany and Netherlands) during the Sovereign Bond Crisis.

The rest of this thesis proceeds as follows, Section 2 shows that the correlation coefficients between base point changes in sovereign bond yields are different from the correlation coefficients between the VaR of sovereign bonds, thus we cannot use the first correlation coefficients measure as a proxy to the second correlation coefficients measure. Subsequently, in Section 3, we select the most appropriate VaR model for EMU sovereign bond market using a punishment scorecard based on a battery of back tests. Section 4 presents the analysis of the pattern of dynamic correlation coefficients between Greece and some other countries. Section 5 distinguishes between "true" contagion and interdependence. And Section 6 summarizes the evidence and inferences made throughout the thesis.

2. Can the correlation between base point changes in bond yields represent the correlation between percentage changes of VaR of bonds?

If the dynamic correlation coefficients between base point changes in bond yields of every two EMU sovereign bonds can efficiently represent the daily correlation coefficients between percentage changes of VaR of those two EMU sovereign bonds, then there is no benefit in focusing our analysis on the VaR. In fact, under such circumstances, using the VaR would just introduce a second layer of estimation risk. Since the goal of section 4 is to identify and analyze the pattern of the correlation coefficients between the tail risks of Greek sovereign bonds and other EMU sovereign bonds, we want to test whether the correlation coefficients between base point changes in bond yields could efficiently represent the correlation coefficients between the percentage changes of bonds' VaR.

As we have discussed in the introduction, CDS is not an appropriate proxy to represent the tail risks of sovereign bond market, because of the lack of transparency and regulation in the CDS market. Therefore, we use the Value at Risk of 5 year Generic Government Rates as a better proxy for the tail risks of EMU 5 year sovereign bond market.

To estimate the tail risks of EMU sovereign bond market, we use the prevailing VaR model, EWMA volatility adjusted historical simulation, proposed by Hull and White (1998), the VaR model that works best in EMU sovereign bond market according to our discussion in section 3 .[3]

We generate two series of correlation estimates between sovereign bonds, one for base point changes in bond yields, the other for the percentage changes of bonds' VaR, using a rolling window of 10, 20 or 30 days.

To examine whether there are significant differences between those two correlation coefficients measures, we calculate the daily difference, $d_{ij,t}$, as equation 1 shows.

$$\mathbf{d_{ij,t} = \hat{\rho}_{ij,t,bp} - \hat{\rho}_{ij,t,VaR\%}} \quad \mathbf{(1)}$$

where $\hat{\rho}_{ij,t,bp}$ is the correlation coefficient between country i's and country j's base point changes in bond yield at time t; and $\hat{\rho}_{ij,t,VaR}$, is the correlation coefficients between the percentage changes of the VaR of country i's and country j's bonds at time t.

Figure 1: Differences between two different correlation measures

The correlation coefficients between base point changes in bond yields and percentage changes of the VaR of German and Italian sovereign bonds are estimated using a rolling window of 10, 20, and 30 days, respectively, ($\hat{\rho}_{Germany,Italy,t,bp}$ or $\hat{\rho}_{Germany,Italy,t,VaR}$, $t = 2006/Jan/2$ to $2013/Dec/31$) as in the graphs V(A) and V(B).[4] Since we estimate the daily correlation coefficients by the rolling window method, we do not have valid correlation coefficients at beginning 10, 20 or 30 days, respectively.

Graphs I, II, and III, depict the daily differences between the correlation coefficients between base point changes of the German and Italian sovereign bond yields and the correlation coefficients between the percentage changes of the VaR of those two markets with window size 10 days, 20 days and 30 days, respectively. $d_{Germany,Italy,t} = \hat{\rho}_{Germany,Italy,t,bp} - \hat{\rho}_{Germay,Italy,t,VaR}$.

---

[3] We will introduce the details of this method in section 3. And the brief idea of this method is to adjust the historical base point changes by current variance and historical variance, and estimate daily VaR by last 500 volatility adjusted base point changes and the risk exposure (present value of 1 base point change).

$$bp^*_{j,t} = \sigma_{j,T}\frac{bp_{j,t}}{\sigma_{j,t}}$$

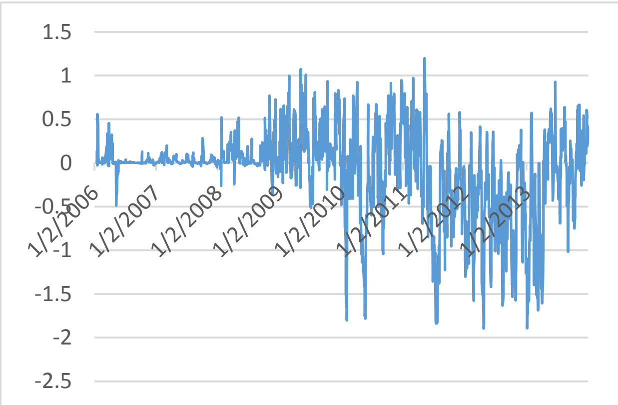
Where $bp_{j,t}$ is the historical base point changes of security j at time t; $\sigma_{j,t}$ is the historical daily standard deviation of base point changes of security j at time t; $\sigma_{j,T}$ is the daily standard deviation of base point changes of security j at target time T; $bp^*_{j,t}$ is the adjusted historical base point changes of security j at time t;
Daily variance is estimated by EWMA method, $\sigma^2_{j,t} = \lambda\sigma^2_{j,t-1} + (1-\lambda)\,bp^2_{j,t-1}$, where $\lambda = 0.94$

[4] The window size of 5 year Generic Government Rates are between 2003 Jan 2nd and 2013 Dec 31st, but we have used first 3 years data to stabilize EWMA model, and valid sample size begins in 2006 Jan 2nd

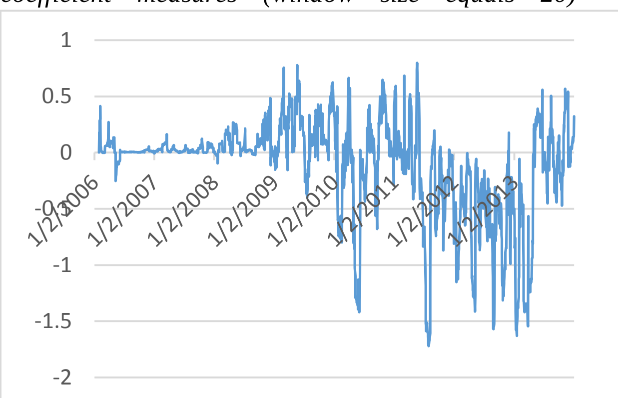
Graph IV depicts the Value at Risk of German and Italian 5 year sovereign bonds. VaR is estimated by EWMA volatility adjusted historical simulation proposed by Hull and White, where $\lambda = 0.94$

Graphs V (A) and V (B) depict the correlation coefficients between base point changes in bond yields and the percentage changes of the VaR of German and Italian 5 year sovereign bonds, respectively.

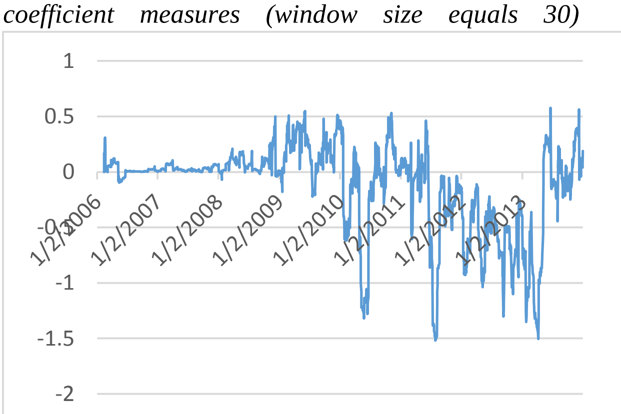
Graph I: the differences between correlation coefficient measures (window size equals 10)



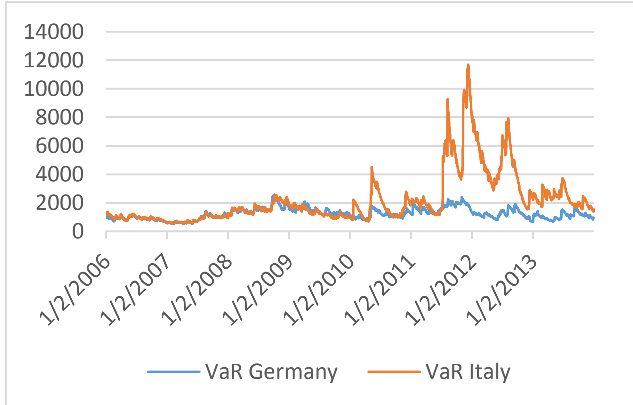
Graph II: the differences between correlation coefficient measures (window size equals 20)



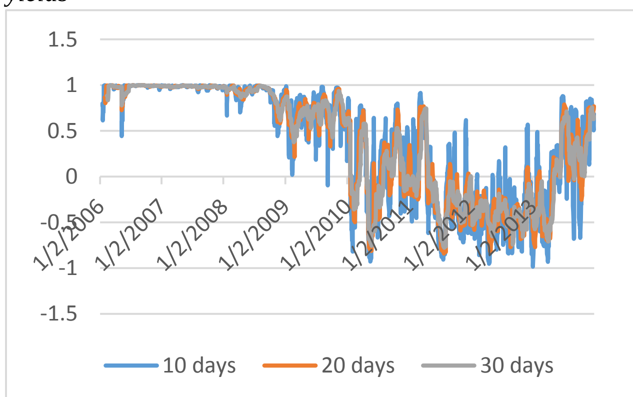
Graph III: the differences between correlation coefficient measures (window size equals 30)



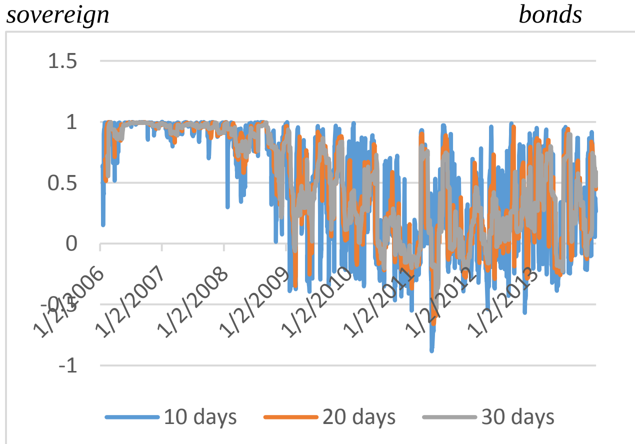
Graph IV: Value at Risk of German and Italian 5 year sovereign bonds



Graph V(A): the correlation coefficients between base point changes of German and Italian Sovereign bond yields



Graph V (B): the correlation coefficients between percentage changes of VaR of German and Italian sovereign bonds



As we can see from Graph I to III of Figure 1, before 2008, two correlation coefficient series track each other quite well. The differences between those two correlation coefficient series seldom deviate from 0. We can also reach a same conclusion by observing Graph V (A) and V (B) of Figure 1, where we can see that the correlation coefficients are always close to 1. Meanwhile, the VaR of German and Italian sovereign bonds are low and stable throughout that period of time, as we can see from Graph IV of figure 1.

Between 2008 and 2009, the differences become more volatile as we can observe from Graph I to III of Figure 1. According to the Graph V (A) and V (B) of Figure 1, the volatility of the correlation coefficients between the percentage changes of the VaR is larger than the volatility of the correlation coefficients between base point changes in bond yields. During those two years, the VaR of German and Italian sovereign bonds have nearly doubled, but those two correlation coefficients series still track each other to some degree, as Graph IV of Figure 1 shows.

Nevertheless, after 2010, when the VaR of Italian sovereign bond is soaring, the differences between those two correlation coefficients measures become very volatile.

All in all, the differences between those two correlation coefficients measures are significant, if the tail risks of either or both of the sovereign bonds are high.

The reason why we could observe such situation could be that VaR will accumulate the effects of recent base point changes in bond yields. Thus, those two correlation coefficients series would be different from each other, especially during the financial turmoil.

We could also draw similar conclusions when analyzing the correlation coefficients between German and Belgian 5 year sovereign bonds, German and Austrian 5 year sovereign bonds, German and Greek 5 year sovereign bonds, and Greek and Italian 5 year sovereign bonds. Thus, it is a general case for the EMU sovereign bond market rather than a specific case for some specific EMU countries.

To complement the evidence from Figure 1, we can also verify whether those two correlation coefficients measures are statistically different from each other using paired t tests in the overall sample period and each subsample period.

The null hypotheses of the paired t tests are that the correlation coefficients between base point changes are equal to the correlation coefficients between percentage changes of VaR, $\hat{\rho}_{ij,t,bp} - \hat{\rho}_{ij,t,VaR} = 0$.

With a single exception between Greek and German sovereign bonds between 2006 and 2013 with the rolling window 10 days, we always reject the null hypothesis at 99% confidence level as Table 1 shows.

Table 1: Paired t test of two correlation coefficients measures

We divide the overall sample period into three subsample, 2006 Jan. - 2007 Dec., 2008 Jan. - 2009 Dec., and 2010 Jan. - 2013 Dec since we have found in previous subsection the differences are relatively small in the first two years, volatile in the second two years, and nearly irrelevant in last three years.

In following table, we report the average of difference between two correlation coefficient measures and also report the result of paired t tests. The null hypothesis of each paired t test is that the correlation coefficients between base point changes of two sovereign bonds equal the correlation coefficients between percentage changes of the VaR of those two sovereign bonds, $\hat{\rho}_{ij,t,bp} - \hat{\rho}_{ij,t,VaR} = 0$. *, **, and ***, mean to reject the null hypothesis at 10%, 5%, and 1% significant level, respectively.

In both measures, correlation coefficients are calculated by last 10, 20 and 30 days and report in Difference_10, Difference_20 and Difference_30, respectively.

Time period	Countries	Difference_10	Difference_20	Difference_30
2006 Jan - 2013 Dec	Germany & Italy	-0.10***	-0.12***	0.13***
	Germany & Belgium	0.10***	0.09***	0.10***
	Germany & Austria	0.10***	0.11***	0.12***
	Greece & Germany	-0.02*	-0.01***	-0.06***
	Greece & Italy	0.11***	0.11***	0.10***
2006 Jan - 2007 Dec	Germany & Italy	0.02***	0.02***	0.02***
	Germany & Belgium	0.04***	0.03***	0.03***
	Germany & Austria	0.04***	0.04***	0.04***
	Greece & Germany	0.03***	0.03***	0.03***
	Greece & Italy	0.03***	0.03***	0.03***
2008 Jan - 2009 Dec	Germany & Italy	0.17***	0.14***	0.14***
	Germany & Belgium	0.10***	0.10***	0.11***
	Germany & Austria	0.08***	0.07***	0.07***
	Greece & Germany	0.11***	0.11***	0.12***
	Greece & Italy	0.10***	0.09***	0.09***
2010 Jan - 2013 Dec	Germany & Italy	-0.28***	-0.32***	-0.33***
	Germany & Belgium	0.14***	0.12***	0.12***
	Germany & Austria	0.13***	0.16***	0.17***
	Greece & Germany	-0.17***	-0.25***	-0.30***
	Greece & Italy	0.19***	0.18***	0.17***

Even though, before 2008, the correlation coefficients between base point changes in bond yields and the correlation coefficients between percentage changes of VaR could track each other quite well as in Graph I to III of Figure 1, and we can still reject the null hypothesis as in Table 1, because the variances of those differences are also small.

After 2008, when the VaR of individual sovereign bonds is increasing and even soaring after 2010, we can observe that both correlation coefficient series fluctuate a lot as in Graph V (A) and V (B) of Figure 1, and the differences between those two correlation coefficients measures are always statistically different from 0.

Only one exception happens between Greece and Germany with the rolling window 10 days, where we can only reject the null hypothesis that the differences between the correlation coefficients measures equal 0 at 10% significant level. However, we reject the null hypothesis in any of the subsample, thus the failure of rejection is due to the increasing variance after 2008.

We can conclude that the correlation coefficients between base point changes in bond yields and the correlation coefficients between the percentage changes of the bonds' VaR are significantly different from each other all the time. Hence, we should estimate the VaR of each security first, and then analyze the correlation coefficients between VaR of Greek sovereign bonds and another EMU sovereign bonds.

3. Choosing the appropriate VaR to measure tail risk

Even though the VaR is a commonly accepted way to measure the market risk, there are still some differences among VaR models and distributional assumptions. The majority of these differences falls into one of the following categories: i) the model to forecast variance; ii) the distribution of standard errors or returns; iii) the explanatory variables in the model.

Because of those differences, the VaR estimates obtained from different models can be very different from each other. Beder (1995) applied 8 common VaR methodologies to three hypothetical portfolios, and found that the estimated VaR from one model could as much as 14 times bigger than the VaR estimated with other models. At best there is an appropriate VaR model for each asset with a certain confidence level and at a certain time period. So, in this section, we briefly review the existing VaR models and choose the appropriate VaR model for the EMU sovereign bond market using a comprehensive set of tests.

3.1 Brief summary of common VaR models

The most popular VaR models are parametric VaR models. The underlying assumption is that returns follow a parametric distribution with some determined parameters. The major differences among models are the parametric distribution in questions, and the way their parameters are estimated, in particular the variance.

In terms of methods to estimate the variance, the simplest method is equally weighted method. In this method, the current variance, $\boldsymbol{\sigma_t^2}$, is estimated using the last k observations as follows.

$$\begin{cases} \boldsymbol{\sigma_t^2 = \dfrac{\sum_{t-1}^{t-k-1}(r_i - 0)^2}{k}} \\ \boldsymbol{r_t \sim i.i.d.\left(0, \sigma_t^2\right)} \end{cases} \qquad (\mathbf{2})$$

Usually, we assume the distribution of returns has zero mean and estimate the dynamic variance, σ_t^2 by equation 2. Then we specify the distribution of r_t, commonly standard normal or student t distribution, and the VaR at 99% confidence level ($VaR_{99\%}$) is equal to the 1st percentile of the profit and loss distribution.

The second method to estimate the variance is the GARCH model. ARCH models were first introduced by Engle (1982) and Bollerslev (1986) and gradually developed into a family of GARCH models, including, for example, the EGARCH introduced by Nelson (1991), the TGARCH introduced by Zakoian (1994) and the GJR introduced by Glosten et al (1993).

Even though GARCH (p, q) is theoretical reasonable, Bollerslev, Chou and Kroner (1992) proved that GARCH (1,1) as in equation 3 could already satisfy our needs in estimating the variance of financial data.

$$\begin{cases} \boldsymbol{r_t = \sigma_t \varepsilon_t \qquad \varepsilon_t \sim i.i.d.(0, 1)} \\ \boldsymbol{\sigma_t^2 = \beta_0 + \beta_1 y_{t-1}^2 + \beta_2 \sigma_{t-1}^2} \\ \textbf{Where } \boldsymbol{\beta_0, \beta_1, \beta_2 > 0, \beta_1 + \beta_2 < 1} \end{cases} \qquad (\mathbf{3})$$

There are two critical assumptions in this model: the variance estimating equation is appropriate, and the standardized residuals are independent and identically distributed.

In addition, we need to specify the distribution of ε_t, commonly standard normal or student t distributions, in order to estimate the GARCH parameters by maximizing log-likelihood function. The VaR is then calculated as previously explained.

The third method to estimate the variance is Exponential Weighted Moving Average (EWMA) approach, which is a special empirical case of GARCH model and promoted by RiskMetrics introduced by a technology group of J.P. Morgan (1996).

$$\begin{cases} \boldsymbol{\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)r_{t-1}^2} \\ \boldsymbol{r_t \sim i.i.d.\left(0, \sigma_t^2\right)} \end{cases} \quad \boldsymbol{(4)}$$

To estimate the variance, λ is usually set to a value of 0.94 or 0.97.[5]

As an alternative to the parametric VaR models, we have Historical VaR models. In these models, the underlying assumption is that returns follow the historical distribution.

The most basic method in this category is the simple historical simulation. In this method, we first choose a sample size, commonly from six months to two years. Then sort portfolio returns within this sample from the worst to the best returns and use $(1-\theta)$ percentile as $\mathrm{VaR}_{\theta\%}$. In this method, every observation within the window is given an equal weight, thus the estimations are biased, because of the changing volatility.

Boudoukh, Rishardson and Whitelaw (1998) proposed the Hybrid Historical Simulation to improve the simple historical simulation model.

In this method, each return in the sample, $r_t, r_{t-1}, r_{t-2} \dots$, is associated to a different exponentially decaying weight, $\frac{1-\lambda}{1-\lambda^k}, \left(\frac{1-\lambda}{1-\lambda^k}\right)\lambda, \left(\frac{1-\lambda}{1-\lambda^k}\right)\lambda^2, \dots$ The returns are sorted from the worst to the best, and the VaR estimate is obtained by summing the corresponding weights until reaching $1-\theta\%$ (one minus confidence level). In this method, Boudoukh, Rishardson and Whitelaw (1998) use 0.97 and 0.99 as λ.

In addition, Hull and White (1998) introduced the volatility adjusted historical simulation methods which adjust historical returns as in equation 5.

---

[5] Fleming, Kriby and Ostdiek (2001) found the optimal decay factor, λ, for daily time series data close to 0.94 and for monthly time series data close to 0.97.

$$\mathbf{r}^*_{\mathbf{j,t}} = \boldsymbol{\sigma}_{\mathbf{j,T}} \frac{\mathbf{r}_{\mathbf{j,t}}}{\boldsymbol{\sigma}_{\mathbf{j,t}}} \quad (\mathbf{5})$$

where $\sigma_{j,T}$ is the most recent GARCH/EWMA estimate of the daily standard deviation of returns, basing on available information at the end of day T-1; $\sigma_{j,t}$ is the historical GARCH/EWMA estimate of the daily standard deviation of returns, basing on available information at the end of day t-1. After assuming the probability distribution of $r_{j,t}/\sigma_{j,t}$ is stationary, we could replace historical returns ($r_{j,t}$) by adjusted historical returns ($r^*_{j,t}$), and then $\mathrm{VaR}_{\theta\%,T}$ equals $1 - \theta\%$ percentile of historical distribution of $r^*_{j,t}$.

As a third set of VaR models we have the Direct VaR models, which estimate the VaR directly from some explanatory variables. The most popular member of the Direct VaR model family is the Conditional Autoregressive VaR (CAViaR), introduced by Engle and Manganelli (2004). The CAViaR model directly forecasts the VaR over time, without specifying the distribution of returns as equation 6 shows.

$$\mathbf{VaR}_{\mathbf{t,\theta\%}} = \boldsymbol{\beta}_{\mathbf{0}} + \boldsymbol{\beta}_{\mathbf{1}}\mathbf{VaR}_{\mathbf{t-1,\theta\%}} + \mathbf{l}\left(\boldsymbol{\beta}_{\mathbf{2}}, \dots, \boldsymbol{\beta}_{\mathbf{p}}, ; \boldsymbol{\Omega}_{\mathbf{t-1}}\right) \quad (\mathbf{6})$$

where Ω_{t-1} is the information set available at time t.

However, all of previous models have their pros and cons.

First, the main advantage of parametric VaR models is that they allow the variance of financial returns to be varying across time, which is a generally accepted fact in financial market. Besides, we can obtain a complete characterization of the continuous distribution of financial returns, which can be used to estimate different risk measures, like expected tail loss, VaR at different confidence level and semi-variance. On the other hand, equally weighted method, GARCH and RiskMetrics models are all subject to three sources of misspecifications: i) the variance estimating equation could be misspecified; ii) the distribution of standardized residuals chosen to build log-likelihood function could be wrong; iii) the standardized residuals may not be independent and identically distributed. In addition, even though we could have better flexibility on tails by using a student t distribution or a generalized error distribution rather than a normal distribution, the limited number of observations on tails and the outliers would reduce the accuracy of the tail estimation.

When comparing with parametric VaR models, historical simulation do not need a specific distribution of returns and historical distribution has a naturally negative skewness and higher kurtosis than normal distribution, but both simple historical simulation and Hybrid Historical Simulation cannot reflect current market volatility. Because of the drawback in adjusting dynamic market volatility of historical simulation methods, Hull and White (1998) proposed the volatility adjusted historical simulation method, and proved that this method could outperform simple historical simulation and Hybrid Historical Simulation when estimating VaR at 99% confidence level, using the historical data of foreign exchange market and equity market.

Direct VaR models are straight forward, but they reply on a complete set of independent variables, which could be varied from market to market and even from time to time.

Since we do not have enough empirical results to support a direct VaR model to estimate sovereign bonds and Hull and White(1998) proved that volatility adjusted historical simulation could outperform other historical VaR models, in this paper, we compare several parametric models (RiskMetric, GARCH and GJR model) with corresponding volatility adjusted historical simulations to test whether volatility adjusted historical simulation could also outperform the parametric methods and to choose an appropriate model to estimate VaR at 99% confidence level in EMU sovereign bond market.

In sovereign bond market, investors could easily access the base point changes of bond yields instead of the returns in equity market, thus we usually use Present Value of a base point decrease (PV01) as risk exposure and adjust VaR estimation process as follows.[6] If we want to estimate $\mathrm{VaR}_{i,99\%,t}$, first we need to estimate the 99th percentile of recent base point changes of country i's sovereign bond yield using a parametric method or a volatility adjusted historical simulation.[7] Then we calculate $\mathrm{VaR}_{i,99\%,t}$ by multiplying the risk exposure (-PV01), as equation 7 shows.

---

[6] For daily data, the first derivative of the Present Value versus interest rate would be a good approximation for PV01, present value of 1 base point change, since the daily base point changes are quite small.

$$\mathrm{PV01}(\mathrm{C_T}, \mathrm{R_T}) \approx \frac{\partial \mathrm{PV}(\mathrm{C_T}, \mathrm{R_T})}{\partial \mathrm{R_T}} \times -1\ \mathrm{b.p} = -\mathrm{T} \times \mathrm{PV}(\mathrm{C_T}, \mathrm{R_T}) \times -0.01\%$$

[7] Present value of sovereign bond will decrease if interest rate increases. Thus, sovereign bond will have extreme loss if the base point change has an extremely positive value. We need to replace financial returns $(\mathrm{r}_{j,t})$ of the original volatility adjusted historical simulation proposed by Hull and White (1998), by base point changes $(\mathrm{bp}_{j,t})$ to estimate VaR in sovereign bond market.

$$\mathbf{VaR_{i,t}} = -\,\mathbf{inf}\left(\mathbf{bp_{i,t}}\right) \times -\mathbf{PV01} \quad (\mathbf{7})$$

where $\inf(.)$ is the inverse of Probability Density Function; $\mathrm{bp}_{i,t}$ is the base point change of security i at time t; PV01 is the Present Value change if the interest rate decreases 1 base point.

Besides, we also make following assumptions in our analysis. First, interest rates are continuous compounding[8]. Second, to standardize the VaR and increase the comparability, our risk exposure (PV01) is equal to 100 in all the sovereign bonds. Third, our positions are rebalanced every day, which means we will rebalance the amount of investments every day to maintain a constant PV01, 100.

3.2 Battery of back testing methods

In order to determine which of the VaR models is the most appropriate for the EMU sovereign bond market, we use a battery of back tests. After completing all tests, we assign a punishment score to each rejection of the validity or independence test, and sum up the punishment scores for each VaR model. In the end, we form a punishment scorecard and choose the VaR model based on the total punishment scores. By doing this, even though we have to set some subjective criteria when forming the scorecard, we could make a relatively objective decision when choosing among VaR models. If we consider some tests to be more important than others, we can simply assign a higher punishing score to them.

We will consider the following five validity and independence tests in our back testing battery: i) the Unconditional Coverage test; ii) the Independence test; iii) the Conditional Coverage test; iv) the Berkowitz, Christoffersen and Pelletier (2007) test (henceforth BCP test); and v) the Unconditional Exceedance Clustering test.

The null hypothesis of the Unconditional Coverage test, introduced by Kupiec (1995), is that the observed exceedance rate equals the expected exceedance rate.

We expect the probability of the exceedance rate (there is an exceedance if the absolute value of the loss of the security is larger than estimated VaR) equals one minus confidence

[8] We have transformed the interest rate from annual compounding or semi-annual compounding into continuous compounding. All the interest rates of the generic sovereign bonds, except Italian sovereign bonds, are annually compounded. The interest rates of Italian sovereign bonds are semiannual compounded.

level, $(1-\theta\%)$, all the time, if the VaR model is appropriate. The loglikelihood ratio test statistic is calculated according to equation 8.

$$\mathbf{LR_{uc}} = \left(\frac{\boldsymbol{\pi}_{\mathbf{exp}}}{\boldsymbol{\pi}_{\mathbf{obs}}}\right)^{\mathbf{n_1}} \left(\frac{\mathbf{1}-\boldsymbol{\pi}_{\mathbf{exp}}}{\mathbf{1}-\boldsymbol{\pi}_{\mathbf{obs}}}\right)^{\mathbf{n_0}} \quad (\mathbf{8})$$

where π_{exp} is the expected exceedance rate, and equals one minus the confidence level $(1-\theta\%)$, π_{obs} is the observed exceedance rate, $\mathrm{n_1}$ is the number of exceedance, $\mathrm{n_0}$ is the number of non-exceedances. Based on the test statistic ($\mathrm{LR_{uc}}$), we have that $-2\ln(\mathrm{LR_{uc}}) \sim \chi^2(1)$ and so we can check whether the null hypothesis is rejected by comparing $-2\ln(\mathrm{LR_{uc}})$ against the appropriate critical value of the chi-square distribution with 1 degree of freedom.

The null hypothesis of the Independence test, derived by Christoffersen (1998), is that the exceedances are independent from each other.

The Independent test is based on the notion that if exceedances are independent, the probabilities of exceedance of nest interest rate is not related to what happens before that.

$$\mathbf{LR_{ind}} = \frac{\boldsymbol{\pi}_{\boldsymbol{obs}}^{\boldsymbol{n1}}(\mathbf{1}-\boldsymbol{\pi}_{\boldsymbol{obs}})^{\boldsymbol{n_0}}}{\boldsymbol{\pi}_{\mathbf{01}}^{\boldsymbol{n_{01}}}(\mathbf{1}-\boldsymbol{\pi}_{\mathbf{01}})^{\boldsymbol{n_{00}}}\boldsymbol{\pi}_{\mathbf{11}}^{\boldsymbol{n_{11}}}(\mathbf{1}-\boldsymbol{\pi}_{\mathbf{11}})^{\boldsymbol{n_{10}}}} \quad (\mathbf{9})$$

where, $\mathrm{n_{10}}(n_{11})$ is the number of exceedances followed by a non-exceedance (exceedance), $\mathrm{n_{00}}(n_{01})$ is the number of non-exceedances followed by a non-exceedance (exceedance), $\pi_{01} = \frac{\mathrm{n_{01}}}{n_{01}+n_{00}}$ and $\pi_{11} = \frac{\mathrm{n_{11}}}{n_{11}+n_{10}}$. We also have $-2\ln(\mathrm{LR_{ind}}) \sim \chi^2(1)$, thus we need to check whether we will reject the null hypothesis by comparing $-2\ln(\mathrm{LR_{ind}})$ against the appropriate critical value of the chi-square distribution with 1 degree of freedom.

The null hypothesis of Conditional Coverage test, also proposed by Christoffersen (1998), is that the observed exceedance rate equals the expected exceedance rate and the exceedances are independent from each other.

$$\mathbf{LR_{cc}} = \frac{\boldsymbol{\pi}_{\mathbf{exp}}^{\mathbf{n1}}\left(\mathbf{1}-\boldsymbol{\pi}_{\mathbf{exp}}\right)^{\mathbf{n_0}}}{\boldsymbol{\pi}_{\mathbf{01}}^{\mathbf{n_{01}}}(\mathbf{1}-\boldsymbol{\pi}_{\mathbf{01}})^{\mathbf{n_{00}}}\boldsymbol{\pi}_{\mathbf{11}}^{\mathbf{n_{11}}}(\mathbf{1}-\boldsymbol{\pi}_{\mathbf{11}})^{\mathbf{n_{10}}}} \quad (\mathbf{10})$$

Since the asymptotic distribution of $-2\ln(\mathrm{LR_{cc}})$ follows a chi-square distribution with 2 degree of freedom, we could check whether we should reject the null hypothesis by checking chi-square test table.

Since both Independent test and Conditional Coverage test could only find out the exceedance clustering problem if exceedances are consecutive, we also include the BCP test, introduced by Berkowitz, Christoffersen and Pelletier (2007) to test higher order exceedance clustering problem.

The null hypothesis of the BCP test is that the exceedances are independent at K order.

$$\mathbf{BCP(K) = n(n+2)\sum_{k=1}^{K}\frac{\hat{\rho}_k^2}{n-k}} \quad (\mathbf{11})$$

where n is sample size; k is the autocorrelation lag considered in the test; $\hat{\rho}_{\mathrm{k}} = \mathrm{Corr}(\mathrm{I}_{\mathrm{t},\alpha} - \alpha, \mathrm{I}_{\mathrm{t+k},\alpha} - \alpha)$ is the lag k sample autocorrelation of the series $\mathrm{I}_{\mathrm{t},\alpha} - \alpha$;

$\mathrm{I}_{\mathrm{t},\alpha} - \alpha = \begin{cases} 1 & \textit{if Profit Loss} < -VaR_{t,\alpha} \\ 0 & \textit{otherwise} \end{cases}$ is the exceedance indicator.

As an asymptotic test, we have $BCP(K) \sim \chi^2(k)$, so we could test whether the null hypothesis should be rejected based on BCP statistic and chi-square distribution with k degree of freedom.[9]

Since all of previous tests could only detect the consecutive independence problem, we also adjust the Unconditional test, named as the Unconditional Exceedance Clustering test, to examine whether the exceedances are clustering at a certain variance level.

The null hypothesis of the Unconditional Exceedance Clustering test is that the observed exceedance rate in each variance decile group equals the expected exceedance rate.

We sort the whole sample by estimated variance and group the whole sample into ten quantile,[10] basing on the decile breakpoints for estimated variance. Then we implement the Unconditional tests on each variance group as equation 8 shows.

3.3 The Punishment Scorecard

---

[9] We will test whether there is higher order (until K=5 order) autocorrelation of exceedances in this thesis.

[10] For instance, VaR with lowest 0% to 10% variance belongs to group 1; VaR with lowest 10% to 20% variance belongs to group 2 and so on.

To quantify the performance of VaR models, we use a scorecard to summarize the performance of VaR models in each of the five tests.

We test the VaR models annually for each country, and for the entire sample period in each test. In Unconditional Coverage, Independence and Conditional Coverage tests, each VaR model has 8 annual test results and 1 total test result for each country; in BCP tests, each VaR model has 40 annual test results (we will test autocorrelation from 1^{st} order to 5^{th} order annually) and 5 total test results; and Unconditional Exceedance Clustering tests have 10 group test results (1 test for each decile group) for each country.

According to the null hypotheses of each test, there are three kinds of problems that make us reject the VaR model: i) the observed exceedance rate is not equal to the expected exceedance rate; ii) the exceedances are not independent from each other, because the VaR model is not sensitive enough to capture changes in market conditions; iii) The exceedances are clustering in some variance groups.

Since the Unconditional tests are the elementary tests for the validity, we give them the most severe punishment scores. Considering that Unconditional tests, Conditional tests and Unconditional Exceedance Clustering tests have overlaps in testing the validity, we give two latter tests relatively low punishment scores. Besides, since we have lots of BCP tests in each country and the rejections of BCP tests for high order autocorrelation problem seem questionable at a high confidence level, so we give them the lowest punishment score per rejection. Also, both Independent and Conditional tests could test independence, and their punishment scores are relatively low because of the overlaps.

After those subjective judgements, we pay almost equal attention to the problem (i) that the observed exceedance may not fit our expectation and the problem (ii) that exceedances are not independent, and put less weight on the last problem that the exceedances are clustering in some variance groups, since Alexander (2009) suggested that the first two problems are the key aspects of the VaR tests.

In any of five tests, if a p value is smaller than 5% but bigger than 1%, the VaR model will receive a punishment score, but if a p value is smaller than 1%, the VaR model will receive a more severe punishment score as table 2 shows.

Table 2. The Punishment Scorecard.

We give different punishment scores to each rejection basing on the importance of tests and potential overlapping among tests. Besides, we also differentiate the punishment score per rejection under 1% and 5% significant level, since the probabilities of making type I and type II error are quite different between those two significant levels. Following table lists the detailed punishment score per rejection in different test and significant level in the thesis.

p value		1%~5%	<1%
Unconditional Tests	annual	2/rejection	4/rejection
	total	6/rejection	12/rejection
Independent Tests	annual	2/rejection	4/rejection
	total	4/rejection	8/rejection
Conditional Tests	annual	2/rejection	4/rejection
	total	4/rejection	8/rejection
BCP Tests	annual[11]	1/rejection	2/rejection
	total	2/rejection	4/rejection
Unconditional Tests(clustering)	decile group[12]	2/rejection	4/rejection

The objective of this scorecard is to quantify the performance of VaR models.

According to the final scorecard, we can qualify the performance of VaR models and find the most efficient VaR model to estimate the tail risk of each sovereign bond market.

Even though we have to make some subjective assumptions in the beginning, it's better to make a sound decision based on subjective assumptions rather than make a totally subjective decision based on dozens of test results.

3.4 Data

We use 5 year Generic Government Rates between Jan 1st 2003 and Dec. 31st 2013 obtained from Bloomberg as 5 year sovereign bond yield during that period. Since we use first three years data to stabilize EWMA model, we just estimate VaR between 2006 and 2013. The countries covered in the sample are Austria, Belgium, France, German, Greece, Italy, Netherlands, Portugal and Spain.[13] We have also included relevant financial data, such as the implied volatility of S&P

[11] If we don't have any exceedance in a sovereign bond market for one year, we will reject all the BCP tests for that year. However, we do not count those meaningless rejections.

[12] The total tests of unconditional tests (clustering) are identical to total tests of unconditional tests.

[13] 5 year Greek government debt data is only available before Mar 13th 2012. In Mar. 13th 2012 Fitch raised Greek sovereign bond out of default category. Because of this, yield to maturity of Greek sovereign bond with longer

500 index options (VIX), and local equity indexes (ATX, BEL20, OMX Helsinki 25, CAC40, DAX, Athex20, ISEQ20, FTSE MIB, AEX index, PSI 20 and IBEX 35) from Bloomberg as global and local factors. The last global factor, the USD/EUR exchange rate, is obtained from FactSet and priced in the US exchange rate method.[14]

To match the data from different countries and different markets, we only consider data during working days. If the data is not available in Bloomberg or FactSet, we use simple average method to interpolate the missing data.[15] As in Appendix 1, all EMU countries included in this study have almost completed series of 5 year Generic Government rates, and just need sporadic interpolations.

We can see from Table 3, for any EMU country, the mean of base point changes is not significantly different from 0. Even though the mean of base point change in the Greek sovereign bond market is relatively big (2.7626), the variance of the Greek sovereign bond market is also large (1293.524).

Table 3: Basic Momentum summary

Following table lists basic statistic momentums of different 5 year EMU sovereign bonds between Jan 1st 2003 and Dec. 31th 2013.

	Austria	Belgium	France	Garman	Greece	Italy	Netherland	Portugal	Spain
mean	-0.08152	-0.08337	-0.08539	-0.10082	2.762661	-0.01861	-0.08634	0.089466	-0.01472
Variance	27.40989	34.24749	26.23718	25.49652	1293.524	81.27417	23.9539	381.8136	82.02864
Skewness	0.533176	-0.01204	0.300469	0.079468	-2.47737	-0.86225	0.200142	1.56018	-1.26961
Excess kurtosis	6.270829	10.21717	3.884917	1.959229	75.20575	18.4382	2.256182	58.45064	16.16104

Also, we can see base point changes are not stationary in any of EMU countries from Appendix 2. To be specific, the variances of base point changes are not constant. Thus, it is necessary to find an appropriate model, EWMA or GARCH, to estimate dynamic variance so we consider parametric VaR models and volatility adjusted historical simulation in this thesis.

3.5 VaR models and scorecard results

maturity, for instance 10 year and 30 year, decreased dramatically, and yield to maturity of 5 year Greek sovereign bond was not available in Bloomberg for one year.

[14] This exchange rate is priced as the amount of dollars needed to purchase one unit of euro.

[15] If $i_{j,t}$, which is the interest rate of sovereign bond market j, at time t, is missing, we will interpolate the missing data by $i_{j,t} = \frac{i_{j,t-1}+i_{j,t+1}}{2}$

Nine different VaR methods are used to estimate the tail risks: three RiskMetrics models, four ARMA (1,0)-GARCH(1,1) models and two ARMA(1,0)-GJR(1,1,1) models. Model **Norm** uses EWMA to estimate daily variance and assume that the standardized base point changes ($\varepsilon_{j,t}$) follow normal distribution as in equation 12

$$\begin{cases} \boldsymbol{\sigma_{j,t}^2 = \lambda\sigma_{j,t-1}^2 + (1-\lambda)bp_{j,t-1}^2} \\ \boldsymbol{bp_{j,t} = \sigma_{j,t}\varepsilon_{j,t} \quad \varepsilon_{j,t} \sim i.i.d.\,N(0,1)} \end{cases} \quad (\mathbf{12})$$

where $bp_{j,t}$ is the base point change of sovereign bond j at time t; $\sigma_{j,t}$ is the standard deviation of sovereign bond j at time t; $\varepsilon_{j,t}$ is standardized base point change of sovereign bond j at time t, in short it is the standard error of sovereign bond j at time t. And $\lambda = 0.94$ according to Fleming, Kriby and Ostdiek (2002). [16]

Model **S.t** uses EWMA to estimate daily variance and use maximizing the log-likelihood function approach to estimate the degree of freedom of student t distribution of standardized base point changes ($\varepsilon_{j,t}$) as in 13

$$\begin{cases} \boldsymbol{\sigma_{j,t}^2 = \lambda\sigma_{j,t-1}^2 + (1-\lambda)bp_{j,t-1}^2} \\ \boldsymbol{\lambda = 0.94} \\ \boldsymbol{bp_{j,t} = \sigma_{j,t}\varepsilon_{j,t} \quad \varepsilon_{j,t} \sim i.i.d.\,student\ t(0,1)} \end{cases} \quad (\mathbf{13})$$

Model **His, 500** is a volatility adjusted historical simulation, in which variance is adjusted by EWMA method, as in 14. And the 99th percentile of base point changes distribution is estimated by last 500 volatility adjusted base point changes in bond yields.

$$\begin{cases} \boldsymbol{\sigma_{j,t}^2 = \lambda\sigma_{j,t-1}^2 + (1-\lambda)bp_{j,t-1}^2} \\ \boldsymbol{\lambda = 0.94} \\ \boldsymbol{bp_{j,t}^{*} = \sigma_{j,T}\frac{bp_{j,t}}{\sigma_{j,t}}} \end{cases} \quad (\mathbf{14})$$

where T indicates the target time when we want to estimate the 99th percentile of the adjusted base point changes distribution, and t indicates historical observations $t \sim [T-1, T-500]$

[16] We also estimate λ by assumption that all the standardized base point change follow same distribution. We can get $\lambda = 0.948445$ by minimizing variance of momentums, mean, variance, excess kurtosis and skewness. Thus, $\lambda = 0.94$ is suitable here.

In GARCH models and GJR models, we cannot assume the base point changes have zero conditional means, since the basic requirement of GARCH model is the mean of standard errors, $v_{j,t}$, equals 0. Thus, we use ARMA(1,0) model to estimate conditional means.

Model **G, Norm** uses ARMA (1,0)-GARCH(1,1) as in 15 and the additional assumption that standardized base point changes ($\varepsilon_{j,t}$) follow normal distribution.

$$\begin{cases} \mathbf{bp_{j,t} = \alpha_0 + \alpha_1 bp_{j,t-1} + v_{j,t}} \\ \mathbf{v_{j,t} = \sigma_{j,t}\varepsilon_{j,t}} \qquad \mathbf{\varepsilon_{j,t} \sim i.i.d.\,N(0,1)} \\ \mathbf{\sigma^2_{j,t} = \beta_0 + \beta_1 v^2_{j,t-1} + \beta_2 \sigma^2_{j,t-1}} \\ \mathbf{\beta_0, \beta_1, \beta_2 > 0, \beta_1 + \beta_2 < 1} \end{cases} \qquad \mathbf{(15)}$$

Model **G, N, His** is another volatility adjusted historical simulation, in which variance is estimated by ARMA (1, 0)-GARCH (1, 1) model as in equation 15 and historical base point changes in bond yields are adjusted by the variances as equation 16 shows. The 99th percentile of base point changes distribution is estimated by last 500 adjusted base point changes in bond yields.

$$\mathbf{bp^*_{j,t} = \alpha_0 + \alpha_1 bp_{j,t-1} + \sigma_{j,T}\frac{v_{j,t}}{\sigma_{j,t}}} \qquad \mathbf{(16)}$$

Model **G, S.t** uses ARMA (1, 0)-GARCH (1, 1) and the additional assumption that standardized base point change follow student t distribution as in equation 17 to estimate daily variance.

$$\begin{cases} \mathbf{bp_{j,t} = \alpha_0 + \alpha_1 bp_{j,t-1} + v_{j,t}} \\ \mathbf{v_{j,t} = \sigma_{j,t}\varepsilon_{j,t}} \qquad \mathbf{\varepsilon_{j,t} \sim i.i.d.\,student\ t(0,1)} \\ \mathbf{\sigma^2_{j,t} = \beta_0 + \beta_1 v^2_{j,t-1} + \beta_2 \sigma^2_{j,t-1}} \\ \mathbf{\beta_0, \beta_1, \beta_2 > 0, \beta_1 + \beta_2 < 1} \end{cases} \qquad \mathbf{(17)}$$

Model **G, S.t, His** uses equation 17 to estimate daily variance, and adjust historical base point changes as in equation 16.

Model **GJR** uses ARMA (1,0) $-$ GJR (1,1,1) and the assumption that standardized errors ($\varepsilon_{j,t}$) are normally distributed to estimate variance and VaR.

$$\begin{cases} \mathbf{bp_{j,t} = \alpha_0 + \alpha_1 bp_{j,t-1} + v_{j,t}} \\ \mathbf{v_{j,t} = \sigma_{j,t}\varepsilon_{j,t}} \qquad \mathbf{\varepsilon_{j,t} \sim i.i.d.\,N(0,1)} \\ \mathbf{\sigma^2_{j,t} = \beta_0 + \beta_1 v^2_{j,t-1} + \beta_2 \sigma^2_{j,t-1} + \beta_3 v^2_{j,t-1}(if\ v_{j,t-1} > 0)} \\ \mathbf{\beta_0, \beta_1, \beta_2 > 0, \beta_1 + \beta_2 < 1} \end{cases} \qquad \mathbf{(18)}$$

Model **GJR, His** is GJR volatility adjusted historical simulation, which use equation 18 to estimate variance and equation 16 to adjust historical base point changes.

According to Panel I and II of Table 4, we find that His, 500 model (EWMA volatility adjusted historical simulation) has the lowest punishment score in any single tests and the lowest total punishment score.[17]

First, S.t (RiskMetrics model with student t distributed $\varepsilon_{j,t}$) has better performance than Norm (RiskMetrics model with normal distributed $\varepsilon_{j,t}$) (Total punishment score is 84 in S.t and 348 in Norm, and S.t has less rejectctions in any of the five tests than Norm). Thus the real distribution of standardized base point changes has fatter tail, since student t distribution are more flexible on tails than normal distribution. Besides, there are two reasons to explain the fact that historical simulation could improve the performance further: i) there is a limited number of observations on tails; ii) standardized base point changes are asymmetrically distributed. Even though student t distribution has good flexibility on tails, there are not enough number of observations to estimate the tails accurately. Or the real distribution of standardized base point changes is not symmetric, thus a symmetric distribution is not a wise choice, as Table 4 shows.

Second, His, 500 model beats all the GARCH models. This might be due to three possible explanations. Frist, coefficients of GARCH models are heavily influenced by outliers, thus biasing the varaince estimation. Second, those coefficients are not constant. Third, conditional means tend to be 0 rather than follow ARMA(1,0) model.

We also find that G,S.t (GARCH model with student t distributed $\varepsilon_{j,t}$) model tends to overestimate the VaR all the time. Even though the student t distribution has fatter tail compared to the normal distribution, it will overestimate daily $\mathrm{VaR}_{i,t,}$ at 99% confidence level. This means that the flexibility in the tails cannot increase the accuracy of variance estimation, because of the influence of outliers and the limited number of observations on the tails.

In addition, the GJR model cannot significantly improve estimations of $\mathrm{VaR}_{j,t,1,99\%}$ compared to the model G, Norm (GARCH model with normally distributed $\varepsilon_{j,t}$).

---

[17] In model **Norm** and **His,500**,our test results are out of sample tests' results, since we do not need any future information when estimating the $\mathrm{VaR}_{1,99\%,t}$

Table 4, Brief summary of back tests

Panel I reports the number of rejections in each test at different significant level. We will exclude the rejections in annual BCP tests if those rejections are caused by absence of exceedance during that year. We also exclude the total Unconditional Exceedance Clustering test, since it is idential to total Unconditional Coverage test.

After multipling corresponding punishment score as in Table 2 and summing up punishment scores in each tests we summarize total punishment scores in each tests and total punishment scores of five tests, and report in Panel II.

Panel I Number of rejection in each test

			Norm	S.t	His,500	G,Norm	G,S.t	GJR	G,N,His	G,S.t,His	GJR,His
Unconditional Coverage test	Annual	1%~5%	8	8	3	8	72	11	3	4	5
		<1%	10	1	0	7	0	6	3	4	2
	Total	1%~5%	0	0	0	2	0	1	0	0	0
		<1%	9	0	0	7	9	8	0	1	0
Independent test	Annual	1%~5%	3	0	0	0	0	0	0	0	0
		<1%	0	0	0	0	0	1	0	0	0
	Total	1%~5%	1	0	0	0	0	0	0	0	0
		<1%	0	0	0	0	0	0	0	0	0
Conditional Coverage test	Annual	1%~5%	3	0	0	0	0	0	0	0	0
		<1%	0	0	0	0	0	1	0	0	0
	Total	1%~5%	1	0	0	0	0	0	0	0	0
		<1%	0	0	0	0	0	0	0	0	0
BCP test	Annual	1%~5%	4	2	0	5	0	4	3	3	2
		<1%	27	8	13	21	0	23	10	11	13
	Total	1%~5%	2	2	2	1	0	2	0	1	0
		<1%	5	5	3	8	45	5	7	6	5
Unconditional Exceedance Clustering test	Different decile	1%~5%	13	11	7	8	90	9	7	8	10
		<1%	14	0	1	8	0	4	4	4	2

Panel II Punishment Scorecard results

	Norm	S.t	His,500	G,Norm	G,S.t	GJR	G,N,His	G,S.t,His	GJR,His
Unconditional Tests	164	20	6	140	252	148	18	36	18
Independent Tests	10	0	0	0	0	4	0	0	0
Conditional Tests	10	0	0	0	0	4	0	0	0
BCP Tests	82	42	42	81	180	74	51	51	48
Unconditional Exceedance Clustering test	82	22	18	48	180	34	30	32	28
Total Score	**348**	**84**	**66**	**269**	**612**	**264**	**99**	**119**	**94**

As Table 5 shows, even though 6 out of 10 countries' sovereign bond markets have statistic significant asymmetric items in GJR(1,1,1) model at 5% significance level as in Table 5, the sign of coefficients of some countries cannot fit our expectation that bad news has more impact than good news. Besides, GJR model only improve total punishment score moderately (269 in G,Norm model, 99 in G,N,His model, 254 in GJR model, and 94 in GJR, His model). As a conclusion, the advantage of asymmetric GARCH model is not obvious when estimating variance in this data set.

Table 5, Asymmetric items in GJR(1,1,1) model

In GJR(1,1,1) model, we assume that good news and bad news have different influence on variance of base point changes as in following equation.

$$\begin{cases} \mathrm{bp}_{j,t} = \alpha_0 + \alpha_1 \mathrm{bp}_{j,t-1} + v_{j,t} \\ v_{j,t} = \sigma_{j,t}\varepsilon_{j,t} \qquad \varepsilon_{j,t} \sim \mathrm{i.i.d.}\, N(0,1) \\ \sigma_{j,t}^2 = \beta_0 + \beta_1 v_{j,t-1}^2 + \beta_2 \sigma_{j,t-1}^2 + \beta_3 v_{j,t-1}^2 (\text{if } v_{j,t-1} > 0) \\ \beta_0, \beta_1, \beta_2 > 0, \beta_1 + \beta_2 < 1 \end{cases}$$

Since the spot interest rate and the price of an existing sovereign bond are negative correlated, β_3, named as Tarch Stat in following table, will report the additional effects of bad news. Following table report the coefficients and p value of the asymmetric item, β_3 in different 5 year sovereign bond between 2006 and 2013.

	Austria	Belgium	France	Germany	Greece	Italy	Netherland	Portugal	Spain
Tarch Stat	-0.03	0.00	-0.02	-0.01	0.13	0.09	-0.02	0.08	0.04
P Value	0.00	0.68	0.06	0.11	0.00	0.00	0.00	0.00	0.00

Third, the volatility adjusted historical simulation could improve the performance in all of parametric models (total punishing score is 269 in G,Norm versus 99 in G,N,His, 1332 in G,S.t versus 119 in G,S.t,His, 264 in GJR versus 94 in GJR,His)

As a conclusion, model **His,500**(EWMA) beats all the other models, with the smallest total pubishment score and individual punishment scores.[18] Besides, we also find that volatility adjusted historical simulation could improve the performance of parametric VaR models.

4. Correlation Coefficients Analysis

4.1 The DCC model and data

There are three objectives in this section: find a potential pattern of the correlation coefficients between the Greek 5 year sovereign bond market and other major EMU 5 year sovereign bond markets; test whether this pattern is consistent among different time periods, especially before and after the Sovereign Bond Crisis; test whether the impact of Greece is the same on vulnerable

[18] Since in this paper, we need to estimate $\mathrm{VaR}_{1,99\%,t}$ rather than forecast $\mathrm{VaR}_{1,99\%,t}$, we don't need to distinguish in sample tests and out of sample tests. However, commonly in sample tests' results will be better than out of sample tests' results. In this paper, surprisingly, out of sample tests' results from **His, 500** beat all the out of sample tests' and in-sample tests' results.

countries (Greece, Italy, Ireland, Portuguese and Spain) and stable countries (Austria, Belgium, France, Germany and Netherland).[19]

Nevertheless, the convergence problem caused by the existence of outliers and flatness of likelihood function, and the riskiness of reaching a local optimum stops us from including all the vulnerable and stable countries into a Multivariate GARCH model, thus, in this section, we focus on the dynamic correlation coefficients between Greece and other EMU top economic entities.

According to Gross Domestic Product (GDP), published by the World Bank, Germany, France, Italy and Spain were top 4 economic entities in the EMU from 2006 to 2013. But, the VaR of German and French 5 year sovereign bonds were quite stable during the entire period; on the contrary, the VaR of Italian, Spanish, and Greek 5 year sovereign bonds increased dramatically between 2008 and 2011, so the Multivariate GARCH model will suffer a convergence problem if we include all those four countries' sovereign bonds. As a result, we use Italy and Spain to represent vulnerable countries and France to represent stable countries. [20]

In addition, we also adjust the sample size in section 4 and section 5, since data series of Greek 5 year sovereign bonds is not available in Bloomberg after Mar. 12th 2012, when the majority of private holders agreed to participate the restructuring of Greek sovereign bonds. Besides, not until Apr. 11th 2014, did Greek 5 year sovereign bonds come back to financial market. Thus, the sample period would be from Jan. 1st 2006 to Dec. 31st 2011.

To obtain dynamic correlation coefficients, we apply the Dynamic Conditional Correlation (DCC) model, which was first introduced by Engle (2002) and is a simplified extension of traditional Multivariate GARCH model. The DCC model has become the main methodology to identify the volatility spillover between countries. For instance Celik (2012) used it to analyze the volatility spillover effects in emerging markets, and Elkhaldi and Chebbi (2013) used it to analyze the volatility spillover effects between different EMU countries. In this analysis, we will use STATA's built-in function, which is calculated as in equation 19.

---

[19] Since Cyprus, Estonia, Latvia, Slovakia and Slovenia joined EMU very late, and data series of Generic Government rates of Luxembourg and Malta are not available in Bloomberg, we exclude those countries from our analysis.

[20] The convergence problem still exists if we only include German, Italian, Spanish and Greek 5 year sovereign bonds in DCC model.

$$\begin{cases} \mathbf{VaR_t\% = \alpha + \varepsilon_t} \qquad \boldsymbol{\varepsilon_t \sim \mathrm{i.i.d.}\, N(0, D_t R_t D_t)} \\ \mathbf{D_t^2 = diag\{w_i\} + diag\{k_i\} \circ \varepsilon_{t-1}\varepsilon'_{t-1} + diag\{\lambda_i\} \circ D_{t-1}^2} \\ \mathbf{v_t = D_t^{-1}\varepsilon_t} \\ \mathbf{Q_t = S(\iota\iota' - A - B) + A \circ v_{t-1}v'_{t-1} + B \circ Q_{t-1}} \\ \mathbf{R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}} \end{cases} \qquad (19)$$

where $\mathrm{VaR_t}\%$ is a column vector including the percentage changes of VaR of Greek, French, Italian and Spanish sovereign bonds at the time t, $(\mathrm{VaR_{1,t}\%, VaR_{2,t}\%, \dots, VaR_{j,t}\%})$; α is a column vector, $(\alpha_1, \alpha_2, \dots, \alpha_j)$; ε_t is a column vector, $(\varepsilon_{1,t}, \varepsilon_{2,t}, \dots, \varepsilon_{j,t})$; D_t^2 is the conditional variance matrix of the residuals (ε_t) at time t, and it is a diagonal matrix; S is the unconditional correlation matrix of standardized residuals (v_t); ι is a column vector of ones; $\circ$ is the operator that means element by element multiplication; R_t is the conditional correlation coefficient matrix of residuals (ε_t) at time t; A is an n by n matrix with identical parameter; B is an n by n matrix with identical parameter; w, k and λ are diagonal matrixes with univariate GARCH parameters, which are different in each univariate GARCH model.

The first Equation is used to estimate the conditional means of the percentage changes of VaR $(\mathrm{VaR_t}\%)$. Because the basic requirement of GARCH models is that the mean of residuals $(\overline{\varepsilon_t})$ equals 0, in this section, we will use an ARIMA (0,1,0) model to estimate the conditional means.

The second and third equations are used to estimate the unconditional variance of $\mathrm{VaR}_t\%$, which we do by using a GARCH (1, 1) model specification. In other words, the current unconditional variance is related to the last unconditional variance and the last residual (the difference between the real base point change of the VaR and the expected base point change of the VaR).

The fourth and fifth equations are used to estimate dynamic correlation coefficients.

Because of the normality assumption on the residuals' probability distribution, $\varepsilon_t \sim \mathrm{i.i.d.}\, N(0, D_t R_t D_t)$, we can estimate parameters by maximizing the log-likelihood equation 10.

$$\mathbf{L = -\frac{1}{2}\sum_{t=1}^{T}\left(n\log(2\pi) + \log|D_t R_t D_t| + \varepsilon_t' D_t^{-1} R^{-1} D_t^{-1} \varepsilon_t\right)} \quad (20)$$

$$\mathbf{= -\frac{1}{2}\sum_{t=1}^{T}\left(n\log(2\pi) + 2\log|D_t| + \varepsilon_t' D_t^{-1} D_t^{-1} \varepsilon_t + \log|R_t| - v_t' v_t + v_t' R^{-1} v_t\right)}$$

Since the DCC model needs some observations to initialize the model, we have excluded the first quarter of 2006 from our analysis.

4.2 Subsample formation.

To distinguish eventual differences of the Greek bond market impact on other bond markets over time, we spilt the whole sample, from Apr. 2006 to Dec. 2011, into three subsamples: Before Crisis; during the Subprime Crisis; and during the Sovereign Bond Crisis.[21]

We use Jan. 2008, the same as Badaoui, Cathcart and EI-Jahel (2013) did, to spilt pre-Crisis subsample and Subprime Crisis subsample, because by the end of 2007, the 10 year Greek sovereign bond yield was still around 5%, that is, at pre-crisis level of 2006.

We consider Oct. 2009 as a beginning point of the Sovereign Bond Crisis, when the Greek government dramatically revised the 2009 budget deficit after the Greek National Election. Alter and Beyer (2014), and Pradigis, Aielli, Chionis and Schizas (2015) also used same beginning point to form the Sovereign Bond Crisis subsample.

Furthermore, a simplified dynamic correlation coefficient analysis between base point changes of sovereign bonds estimated by EWMA model ($\lambda = 0.94$), as in Appendix 3, can also support our subsample formation.

According to Appendix 3, the estimated correlation coefficients between the base point changes of German 5 year sovereign bond market and other EMU countries' 5 year soveregin bond markets were close to 1 before 2008.

After the Subprime Crisis, especially after the bankruptcy of Lehman Brothers at the end of 2008, the estimated correlation coefficients between base point changes of Germany and other countries began to diverge. After the Sovereign Bond Crisis, around 2010, those estimated correlation coefficients were even more volatile than before.

The pattern of correlation coefficients between the base point changes of French 5 year sovereign bond market and other EMU countries' 5 year sovereign bond markets seems similar.

[21] We drop the correlation coefficient estimates in the first quarter of 2006 to initialize the DCC model, but we do not need this process in section 5. So, the sample period in section 4 is between Apr. 2006 and Dec. 2011, and sample period in section 5 is between Jan. 2006 and Dec. 2011.

Therefore, we spilt the whole sample period into three subsamples as follows:

Before Crisis, Jan. 1st 2006 [22]to Dec. 31st 2007; **Subprime Crisis,** Jan. 1st 2008 to Sep. 30th 2009; **Sovereign Bond Crisis,** Oct. 1st 2009 to Dec. 31st 2011

4.3 Correlation and spillover effects analysis

4.3.1 Entire Sample Period

In the period Before Crisis (2006 and 2007) the estimated VaR of Greek, French, Italian and Spanish 5 year sovereign bond markets were quite similar as we can see from Graphs I and II of Figure 2, and percentage changes of VaR of Greek 5 year soveregin bonds and percentage changes of VaR of other countires' 5 year sovereign bonds are highly correlated (correlation coefficients are around 0.9 all the time).

During the Subprime Crisis (2008 and 2009), estimated VaR of each countries could still track each other to some degree, but the dynamic correlation coefficients between the percentage changes of VaR of Greece and the percentage changes of VaR of other countries started to decrease and became more volatile, especially after Nov. 2008.

During the Sovereign Bond Crisis (2010 and 2011), there were some volatility spillover effects in the vulnerable countries, according to Graphs I and II of Figure 2, since the VaR of the Italian and Spanish 5 year sovereign bond markets increased abruptly, around the middle of 2010 and the end of 2011, when VaR of the Greek 5 year sovereign bond market was exploding.

However, French 5 sovereign bond was relatively stable all the time, except in the end of 2011.

Since the level of VaR and the correlation coefficients between percentage changes of VaR had changed significantly during the crises, we need to do a further analysis in each subsample to check

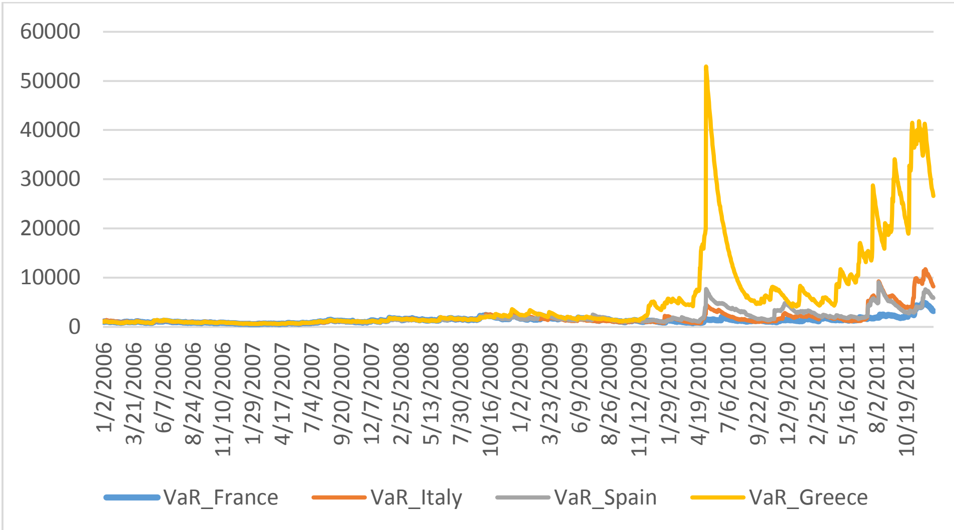
Figure 2, Dynamic Correlation correaltion Analysis for whole sample period

Value at Risk of French, Greece, Italian and Spanish 5 year sovereign bond markets are estimated by the EWMA volatility adjusted historical simulation model (λ=0.94 and window size n=500), as in Garph I. Since VaR of Greek 5 year sovereign bond market is so huge compared with other EMU countries, we exclude Greek 5 year sovereign bond market in Graph II.

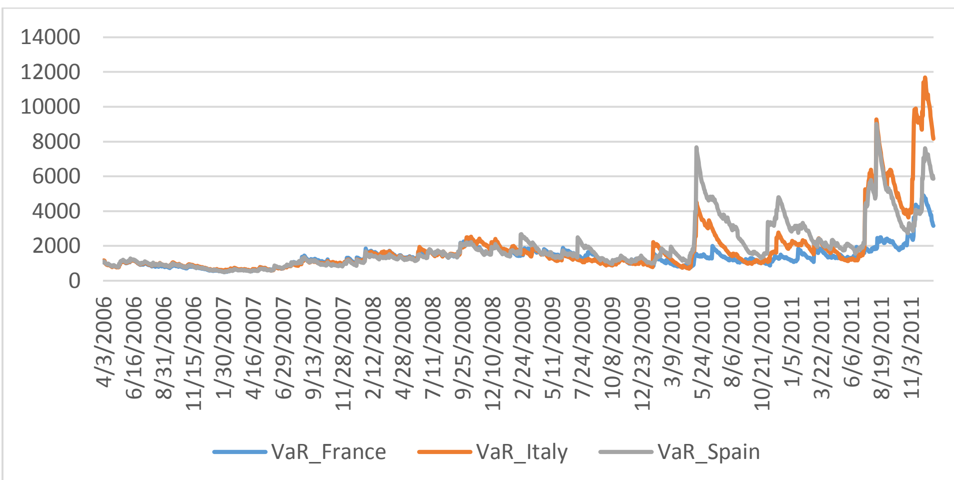
Daily correlation coefficients between the percentage changes of VaR of Greek and other countries are estimated by DCC model as in Graph III.

[22] We need several years to stabilize our EWMA model. Thus even though we have data from Jan. 1st 2003, we cannot begin our analysis at that time.

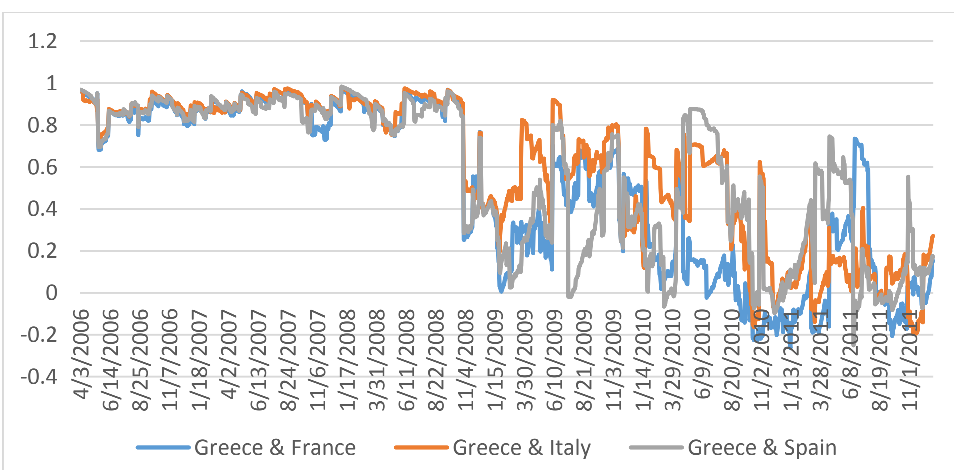
Graph I, Value at Risk of French, Greek, Italian and Spanish 5 year sovereign bond markets



Graph II, Value at Risk of French, Italian, Spanish 5 year sovereign bond markets



Graph III, Correlation coefficients between VaR of Greek and other countries' 5 year sovereign bond markets



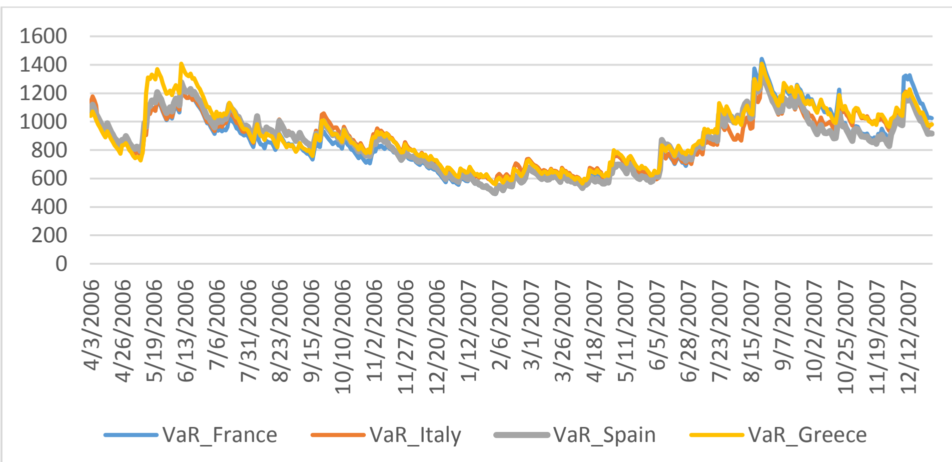
the detail.

4.3.2 Before Crisis

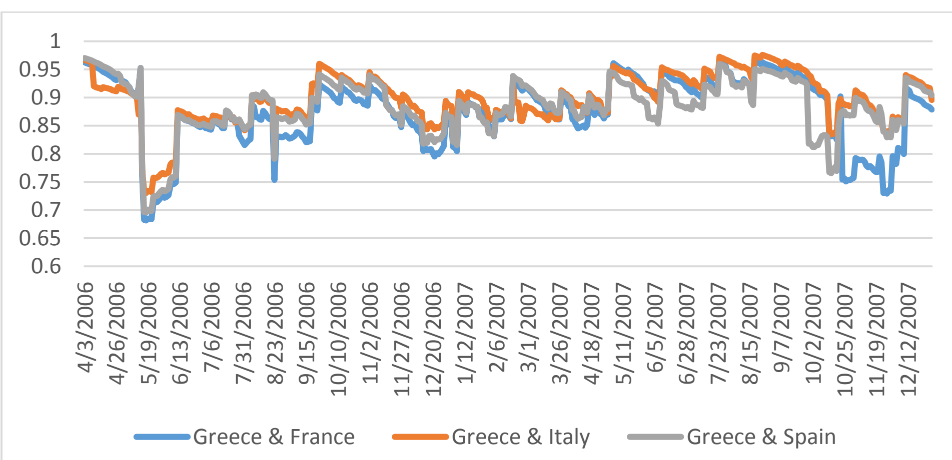
Focusing now only on the Before Crisis period (2006 and 2007), we can see from Graph I of Figure 3 that the VaR of Greek, French, Italian and Spanish 5 year sovereign bond markets were similar during this entire period. In addition, the correlation coefficients between the percentage changes of VaR of Greek and other countries' 5 year sovereign bond markets were most of the time close to 0.9 throughtout this period. The only exception where the brief episodes when VaR of sovereign bond markets were relatively high, is accompanied by relative low correlation coefficients between the percentage changes of VaR of Greek and other countries' 5 year sovereign bond markets.

Figure 3, Dynamic correlation correaltion Analysis Before Crisis

Graph I, Value at Risk of French, Greek, Italian and Spanish 5 year sovereign bond markets



Graph II, Correlation coefficients between VaR of Greek and other countries

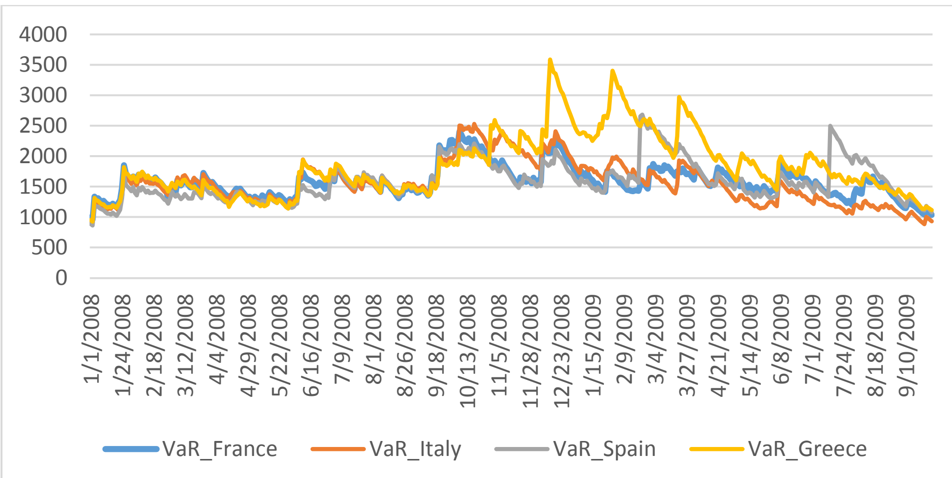


The volatility spillover effects are obvious during this period: increases in the VaR of Greeek 5 year soveregin bond market are accompanied by increases in VaR of other 5 year sovereign bond markets as Graph I of Figure 3 shows, but the stronge correlation will be impaired if the increases in Greek 5 year sovereign bond market are abrupt as in may 2006.

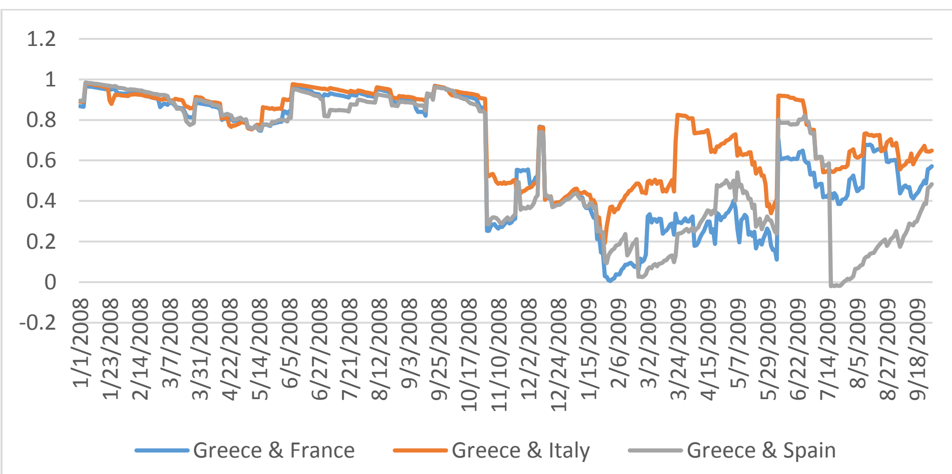
4.3.3 Subprime Crisis

Figure 4, Dynamic Correlation correaltion Analysis During the Subprime Crisis

Graph I, Value at Risk of French, Greek, Italian and Spanish 5 year sovereign bond markets



Graph II, Correlation coefficients between VaR of Greek and other countries



Graph I of Figure 4 shows that the VaR of Greek, Italian, Spanish and French 5 year sovereign bond markets remained relatively close in the first half of the Subprime Crisis period, until a national confict between the Government polices and the general public broke out in Greece at the end of 2008. Also, we can see the bankruptcy of Lehman Brother in Sep. 2008 influenced the entire EMU sovereign bond market, but it had not broken the strong connection between Greek and other countries' 5 year sovereign bond markets as in Graph I and II of Figure 4. As Graph II of figure 4 shows us, unlike the first half of Subprime Crisis period, the second half was characterized by relatively low and volatile correlation coefficients between Greek and other sovereign bond markets. Nonetheless, there was a recovery of the correlation coefficients between Greek and Italian and between Greek and French bond markets to levels close to those prevalent in 2008 during the second and third quarter of 2009, when markets calmed down.

There is a moderate increase in VaR of Greek 5 year sovereign bonds because of the bankruptcy of Lehman Brother, the VaR of Greek and other countries' sovereign bond markets are still closely related to each other. In contrast, the VaR of the Greek sovereign bond market registered one sudden jump during the Subprime Crisis because of country specific events as mentioned before, and the strong correlation between Greece and other countries broke down immediately once those jumps occurred as we can see in Graph I and II of Figure 4.

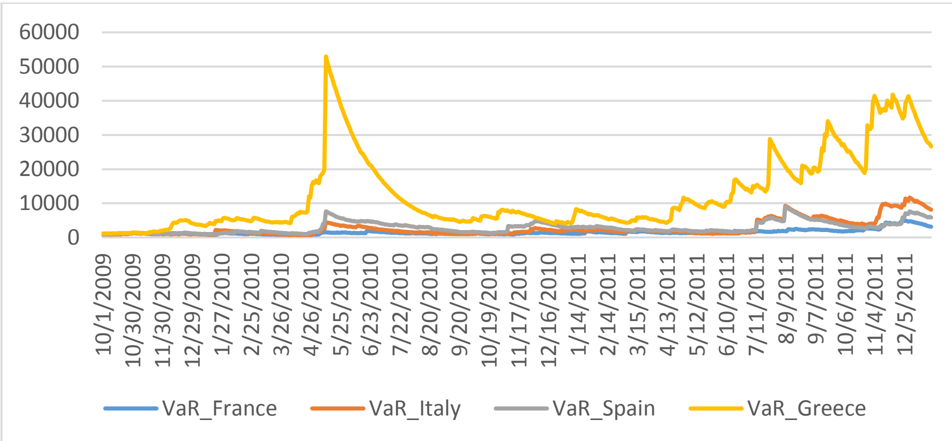
4.3.4 Sovereign Bond Crisis

During the Sovereign Bond Crisis period, there were two episodes of dramatic increase in the VaR of the Greek sovereign bond market. The first increase was in Apr. 11th 2010, when the Greek government announced that it would need help from the International Monetary Fund, even though the European Union had agreed to offer a 30 billion euro bailout 5 days before. Also, around the same time, Standard & Poor's downgraded Greek credit rating to non-investmnet grade (BB+). As a result, the VaR of Greek 5 year sovereign bond market soared in April 2010 as Graph II of Figure 5 shows. The second episode took place during most of the year of 2011, when the VaR of Greek Sovereign bond market surged from around 5,000 to 40,000 as a consequence of Fitch, Moody and Standard and Poor's successive downgrades of the Greek credit rating.

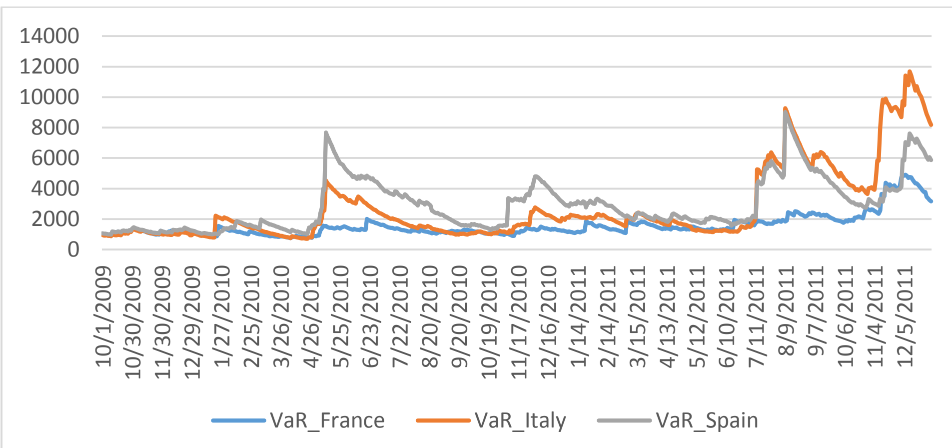
During both episodes, the VaR of the vulnerable countries, Italy and Spain, were also increasing, which indicated the spillover effects. However, only during the first of those episodes (April 2010), did the correlation coefficients between percentage changes of VaR of Greek and the vulnerable countries' sovereign bond markets tended to increase. During the second episode, the correlation coefficients actually tended to desrease.

Figure 5, Dynamic Correlation correaltion Analysis During the Sovereign Bond Crisis

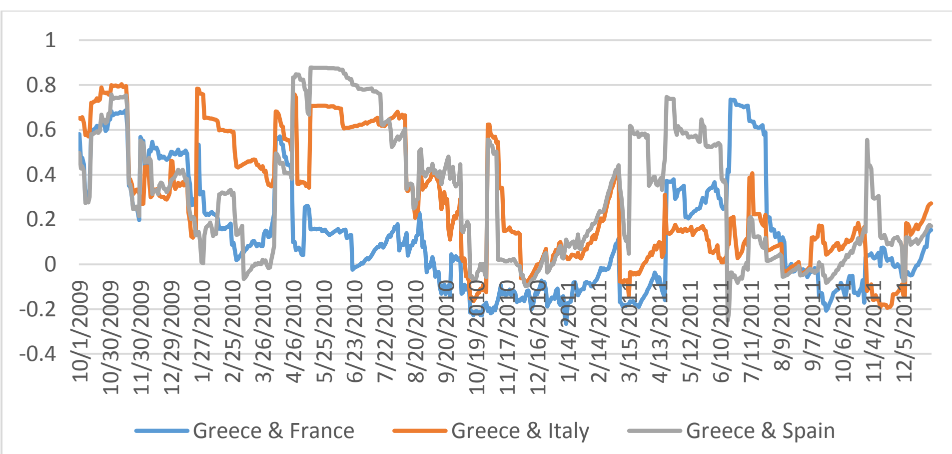
Graph I, Value at Risk of French, Greek, Italian and Spanish 5 year sovereign bond markets



Graph II, Value at Risk of French, Italian, Spanish 5 year sovereign bond markets



Graph III, the Correlation coefficients between VaR of Greek and other countries' sovereign bond markets



Besides, there was also a moderate increase in Greek soveregin bond at the end of 2009, because of the noteworthy upward revision of the forecast of the Greek government budget for the 2009 and correlation coeffcients between Greek and other countries' 5 year sovereign bonds declined significantly from around 0.8 to around 0.4 as Graph III of Figure 5 depicts.

4.3.5 Summary

In brief, in the Before Crisis period, the correlation coefficients between the percentage changes of VaR of the Greek 5 year sovereign bond markets and the percentage changes of VaR of vulnerable countries' 5 year sovereign bond markets were highly correlated, which indicated strong spillover effects between Greece and other countries, and VaR of all the EMU countries were quite low, just around 1,000.

During the Subprime Crisis period, even though there was still an obvious spillover effect between Greece and other countries in Sep. 2008 when Lehman Brother was bankrupt, the spillover effects seemed obscure at the end of 2008 when there broke out a police turmoil in Greece. At the end of 2008 VaR of the Greek sovereign bond market increased significantly and achieved 3,000, while the trend of the correlation coefficients between the percentage changes of VaR of Greece and other countries were the opposite of the trend of VaR of the Greek sovereign bond market.

During the Sovereign Bond Crisis period, there are still volatily spillover effects during each episode, at least at the beginning of each episode, but the increases of VaR of other countries' 5 year soveregin bonds are more moderate than those of Greek 5 year sovereign bonds. The correlation coefficients between the percentage changes of VaR, and VaR of the Greek sovereign bond market moved in the same direction in the middle of 2010, but in the opposite direction at the end of 2009 and the end of 2011.

Nonetheless, the VaR of Franch 5 year sovereign bond was quite stable despite the fluctuation of Greek 5 year sovereign bond market.

4.4 Average correlations by Greek VaR deciles

According to the analysis performed in the previous subsection, there appears to exist an inverse relationship between the VaR of Greek sovereign bond market and the correlation between percentage changes of VaR of Greek and other sovereign bond markets, which is occasionally contradicted by spillover episodes. In this subsection, we create 10 decile groups based on the VaR of Greek sovereign bond market for the entire sample period, which results in 150 observations per group, and compute the average correlation coefficients in each group. We then perform a T-test for differences in those average correlations between each consecutive group.

The results are reported in Table 6 in which we can clearly see that there is almost a monotonous decrease in the average correlation coeffcients between the percentage changes of VaR of the Greek sovereign bond market and other countries' sovereign bond markets. Furthermore, those differences are almost all statistically significant at 1% significance level, which provides strong evidence for the inverse relationship between the VaR of Greek sovereign bond market and the correlation coefficients between percentage changes of VaR of Greece and other sovereign bond markets that were already apparent from the graphs in the previous subsection.

Table 6, Average correlation coefficients between the percentage changes of VaR

We include sample period between Apr. 2nd 2006 and Dec. 31st 2011, and form 10 groups by deciles of the ascendingly ranked Greek 5 year sovereign bond market's VaR. Table reports the means of the correlation coeffcients between percentage changes of VaR of Greek 5 year sovereign bond market and percentage changes of VaR of other sovereign bond markets. As a result, group 1 is the smallest Greek VaR decile, and group 10 is the largest the Greek VaR decile.

Table also report the t test results testing whehter there is a statistically significant difference between average correaltion coefficients in this group and average correlation coefficeint in last group.[23] For instance, in group 2, the null hypothesis is that the average correaltion coefficient in group 2 equals the average correlation coefficient in group 1; in gropu 3, the null hypothesis is that the average correlation coefficient in group 3 equals the average correlation coefficient in group 2.

*,**, and ***, means t tests are significant at the 10%, 5%, and 1% significant level, respectively.

Greek VaR	Observations	Greece& Italy	Greece& Spain	Greece& France
1	150	0.89	0.88	0.88
2	150	0.91***	0.90***	0.89
3	150	0.87***	0.83***	0.83***
4	150	0.82***	0.75***	0.77***
5	150	0.80	0.64***	0.72*
6	150	0.68***	0.56**	0.54***
7	150	0.35***	0.23***	0.17***
8	150	0.22***	0.23	0.01***
9	150	0.30***	0.40***	0.22***
10	150	0.20***	0.28***	0.03***

[23] Detailed t tests results are included in Appendix 4

Another thing that is worth noting is that the average correlation coefficients between Greece and France are, in general, lower than those between Greece and the other two vulnerable countries, when the VaR of the Greek bond market is higher. This result is not surprising, since Italy and Spain were more vulnerable to spillover episodes originating in the Greek bond market than France.

5. Distinguishing shift contagion from interdependency.

In the previous section, we found that, in general, there are obvious spillover effects between Greece and other EMU countries, but the correlation coefficients between the percentage changes of VaR of Greek and another EMU country' 5 year sovereign bond market tend to decrease, when the tail risks of Greek 5 year sovereign bond market increases. Besides, the patterns of those correlation coefficients are different among different subsamples.

However, the analysis performed in the previous section can neither show us how other EMU countries' sovereign bond markets respond to a Greek credit event, which is defined as the unexpected increase in tail risks of the Greek sovereign bond market, nor indicate the sources of those responses. In fact, in recent literature, efforts have been made to analyze the sources of the contagion effects during the Sovereign Bond Crisis, and to summarize those sources into two categories: the "real" contagion between any two sovereign bond markets of EMU countries and the interdependence among EMU countries.

Because of the integration of capital markets in recent decades, interdependence is strong among EMU financial markets, especially after adopting the same currency and forming the centralized monetary policy making system. Thus all of EMU sovereign bond markets are driven by their local factors and some global fundamental factors. Unlike interdependence, real contagion is usually associated with investors' behaviors, such as herding effect and index tracking, so it is necessary to distinguish the effects of fundamentals-based interdependence and "real" shift contagion during credit events.

For instance, Constancio (2012) reported that bad announcements about Italy reduce the gap between sovereign bonds' CDS spread issued by Italy and Spain. Mike and de Haan (2012) announced that both announcements about development bailout of Greece affect the sovereign bonds of Portugal, Spain and Ireland. Abderrazak Alkhaldi and Tarek Chebbi (2013) reported that exchange rate, market performance, implied volatility of Europe market and some other factors could statistically influence the correlation between sovereign bonds. The first two articles can help in explaining "real" shift contagion, and the last tries to reveal the potential fundamental channels of interdependence.

Under the market efficiency hypothesis, if there is a "real" shift contagion in another country after a Greek credit event, the tail risk of that country' sovereign bond market would have an abrupt shift immediately even after excluding the explanatory power of global and country-specific exogenous factors. Thus, in this section, we will investigate whether after a Greek credit event there is a shift contagion in another EMU country after excluding the effects of interdependence, the explanatory power of global and country-specific fundamental factors.

5.1 The shift contagion model

To test whether there is a "real" shift contagion in another EMU country after a Greek credit event, we need to identify the credit events of the Greek sovereign bond market first.

Considering a credit event is an unexpected loss in sovereign bond market, we use Value at Risk at 99% confidence level ($\mathrm{VaR}_{99\%}$) as the threshold to detect the credit events rather than two standard deviations of financial data as Kaminsky and Reinhart (2007) did. Since no one can obtain the real standard deviation of any financial data for a future period, the indicator suggested by Kaminsky and Reinhart (2007) had a severe look ahead bias.

In short, the Greek credit event indicator ($\mathrm{C_t}$) is defined as following equation.

$$\mathbf{C_t = I(L_{Greece,t} - VaR_{Greece,99\%,t} > 0)} \quad \textbf{(21)}$$

where I(.) is an indicator function, $\mathrm{L_{Greece,t}}$ equals the opposite number of the daily profit and loss of 5 year Greek sovereign bond market at time t ($\mathrm{L_{Greece,t} = -P\&L_{Greece,t}}$), and $\mathrm{VaR_{Greece,99\%,1,t}}$ is the threshold value which reflects the market expectation of the maximum daily loss of Greek sovereign bond market at time t with the 99% confidence level. Thus, whenever the real loss of Greek 5 year sovereign bond market exceeds $\mathrm{VaR_{Greece,99\%,t}}$, $\mathrm{C_t}$ equals one, otherwise $\mathrm{C_t}$ equals zero.

In this analysis we regress $VaR_{i,t}\%$ (the percentage changes of VaR of the sovereign bond i at time t) on: global factors ($\mathrm{g_t}$) which is a $(\mathrm{G} \times 1)$ vector of the global factors that capture observed financial market interdependence at time t, country-specific factors ($s_{i,t}$) which is a ($S \times 1$) vector of observed country-specific factors that could influence sovereign bond market at time t, and $C_{G,t}$ (the dummy variable for Greek credit events). [24]

$$\mathbf{VaR_{i,t}\% = \alpha_i' g_t + \beta_i' s_{i,t} + \gamma_i' C_{G,t} + u_{i,t}} \quad \mathbf{(22)}$$

Since $u_{i,t}$ has heteroscedasticity problems, we will use the White heteroscedasticity-consistent covariance matrix estimator (HCCME) suggested by Eicker (1963) and White (1980) rather than simple homoscedastic covariance matrix.

In addition, all the global and country-specific factors will be split into positive and negative components, in case good and bad news will influence the individual sovereign bond market asymmetrically. And we also use the first three lags of global and country-specific variables to test the lagged influence of those factors on interdependency.

5.1.1 Global factors:

We use the percentage changes of the implied volatility of the S&P 500 (VIX) and the percentage changes of daily USD/EUR Exchange rate as global exogenous factors.

According to the Interest Rate Parity theorem of Stein (1962) as in equation 22, the spot USD/EUR exchange rate ($E_{\$/€,t}$) can directly influence the EUR risk free interest rate ($R_{€,t}$), controlling the USD risk free interest rates ($R_{\$,t}$) and expected USD/EUR exchange rates ($E^e_{\$/€,t}$). Thus, rapid rise or fall in the USD/EUR exchange rate can increase the tail risks of sovereign bond markets, by changing the spot EUR risk free interest rate dramatically.

$$\mathbf{R_{\$,t} = R_{€,t} + \frac{E^e_{\$/€,t} + E_{\$/€,t}}{E_{\$/€,t}}} \quad \mathbf{(23)}$$

Because of the integration of Global financial markets, US, as the biggest economic entity in the world since 1980, can effectively influence the global economic climate.[25] Thus the implied

[24] In all of following regression, we could get a slightly higher R-square if we regress $dVaR_{i,t}$ rather than $VaR_{i,t}\%$ on global factors, country specific factors and credit events. But it makes more economic sense to regress $VaR_{i,t}\%$ on those independent variables, since all independent variables are percentage changes except credit events indicators

[25] According to International Monetary Funds, GDP of the United States is 15,518 billion dollar in 2011, and the country with second largest GDP, China, has only half of that amount, 7,314 billion dollar in 2011. Besides, Japan, the third largest economic entity, has 5,906 billion dollar GDP in 2011. Similar scenario happens in 2012, the US as top economic entity has 16,163 billion dollar GDP in 2012, China as the second largest economic entity has 8,387

volatility of S&P500 index (VIX) provided by the Chicago Board Options Exchange can be considered as a global factor. The choice of VIX as a global factor is also made by Abderrazak Alkhaldi and Tarek Chebbi (2013) who reported that VIX can influence the correlation between GIIPS countries' sovereign bonds during the Sovereign Bond Crisis.

It is known that the Sovereign Bond Crisis is a consequence of the Subprime Crisis, so there should be a positive correlation between the implied volatility of S&P 500 (VIX) and the tail risks of EMU Sovereign bond markets during the Subprime Crisis. Therefore, we will expect positive coefficients on the positive component of the percentage changes of VIX in the regression.

5.1.2 Country-specific factor

We use the percentage returns of local equity index, as the country-specific factor. This choice is motivated by the fact that bonds and stocks are typical substitutes in a portfolio. For instance, Doeswijk, and Lam (2014) reported that equities and government bonds are the top two components in global multi-asset market portfolios in 2012, with portfolio weights of 36.6% and 29.5% respectively, and they also reported that between 1980 and 2012 the portfolio weight on sovereign bonds tended to increase when the portfolio weight on equities decrease. Since bond markets and equity markets are substitute markets for investors, both dramatic increases and decreases in the local equity market should significantly influence the yields of that local sovereign bond market. Because the VaR of sovereign bond markets will increase once there are huge base point changes in interest rates, the VaR of sovereign bond markets should increase in both scenarios.

5.2 Factors and model test

So far, we have only reasoned that the global and country specific factors we chosen are theoretically helpful in predicting the percentage changes of the VaR of EMU sovereign bond markets. We still have to test whether those factors are really statistically significant and reasonable. Besides, we also need to test the number of lags of each factor that we need to include in the shift contagion model.

---

billion GDP in 2012, and the third largest economic entity, Japan, has 5,954 billion GDP in 2012. Thus, the US is big enough to influence global macroeconomic condition during that period.

Toward that end, we regress the percentage changes of the tail risks of each individual sovereign bond market on the last three days' country specific or global factor as in equation 24, to choose appropriate factors and lags in each shift contagion model.

$$\mathbf{VaR_{j,t}\% = \alpha + \beta_1 X^{+}_{t-1} + \beta_2 X^{+}_{t-2} + \beta_3 X^{+}_{t-3} + \beta_4 X^{-}_{t-1} + \beta_5 X^{-}_{t-2} + \beta_6 X^{-}_{t-3} + \varepsilon_t} \quad (\mathbf{24})$$

where X^{+}_{t-1} equals the percentage changes of factor X at time t-1 if that factor is positive, and equals 0 otherwise; and X^{-}_{t-1} equals the percentage changes of factor X at time t-1 if that factor is negative, and equals 0 otherwise. We run this regression three times for each country, one for each factor: USD/EUR exchange rate, VIX, and the local equity index.

As we can see from Table 7, both the coefficients of the first lags of the positive and negative exchange rates are statistically significant at 5% significant level in France, Germany, Greece, Italy, Netherlands, Portugal and Spain, and the signs of those coefficients are the same as our theoretical expectation in previous subsection. Besides, in Austria, the coefficient of the first lag of negative exchange rates is statistically significant at 5% significant level, and the coefficient of the first lag of positive exchange rates is marginally statistically significant. And the only exception is Belgium. Since the coefficients of the first lags of the positive percentage changes of exchange rates are around 1, when the positive (negative) USD/EUR exchange rates increase (decrease) 1%, the VaR of other EMU country also increases 1% the next day. All the coefficients of the second and third order lags of exchange rates are not statistically significantly different from 0, and the absolute values of those coefficients are much smaller than that of the coefficients of first lags, so we will not consider them in the shift contagion model. We could also draw similar conclusion in each subsample from Appendix 5.

The coefficients of first lags of positive VIX (the implied volatility of S&P 500 index) are statistically significant for all the EMU countries at 5% significant level, and 7 out of 9 coefficients of first order lags of negative VIX are at least marginally statistically significant. For the higher order lags, only the coefficient of second order lag of negative VIX is statistically significant in Italy, so we will not consider the second or the third order lagged VIX. Besides, the signs of the first lags are coincident with our expectation, but the signs of the second and third lags are variable. According to Appendix 5, the first lags of positive VIX are still important in each subsample, and the first lags of negative VIX are also important in the Subprime Crisis and the Sovereign Bond Crisis subsample. So we choose to use the first lags of the positive and negative VIX.

Table 7: factors and higher order lags tests

We regress the percentage changes of VaR of each EMU sovereign bond market on last three days country specific and global factor between 2006 and 2011, respectively.

$$\mathrm{VaR}_{j,t}\% = \alpha + \beta_1 X^{+}_{t-1} + \beta_2 X^{+}_{t-2} + \beta_3 X^{+}_{t-3} + \beta_4 X^{-}_{t-1} + \beta_5 X^{-}_{t-2} + \beta_6 X^{-}_{t-3} + \varepsilon_t$$

Where X^{+}_{t-1} equals the percentage changes of the factor X at time t-1 if that factor is positive, and X^{-}_{t-1} equals the percentage changes of the factor X at time t-1 if that factor is negative. Since all the factors are percentage changes, the interpretation of the coefficients (β) is that when the factor X changes 1%, the VaR of individual sovereign bond i changes $\beta\%$ in average. Lag 1 is the first lag of the corresponding factor. In other words, it equals the value of financial factor at time t-1; lag 2 is the second lag of the corresponding factor; and lag 3 is the third lag of the corresponding factor.

$\mathrm{r\_USD/EUR}+$ and $\mathrm{r\_USD/EUR}-$ are positive and negative components of USD/EUR exchange rates, respectively; $\mathrm{r\_VIX}+$ and $\mathrm{r\_VIX}-$ are positive and negative components of implied S&P 500 volatility, respectively; $\mathrm{r\_local\_index}+$ and $\mathrm{r\_local\_index}-$ are positive and negative components of local equity index, respectively.

*,**, and ***, means t tests are significant at the 10%, 5%, and 1% significant level, respectively.

	Austria	Belgium	France	Germany	Greece	Italy	Netherland	Portugal	Spain
r_USD/EUR+									
lag 1	0.66*	0.39	1.49***	1.41***	2.04***	1.20***	1.21***	1.17**	1.49***
lag 2	-0.32	0.05	-0.17	-0.20	-0.10	0.17	0.04	-0.12	0.23
lag 3	0.28	1.19	0.02	-0.23	-0.62*	-0.37	-0.06	-0.47	-0.24
r_USD/EUR-									
lag 1	-1.43***	-0.98	-1.17***	-1.94***	1.27***	-2.01**	-1.68***	0.99**	1.65**
lag 2	0.21	0.30	0.10	0.57**	0.14	-0.54	0.58	0.23	-0.08
lag 3	0.45	-0.39	0.06	0.18	-0.41	0.31	0.20	0.00	-0.21
Constant	0.00	-0.01*	-0.01***	-0.01**	0.00	-0.01**	-0.01**	-0.01	-0.01**
r_VIX+									
lag 1	0.18***	0.20***	0.20***	0.21***	0.10**	0.24***	0.19***	0.08***	0.21***
lag 2	0.00	-0.05	0.00	-0.05	0.02	-0.02	-0.05	0.02	-0.04
lag 3	0.03	0.04	0.06	0.03	0.04	0.07	0.08	0.06	0.11
r_VIX-									
lag 1	-0.08**	-0.10***	-0.09**	-0.10***	0.10	-0.14*	-0.11***	-0.13	-0.17*
lag 2	-0.02	0.03	0.02	0.03	0.03	0.10	0.03	0.04	0.04
lag 3	-0.02	0.00	0.00	0.01	0.01	0.01	-0.01	0.01	-0.03
Constant	-0.01***	-0.01*	-0.01***	-0.01***	-0.01	-0.01*	-0.01***	0.00	-0.01**
r_local_index+									
lag 1	0.45*	0.84**	0.79***	0.91***	1.17**	0.88**	0.82***	1.43*	1.21**
lag 2	-0.17	-0.59	-0.21	-0.16	-0.15	-0.13	-0.18	-0.26	-0.10
lag 3	-0.07	-0.28	-0.19	-0.38***	-0.36***	0.39**	-0.16	-0.47***	-0.42***
r_local_index-									
lag 1	-0.59***	1.12***	-0.99***	-1.20***	-0.88***	1.08***	-0.97***	-1.32***	-1.14***
lag 2	0.13	0.26	0.18	0.31**	-0.24	-0.14	0.20	-0.02	0.09
lag 3	0.05	0.28	0.18	0.35**	0.33*	0.32	0.22	0.19	0.02
Constant	0.00	0.00*	-0.01**	0.00**	-0.01**	-0.01**	-0.01**	-0.01**	-0.01***

As for local equity indices, we also observe strong supportive evidences (both sign and t statistic) from the first lags of both positive and negative percentage returns of the corresponding local equity indices, but we also find some coefficients of higher order lags are also statistically significant at 5% significant level. Nonetheless, the absolute values of the coefficients for the higher order lags are much smaller than those for the first lags. For example, in Greece, even though the coefficient of the first order lags and the third order lags of the local equity index are both statistically significant at 5% significant level, the values of those coefficients are 1.17 and -0.36 respectively. Besides, the coefficients of the third order lags of local equity are statistically different from 0 only occasionally in each subsample, but the first lags of local equity index are very important in predicting interdependency. Thus, first order lagged local equity indices are playing much more important roles in interdependence than higher order lagged factors.

All in all, the signs of the first lagged local and glocal factors are what we expected, and the first lagged fundamental factors are statistically significant across most EMU counrties. Thus our model will include the first lagged positive and negative USD/ERU exchage rates, VIX, and local equity indices as explanaotry variables.

Then we will regress the VaR% on global and counrty specific factors together to test whether the multivariate regression works, and whether there exist multicollinearity problems.

As we can see from Panel I of Table 8, all the factors, except L.r_VIX-, are at least marginally statistically significant at 5% significant level in most cases, and the signs of each coefficients are the same to our expectation. However, when fosucing on subsamples, local equity index, especially when it is negative, is a critical country-specific factor all the time, but VIX is helpful in predicting interdependency only during the Sovereign Bond Crisis. Even though all the coefficients of exchange rates are not statistically different from 0 at 1% and 5% signficant level, in the Before Crisis subsample, the values of coefficients of positive exchange rates are around 1, which means the VaR of individual 5 year sovereign bond market will increase 1%, if lagged positive USD/EUR exchange rates increase 1%. In subsamples, the signs of coefficients are different from our

Table 8: multivariate regression

L.r_USD/EUR+ equals the first lagged r_USD/EUR+; L.r_USD/EUR- equals the first lagged r_USD/EUR-, L.r_VIX+ equals the first lagged r_VIX+, L.r_VIX- equals the first lagged r_VIX-; L.r_local_index+ equals the first lagged r_local_index+; L.r_local_index- equals the first lagged r_local_index-.

$VaR\% = \alpha + \alpha_i' g_t + \beta_i' s_{i,t} + u_{i,t}$ where g_t is a vector of all the global factors: L.r_USD/EUR+, L.r_USD/EUR, L.r_VIX+ and L.r_VIX-; $s_{i,t}$ is a vector of country-specific factors: L.r_local_index+ and L.r_local_index-;

We use the entire sample in Panel I, the Before Crisis subsample in Panel II, the Subprime Crisis subsample in Panel III and the Sovereign Bond Crisis subsample in Panel IV.

*,**, and ***, means t tests are significant at the 10%, 5%, and 1% significant level, respectively.

Panel I: the entire sample period

	Austria	Belgium	France	Germany	Greece	Italy	Netherland	Portugal	Spain
L.r_USD/EUR+	0.41	0.22	1.13***	1.04***	1.51**	0.69*	0.83**	0.61	0.83*
L.r_USD/EUR-	-0.93**	-0.42	-0.44	-1.19***	-0.62	-1.18	-1.00***	-0.13	-0.79
L.r_vix+	0.16***	0.15**	0.16***	0.14***	0.05	0.18**	0.14***	0.01	0.16*
L.r_vix-	-0.06	-0.05	-0.05	-0.03	-0.11	-0.10	-0.06	-0.08	-0.09
L.r_local_index+	0.34	0.63*	0.53*	0.69**	0.94**	0.63*	0.58**	1.13*	1.01**
L.r_local_index-	-0.20	-0.55**	-0.49**	-0.55***	-0.78***	-0.50**	-0.43**	-1.23***	-0.67***
Constant	-0.01***	-0.01***	-0.01***	-0.02***	-0.02***	-0.02***	-0.01***	-0.01***	-0.19***

Panel II: the Before Crisis period

	Austria	Belgium	France	Germany	Greece	Italy	Netherland	Portugal	Spain
L.r_USD/EUR+	0.73	0.91	0.75	0.98	1.08	1.22*	0.91	1.00	1.00
L.r_USD/EUR-	0.25	0.16	0.46	0.17	0.07	-0.27	-0.37	-0.63	0.43
L.r_vix+	0.05	0.09	0.02	0.00	0.09	0.03	0.06	0.05	0.04
L.r_vix-	0.00	-0.01	0.02	0.01	0.01	0.00	-0.01	0.01	0.02
L.r_local_index+	0.22	0.28	0.58	0.55*	-0.21	0.15	0.25	0.16	0.48
L.r_local_index-	-1.15***	-1.37**	-1.47**	-1.96***	-0.47	-1.14**	-1.39**	-1.46	-1.57**
Constant	-0.01**	-0.01***	-0.01**	-0.01***	0.00	-0.01**	-0.01**	-0.01**	-0.01***

Panel III: the Subprime Crisis period

	Austria	Belgium	France	Germany	Greece	Italy	Netherland	Portugal	Spain
L.r_USD/EUR+	0.60	0.54	1.23**	1.25**	1.61**	1.02**	0.89*	0.94	1.41*
L.r_USD/EUR-	-0.87*	-0.29	-0.68	-0.94*	-0.70	-0.67	-0.66	-0.51	-0.37
L.r_vix+	0.13*	0.09	0.04	0.06	0.08	0.08	0.06	0.10	0.05
L.r_vix-	-0.02	-0.02	0.02	0.06	0.01	0.01	0.00	-0.10	-0.04
L.r_local_index+	0.51	1.09*	0.94**	0.92**	0.61	0.59	0.85**	0.84	0.78*
L.r_local_index-	0.00	-0.35	-0.57***	-0.50**	-0.18	-0.10	-0.45**	-0.42*	-0.44**
Constant	-0.01***	-0.01***	-0.02***	-0.02***	-0.01***	-0.01***	-0.02***	-0.02***	-0.02***

Panel IV: the Sovereign Bond Crisis period

	Austria	Belgium	France	Germany	Greece	Italy	Netherland	Portugal	Spain
L.r_USD/EUR+	-0.15	-0.45	1.55*	1.00*	1.54	-0.04	0.85*	-0.08	-0.13
L.r_USD/EUR-	-1.44*	-0.55	-0.61	-2.41***	-1.87*	-2.32	-1.85**	0.32	-2.02
L.r_vix+	0.21***	0.17	0.31**	0.24***	-0.01	0.29	0.19***	-0.16	0.25
L.r_vix-	-0.17*	-0.16**	-0.21**	-0.16**	-0.34	-0.31**	-0.19**	-0.11	-0.25**
L.r_local_index+	0.18	0.16	-0.21	0.53**	1.45**	0.83	0.30	1.95	1.50*
L.r_local_index-	-0.31	-1.06	-0.15	-0.33	-1.53***	-0.88*	-0.53	-2.76**	-0.83
Constant	-0.01**	-0.01	-0.01***	-0.02***	-0.04**	-0.03***	-0.02***	-0.02	-0.03***

expectation occassionally, but none of those opposite signs are statistically significant at 5% significant level. Although multivariate regressions in subsamples suggest that VIX is not important before the Soveregin Bond Crisis, we still include that factor to be consistent.

Table 9: multicollinearity problem tests

Fllowing table reports the value of variance inflation factor, VIF, of each independent variable. Chatterjee and Price (1991) suggested that VIF=10 would be the threlshold number to alert the potential collinearity problem.

	Austria	Belgium	France	Germany	Greece	Italy	Netherland	Portugal	Spain
Panel I: the entire sample period									
L.r_USD/EUR+	1.22	1.20	1.24	1.20	1.19	1.26	1.23	1.21	1.23
L.r_USD/EUR-	1.29	1.26	1.30	1.29	1.24	1.34	1.27	1.28	1.33
L.r_vix+	1.33	1.46	1.55	1.52	1.25	1.47	1.49	1.34	1.46
L.r_vix-	1.21	1.31	1.29	1.27	1.17	1.37	1.27	1.23	1.28
L.r_local_index+	1.29	1.36	1.37	1.32	1.22	1.27	1.32	1.27	1.35
L.r_local_index-	1.44	1.54	1.68	1.62	1.29	1.64	1.55	1.41	1.62
Panel II: the Before Crisis period									
	Austria	Belgium	France	Germany	Greece	Italy	Netherland	Portugal	Spain
L.r_USD/EUR+	1.22	1.20	1.20	1.20	1.22	1.20	1.20	1.20	1.20
L.r_USD/EUR-	1.23	1.21	1.22	1.23	1.24	1.22	1.22	1.20	1.20
L.r_vix+	1.26	1.38	1.43	1.45	1.26	1.36	1.34	1.21	1.33
L.r_vix-	1.14	1.27	1.24	1.20	1.17	1.22	1.24	1.12	1.23
L.r_local_index+	1.21	1.34	1.33	1.29	1.25	1.31	1.32	1.13	1.29
L.r_local_index-	1.36	1.46	1.55	1.55	1.38	1.48	1.43	1.20	1.39
Panel III: the Subprime Crisis period									
	Austria	Belgium	France	Germany	Greece	Italy	Netherland	Portugal	Spain
L.r_USD/EUR+	1.21	1.17	1.21	1.17	1.16	1.22	1.23	1.19	1.20
L.r_USD/EUR-	1.27	1.20	1.24	1.24	1.21	1.25	1.22	1.22	1.23
L.r_vix+	1.43	1.67	1.70	1.68	1.35	1.57	1.82	1.40	1.67
L.r_vix-	1.25	1.30	1.28	1.34	1.21	1.25	1.30	1.26	1.28
L.r_local_index+	1.34	1.33	1.31	1.33	1.19	1.31	1.33	1.27	1.30
L.r_local_index-	1.54	1.69	1.76	1.73	1.40	1.63	1.84	1.39	1.73
Panel IV: the Sovereign Bond Crisis period									
	Austria	Belgium	France	Germany	Greece	Italy	Netherland	Portugal	Spain
L.r_USD/EUR+	1.36	1.36	1.43	1.40	1.35	1.44	1.38	1.34	1.40
L.r_USD/EUR-	1.45	1.50	1.51	1.46	1.36	1.59	1.46	1.49	1.62
L.r_vix+	1.47	1.61	1.81	1.72	1.28	1.67	1.77	1.53	1.60
L.r_vix-	1.39	1.53	1.50	1.39	1.23	1.47	1.44	1.44	1.46
L.r_local_index+	1.50	1.63	1.68	1.52	1.28	1.66	1.56	1.49	1.58
L.r_local_index-	1.59	1.80	2.05	1.87	1.28	2.01	1.94	1.71	1.98

The decreases of all the t statistics could be explained by the fact that explanatory variables are not orthonogal. Thus we also need to test whether there is a multicollinearity problem by variance inflation factor (VIF).

As in Table 9, since all the Variance Inflation Factors are far smaller than 10, which is the threshold value suggested by Chatterjee and Price (1991) to detect the potential multi-collinearity problem, we do not need to exclude factor to avoid multi-collinearity problem.

5.3 Greek impact on other EMU countries

Based on the conclusions reached above, we will use the lagged positive and negative values of the USD/EUR exchange rate, VIX and local index to explain the interdependency, and the dummy variable of the Greek credit events to detect the shift-contagion as following equation indicates.

$$\mathbf{VaR_{j,t}\% = \alpha + \beta_1 \frac{USD^+}{EUR_{t-1}} + \beta_2 VIX^+_{t-1} + \beta_3 Local_{index}{}^+_{t-1}} \quad (\mathbf{25})$$

$$\mathbf{+\beta_4 USD/EUR^-_{t-1} + \beta_5 VIX^-_{t-1} + \beta_6 Local\_index^-_{t-1} + \beta_7 C_t + \varepsilon_t}$$

We will test whether the shift-contagion exists on the day of a credit event, the day after a credit event, and two days after a credit event. Besides, we also test the cumulative effect of a credit event by testing whether the average shift-contagion is statistically significant during those three days. Cumulative credit event equals one at the credit event day and the following two days, and it equals to zero otherwise. Therefore, C_t in equation 25 will have these four different specifications.

As we can see from Panel I of Table 10, on the day of credit events and two days after credit events, none of shift contagion coefficients are statistically significant, and the values of the coefficients of global and country-specific factors are almost identical to those of our multivariate regression without Greek credit events indicator.

Table 10: Greek impact on other countries

This table illustrate potential interdependence and 'real' shift-contagion in each EMU country. C_t is the Greek credit events indicator; L.Greek Event is the lagged Greek credit events indicator; L2.Greek Event is the second order lags of the Greek credit events indicator. $\mathrm{L.Greek\ Event_t = Greek\ Event_{t-1} = C_{t-1}}$; $\mathrm{L2.Greek\ Event_t = L.Greek\ Event_{t-1} = Greek\ Event_{t-2}}$

And Cum. Greek Event is the explanatory variable to measure average effect of Greek events in the following three days. $\mathrm{Cum.Greek\ Event_t} = \sum_{i=0}^{2}(C_{t-i})$

Panel I reports the regression results use the entire sample, Panel II uses the Before Crisis period, Panel III uses the Subprime Crisis period and Panel IV use the Sovereign Bond Crisis period. *,**, and ***, means t tests are significant at the 10%, 5%, and 1% significant level, respectively. I have not reported the detailed coefficients of the global and local factors in subsample regressions, but the results are available if requested.

Panel I: the entire sample period								
	Austria	Belgium	France	Germany	Italy	Netherland	Portugal	Spain
L.r_USD/EUR+	0.41	0.23	1.13***	1.04***	0.69*	0.83**	0.61	0.83*
L.r_USD/EUR-	-0.92**	-0.42	0.44	-1.19***	-1.19	-1.00***	-0.13	-0.90
L.r_vix+	0.16***	0.15**	0.16***	0.14***	0.18**	0.14***	0.01	0.16*
L.r_vix-	-0.06	-0.05	-0.05	-0.03	-0.10	-0.06	-0.08	-0.09
L.r_local_index+	0.34	0.64*	0.54*	0.68**	0.63*	0.59**	1.13*	1.01**
L.r_local_index-	-0.20	-0.55**	-0.48**	-0.55***	-0.49**	-0.42**	-1.23***	-0.66***
Greek Event	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.12
Constant	-0.01***	-0.01***	-0.01***	-0.02***	-0.02***	-0.01***	-0.01**	-0.02***
L.r_USD/EUR+	0.16	0.04	0.99**	0.82**	0.39	0.68**	0.34	0.60
L.r_USD/EUR-	-0.76*	-0.29	-0.31	-1.06***	-0.95	-0.88**	0.00	-0.65
L.r_vix+	0.16***	0.15**	0.16***	0.14***	0.18**	0.14***	0.02	0.16*
L.r_vix-	-0.08**	-0.08*	-0.73*	-0.05	-0.14**	-0.08**	-0.11	-0.12**
L.r_local_index+	0.23	0.38	0.35	0.58***	0.34	0.39*	0.92	0.79*
L.r_local_index-	-0.19	-0.50**	-0.46**	0.53***	-0.46**	-0.41**	-1.12***	-0.60***
L.Greek Event	0.11***	0.10***	0.09***	0.09***	0.17***	0.09***	0.13***	0.12***
Constant	-0.01***	-0.01***	-0.01***	-0.01***	-0.02***	-0.01***	-0.01**	-0.02***
L.r_USD/EUR+	0.42	0.24	1.13***	1.03***	0.66*	0.82**	0.59	0.83*
L.r_USD/EUR-	-0.92**	-0.42	-0.43	-1.19***	-1.17	-0.99***	0.13	-0.79
L.r_vix+	0.16***	0.16**	0.16***	0.14***	0.18**	0.14***	0.01	0.16*
L.r_vix-	-0.63	-0.05	-0.05	-0.03	-0.10	-0.06	-0.08	-0.09
L.r_local_index+	0.34	0.62*	0.53*	0.69**	0.64*	0.58**	1.14**	1.01**
L.r_local_index-	-0.20	-0.55**	-0.49**	-0.55***	-0.51**	-0.43**	-1.22***	-0.67***
L2.Greek Event	-0.01	-0.01	0.00	0.00	0.02	0.00	0.02	-0.05
Constant	-0.01***	-0.01***	-0.01***	-0.02***	-0.02***	-0.01***	-0.01**	-0.02***
L.r_USD/EUR+	0.31	0.14	1.05**	0.95**	0.50	0.74**	0.47	0.71
L.r_USD/EUR-	-0.87**	-0.38	-0.41	-1.16***	-1.12	-0.95**	-0.11	-0.77
L.r_vix+	0.15***	0.15**	0.16***	0.14***	0.17**	0.14***	0.01	0.16*
L.r_vix-	-0.06	-0.05	-0.05	-0.33	-0.10	-0.06	-0.08	-0.09
L.r_local_index+	0.32	0.59*	0.49*	0.65**	0.58*	0.54**	1.09*	0.97**
L.r_local_index-	-0.19	-0.52**	-0.45**	-0.51***	-0.44**	-0.40**	-1.12***	-0.60***
Cum.Greek Event	0.03***	0.03**	0.03***	0.03***	0.07***	0.04***	0.05***	0.05***
Constant	-0.01***	-0.01***	-0.01***	-0.02***	-0.02***	-0.02***	-0.01***	-0.02***

Panel II: the Before Crisis period								
	Austria	Belgium	France	Germany	Italy	Netherland	Portugal	Spain
Greek Event	0.03	0.05	0.05	0.03	0.06	0.05	0.06	0.05
L.Greek Event	0.16*	0.16*	0.11	0.12	0.15*	0.13	0.12*	0.15*
L2.Greek Event	0.04	0.03	0.04	0.05	0.05	0.04	0.03	0.04
Cum.Greek Event	0.08**	0.08**	0.07**	0.07*	0.09**	0.08**	0.07**	0.08**

Nevertheless, all the shift contagion of the Greek credit event on the day after credit events are statistically significant and have the expected positive sign, and the absolute values of coefficients of exchanges rates and local equity indexes decrease. This means that there are statistical evidences pointing towards the existence of shift contagions in all EMU countries on the day after a Greek credit event.

Table 10-- *Continued*

Panel III: the Subprime Crisis period								
	Austria	Belgium	France	Germany	Italy	Netherland	Portugal	Spain
Greek Event	0.01	0.02	0.02	0.00	0.01	0.01	0.01	0.01
L.Greek Event	0.18***	0.18***	0.14***	0.14***	0.17***	0.12***	0.17***	0.15***
L2.Greek Event	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	-0.01	-0.02
Cum.Greek Event	0.06**	0.06***	0.05**	0.04**	0.05**	0.04**	0.05**	0.04**
Panel IV: the Sovereign Bond Crisis period								
	Austria	Belgium	France	Germany	Italy	Netherland	Portugal	Spain
Greek Event	-0.02*	-0.02*	-0.01	0.00	0.01	0.00	-0.02**	0.00
L.Greek Event	0.02	-0.01	0.03*	0.03	0.18	0.03*	0.10	0.09**
L2.Greek Event	-0.03***	-0.04***	-0.01	0.00	0.04	0.00	0.05	0.00
Cum.Greek Event	-0.01	-0.02**	0.01	0.01	0.08*	0.01	0.05	0.03*

This shift contagion also has a reasonable economic significance. The coefficients of lagged credit event dummy variables are around 0.1 (0.11 in Austria, 0.10 in Belgium, 0.09 in France, 0.09 in Germany, 0.17 in Italy, 0.09 in Netherlands, 0.13 in Portugal and 0.12 in Spain), which means if there is a credit event in Greece sovereign bond market, the tail risk of another EMU country' sovereign bond market will increase around 10% on the day after that credit event. Furthermore, the impact is larger on the vulnerable countries (Italy, Spain and Portugal) than that on stable countries (Austria, Belgium, France, Germany and Netherlands), which is what one would expect, even though the difference in the impact on the two groups of countries is not very large. This can be partly explained by the fact that we are measuring the impact of Greek credit events on the percentage changes of other countries' tail risk.

Looking at the cumulative effect of a Greek credit event, we can see that all the coefficients on the cumulative Greek credit event are also statistically significant and positive (0.03 in Austria, 0.03 in Belgium, 0.03 in France, 0.03 in Germany, 0.07 in Italy, 0.04 in Netherlands, 0.05 in Portugal and 0.05 in Spain). That is, if there happens a Greek credit events in Greek 5 year sovereign bond market, tail risks of another EMU country' 5 year sovereign bond market will increase at least 3% per day in the following three successive days. Again, this shift contagion has economic significance, and it is stronger for the vulnerable countries than for the stable countries.

According to Panel II to IV of Table 11, the cumulative effects of Greek credit events are both statistically and economically significant in the Before Crisis subsample and the Subprime Crisis subsample. In the Before Crisis subsample, shift contagion seems moderate, since the signs of shift-contagion on the day of credit events and the following two days are all positive, but only 5 out of 8 coefficients of the shift-contagion on the day after credit events are statistically significant at 10% significant level. In the Subprime Crisis period, the statistically significant shift-contagion on the day after Greek credit event always follows a tiny reverse. In the Sovereign Bond Crisis subsample, the cumulative effects of Greek credit events disappear totally in stable countries (-0.01 in Austria, -0.02 in Belgium, 0.01 in France, 0.01 in Germany and 0.01 Netherlands), and when the tail risk of the 5 year Belgian sovereign bond market has statistically significant decreases at 5% significant level in those three days. In vulnerable countries, even though the shift-contagions on the day after Greek credit events are not statistically significant at any significant level (0.18 in Italy, 0.10 in Portugal and 0.09 in Spain), the tail risk of vulnerable countries will still increase at least 9% on the day after Greek credit events.

As Figure 2 to 5 shows, the VaR of Greek 5 year sovereign bond market has significantly increased in Subprime Crisis and even soared in the Sovereign Bond Crisis (the mean and median of VaR are 903.61 and 889.37 before crisis, 1832.91 and 1699.28 during the Subprime Crisis, and 12635.97 and 7260.19 during the Sovereign Bond Crisis). What we have observed in the subsample analysis that shift-contagion tends to be insignificant during the Sovereign Bond Crisis period when VaR of Greek sovereign bond market is soaring, is in line with the conclusion of section 4. However, we cannot analyze the shift-contagion effects of each variance decile group, since we only have 19 exceedances in total.

6. Summary

In this paper, we first discuss the prevailing methods of Value at Risk models, prove the superiority of the volatility adjusted historical simulation models, and choose the EWMA volatility adjusted historical simulation as the most appropriate VaR model by a punishment scorecard. Besides, we also find that the real distribution of base point changes is not symmetric and has a fatter tail than normal distribution, which fits our expectation, but an asymmetric GARCH model (GJR model) cannot dramatically improve the performance of VaR estimates.

After that, in section 4, we find, between 2006 and 2011, even though there are obvious volatility spillover effects during all the episodes when Greek sovereign bonds have dramatic increases, the overall correlation coefficients between percentage changes of VaR of Greek and another EMU country's (Italian, Spanish or French) 5 year sovereign bond market tend to decrease, if the VaR of the Greek 5 year sovereign bond increases. Besides, the correlation coefficients decrease faster in stable country (France) than in vulnerable countries (Italy and Spain), when VaR of Greek sovereign bond market is high.

This pattern can be explained by the following reason. During the Subprime Crisis and the Sovereign Bond Crisis, the abrupt increases in tail risks of Greek sovereign bond markets mainly came from Greek specific political and financial turmoil, so the correlation between Greek and other EMU sovereign bond markets were weaken after those abrupt increases.

However, those volatility spillover effects can be explained by the interdependence among EMU countries and the fear of potential contagions. As a result, investors make a tradeoff between particularity of the Greek sovereign bonds and generality of EMU countries' sovereign bonds. Therefore, even though the increases of Greek sovereign bond mainly came from Greek specific problems, there existed gradually weakened volatility spillover effects between Greece and other EMU countries during each episodes, when VaR of Greek sovereign bond is increasing.

In section 5, we expand our sample from three top economic entities (Italy, Spain and France) to all EMU countries with available 5 year sovereign bond market data during that period, and focus on "real" shift contagion effects of Greek credit events in other EMU countries. [26]

We find that "real" shift contagions in other EMU countries' sovereign bond markets exist on the day after Greek credit events (their tail risks will increase around 10% within one day). However, most of shift contagion effects come from the Before Crisis subsample and Subprime Crisis subsample (VaR of other EMU countries' sovereign bond markets increase around 12% and 15% respectively). The cumulative shift contagion effects of the Greek credit event day and the

[26] 5 year Irish sovereign bond also have severe data missing problem. 5 year Irish sovereign bond data is not available in Bloomberg during 10/25/2007-6/28/2003; 2/3/2011-1/20/2010; 12/5/2005-11/16/2005; 2/2/2004-11/7/2003;

following two days are not statistically significant in the Sovereign Bond Crisis period. In stable countries, the VaR increases at most 1% each day, however in vulnerable countries, we could still observe non-statistically but economically significant increases.

This result can be explained by the following. When risk of each sovereign bond is relatively low, all 5 year sovereign bonds issued by EMU countries are good substitutes, since all the securities are denominated by the same currency euro, have the same maturity 5 years, and are backed by a same Economic Union EMU. Also, the significant shift contagions could also account for centralized monetary policies and low trading barrier among EMU.

While, the exploding risks of Greek sovereign market gradually makes Greek sovereign bond stand out, but not in a good way. And Pitch, S&P and Moody downgraded Greek sovereign bond in succession on account of Greek country specific risk, like high Debt/GDP ratio, high deficit, and unstable politic situation. Thus, shift contagions in other EMU countries are not statistically significant, during the Sovereign bond Crisis. Nevertheless, investors are worried about potential volatility spillover, especially in vulnerable countries (Italy, Portugal and Spain), thus those countries still have some non-statistically but economically significant shift contagions.

Admittedly, there are still some problems in the shift contagion model. First, the coefficients are not constant in the entire sample. For instance, general investors may be reluctant to increase their investments in foreign securities, especially those denominated by a foreign currency, in the normal period, since the foreign securities have higher agency costs than their domestic securities and the foreign currencies are less liquidity than their domestic currency. Thus, VIX, the implied volatility of S&P 500 index, is less critical and even irrelevant before crisis. However, during crisis, the demand of the foreign securities as the financial substitutes increases, since the demand of the domestic securities drops. Besides, we do not claim that we have exhaustively included the set of global and local factors that could influence interdependence, for that reason our model might be underspecified.

References

Alexander, C. 2009. ***Market Risk Analysis Vol IV: Value at Risk models***, John Wiley & Sons

Alter, A., & Beyer, A. 2014, The dynamics of spillover effects during the European sovereign debt turmoil, ***Journal of Banking & Finance,*** 42: 134-153

Audige, H. 2013. ***A new approach of contagion based on STCC-GARCH models: An Empirical application to the Greeck crisis***, Working paper Economix n. 2013-2

Beder, T. S. 1995. VaR: Seductive but Dangerous, ***Financial Analyst Journal***, Sep-Oct, 12-24

Berkowitz, J. , Christoffersen, P., & Pelletier, D. 2010. Evaluating Value at Risk models with Desk-Level Data, ***Management Science***, 57: 2213-2227

Bessler, W. & Wolff, D. 2014. Hedging European government bond portfolios during recent sovereign debt crisis, ***Journal of International Financial Markets, Institutions and Money***, 33: 379-399

Bollerslev, T. 1986. Generalized Autoregressive Conditional Heteroskedasticity***, Journal of Econometrics*** 31:307-327

Bollerslev, T., Chou, R. Y., & Kroner, K. F. 1992. ARCH modeling in finance: A review of the theory and empirical evidence, ***Journal of Econometrics,*** 52:5-590

Boudoukh, B., Richardson, M., & Whitelaw, R. 1998. The Best of Both Worlds, ***RISK*** 11:64-67

Buchholz, M. & Tonzer, L. 2013. ***Sovereign credit risk co-movement in the Eurozone: simple interdependence or contagion?*** INET Workshop 2013 "Interlinkage and Systemic Risk" Polytechnic University of Marche, July 4-5,2013

Celik, S. 2012. The more contagion effect on emerging markets: The evidence of DCC-GARCH model, ***Economic Modelling*** 29: 1946-1956

Clare, A. D., & Lekkos, I. 2000. ***An Analysis of the Relationship between National Bond Markets.*** Working Paper No. 123, Bank of England

Chatterjee, S., & Price, B. 1991. ***Regression diagnostics.*** New York: John Wiley & Sons

Christoffersen, P. 1998, Evaluating interval forecasts, ***International Economic Review,*** 39: 841-862

Constancio, V. 2012. Contagion and European Debt Crisis, ***Financial Stability Review,*** 16: 109-122, Bank of France

Doeswijk, R., Lam, T., & Swinkels, L. 2014. The global multi-asset market portfolio, 1959-2012, ***Financial Analysts Journal,*** 70(2): 26-41

Elkhaldi, A., Chebbi, T. & Naoui, K. 2013***. Measuring contagious effects on euro area debt crisis using daily CDS spread changes***, paper presented in 1st TSFS Finnace Conference, TSFS 2013, Sousse, Tunisia.

Engle, R. F. 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation, ***Econometrica*** 50:987-1007

Engle, R. F. 2002. Dynamic conditional correlation: A simple Class of Multivariate GARCHModels, ***Journal of Business & Economic Statistics,*** 20:399-350

Engle, R. F., & Manganelli, S. 2004. CAViaR: Conditional autoregressive Value at Risk by regression quantiles, ***Journal of Business & Economic Statistics*** 22:367-381

Fleming, J., Kirby, C., & Ostdiek, B. 2002. The Economic Value of Volatility Timing, ***Journal of Finance,*** 56:329-352

Forbes, K. J., & Rigobon, R. 2001. Contagion in Latin America: Definitions, measurement, and policy implications, ***Economia*** 1(2): 1-46.

Forbes, K. J., & Rigobon, R. 2002. No contagion, only interdependence: Measuring stock market comovements, ***Journal of Finance*** 57(5): 2223-2261.

Glosten, L. R., Jagannathan, R. & Runkle, D. E. 1993. On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks, ***Journal of Finance,*** 48(5): 1779-1801

Gunduz, Y., & Kayay, O., 2013. ***Long Memory and Correlation Dynamics of Eurozone Sovereign CDSs***, 30th French Finance Association Conference, which was held from May 2013

Hong, Y., Liu, Y. & Wang, S., 2009, Granger causality in risk and detection of extreme risk spillover between financial markets, ***Journal of Econometrics,*** 150(2):271-287

Hull, J., & White, A., 1998, Incorporating volatility updating for value-at –risk, ***Journal of Risk***, 1(1) fall: 5-19.

Kalbaska, A., & Gatkowski, M. 2012. Eurozone Sovereign Contagion: Evidence from CDS Market (05-2010), ***Journal of Economic Behavior & Organization***, 83: 657-673.

Kaminsky, G. L., & Reinhart, C. M. 2000. On crisis, contagion, and confusion, ***Journal of International Economics,*** 51:145-168

Kendall, M. G. 1940, Note on the distribution of quantiles for large samples, ***Supplement to the Journal of the Royal Statistical Society,*** 7(1): 83-85

Mink, M. & Haan, J. D. 2012, ***Contagion during the Greek Sovereign Debt Crisis***, DNB working paper No. 335, De Nederlandsche Bank NV, P.O. Box 98, Netherlands

Mission, S., & Watzaka, S. 2011. ***Financial Contagion and European Debt Crisis.*** Working paper 3554, CESifo

Nelson, D. B. 1991, Conditional heteroskecadticity in asset returns: A new approach, ***Econometrica*** 59: 347-370

Polanski, A., & Stoja, E. 2014, Co-dependence of extreme events in high frequency FX returns, ***Journal of International Money and Finance***, 44:164-178

Pragidis, I. C., Aielli, G.P., Chionis, D., & Schizas, P. 2015. Contagion effects during financial crisis: Evidence from the Greek sovereign bonds market, ***Journal of Financial Stability,*** 18: 127-138

Reboredo, J. C. & Ugolini, A. 2015 Systemic risk in European sovereign debt markets: A CoVaR-copula approach, ***Journal of Internal Money and Finance,*** 51:214-244

Revisions to the Basel II market risk framework, 2009, Bank for International Settlements, press, CH-4002 Basel, Switzerland

RiskMetrics Group, 1996, ***RiskMetrics-Technical Document,*** New York: J.P. Morgan/Reaters

Satterthwaite, F.E. 1946. An approximate distribution of estimates of variance components, ***Biometrics Bulletin*** 2: 110-114

Simone, M. & Robert, F.E. 2011. ***Value at Risk Models in Finance.*** Working paper no. 75, Page 23-56, European Central Bank, Kalserstrasse 29, D-60311 Franfurt am Main, Germany.

Stein, J. L. 1965. The Froward Rate and the Interest Parity, ***The Review of Economic Studies,*** 32(2): 113-126, Oxford University Press

Sy, A. N. R. 2004. Rating the rating agencies: Anticipating currency crises or debt rises? ***Journal of Banking and Finance*** 28, 28452867.

Skintzi, V. D., & Refenes, A. N. 2006. Volatility spillovers and dynamic correlation in European Bond markets, 2006, ***Journal of International Financial Markets, Institutions and Money***, 16(1): 23-40

Welch, B. L. 1947. The generalization of “student’s” problem when several different population variances are involved, ***Biometrika*** 34:28-35

White, H. , 1980. A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity***, Econometrica,*** 48: 817-838

Zakoian, J. M. 1994. Threshold heteroskedastic models***, Journal of Economic Dynamics and Control***, 18(5): 931-955

Appendix

Appendix 1: Summary of Data missing problem and number of adjustments

To estimate the daily VaR of different 5 year sovereign bonds, we first need to use the linear interpolation method to interpolate the missing values. Since interpolations are just estimated interest rates rather than real interest rates, if there are too many interpolations in the sample, we will get a distorted VaR model.

Thus, the following table report the number of missing value in each sovereign bond between 2003 and 2013, if there are more than four consecutive missing values, we will report the beginning date and ending date of the data missing period. If we don’t have consecutive missing values, we will report an N/A. If there are too many missing value in one country, we will report a ‘drop’ and drop that country.

Country	Number of missing value	Data missing period
Austria	1	N/A
Belgium	1	N/A
Finland	Drop	Drop[27]
France	1	N/A
German	0	N/A
Greece	2	12/31/2013 3/13/2012
Ireland	Drop	Drop
Italy	1	N/A
Netherland	1	N/A
Portugal	6	N/A
Spain	1	N/A

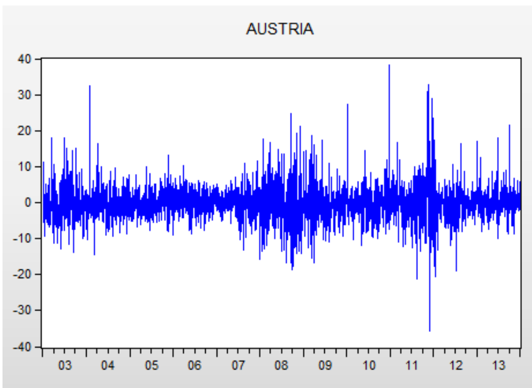
[27] 5 year Finnish sovereign bond have severe data missing problem. 5 Year Finnish sovereign bond data is not available in Bloomberg during 8/29/2013-5/13/2013; 5/31/2007-1/31/2007; 12/12/2006-1/26/2007; 10/21/2003-9/30/2003; 5/15/2003-4/15/2003.
5 year Irish sovereign bond also have severe data missing problem. 5 year Irish sovereign bond data is not available in Bloomberg during 10/25/2007-6/28/2003; 2/3/2011-1/20/2010; 12/5/2005-11/16/2005; 2/2/2004-11/7/2003; Thus I exclude those two data from analysis.

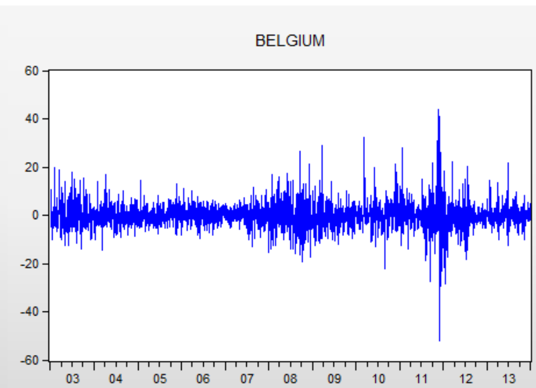
Appendix 2 Heteroscedasticity problem of base point change

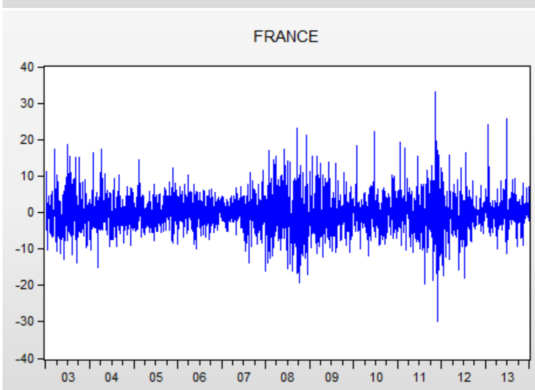
If base point changes of each country's 5 year sovereign bonds are homoscedastic, we don't need to introduce a GARCH or EWMA model to estimate the dynamic variance. Thus, we would like to test whether base point changes of each country's 5 year sovereign bonds has heteroscedasticity problem before introducing any variance estimation model.

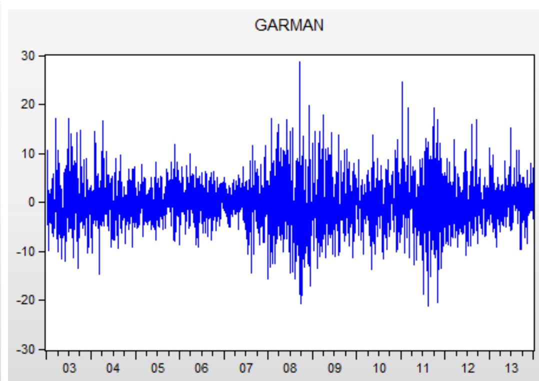
To do so, we regress base point changes of each country's 5 year sovereign bonds on a constant and get residuals as following equation. $bp_{j,t} = \alpha + u_{j,t}$, where $bp_{j,t}$ is the base point change of country j's 5 year sovereign bonds at time t, and $u_{j,t}$ is the residuals of country j's 5 year sovereign bond at time t.

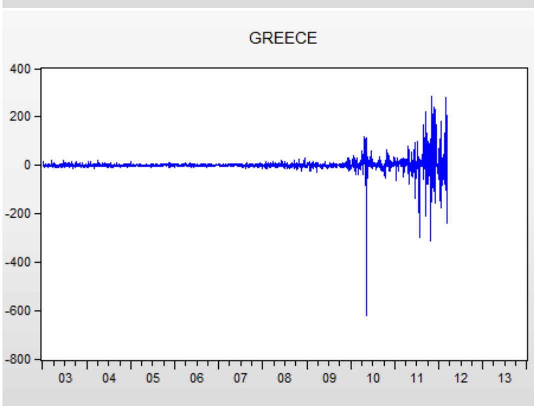
Following graphs depicts $u_{j,t}$ for each country's 5 year sovereign bonds between 2003 and 2013.

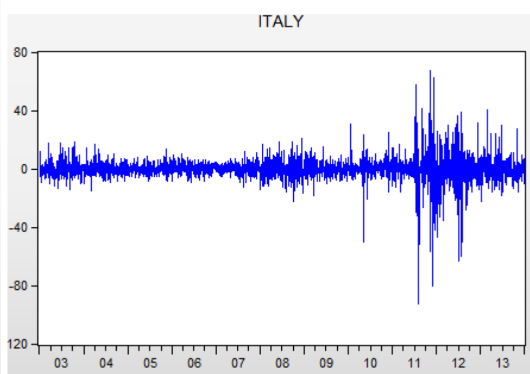


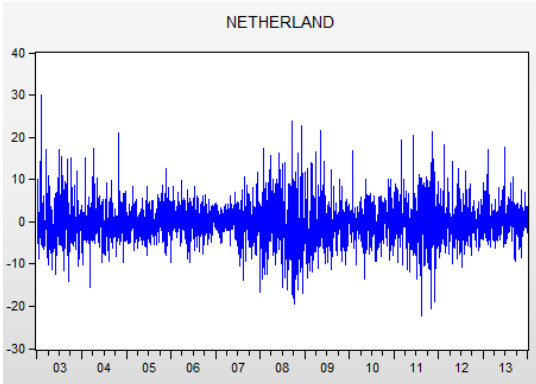


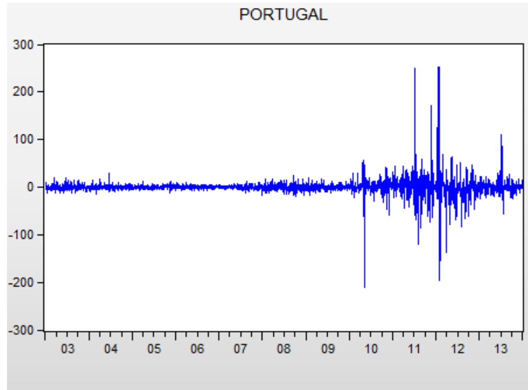


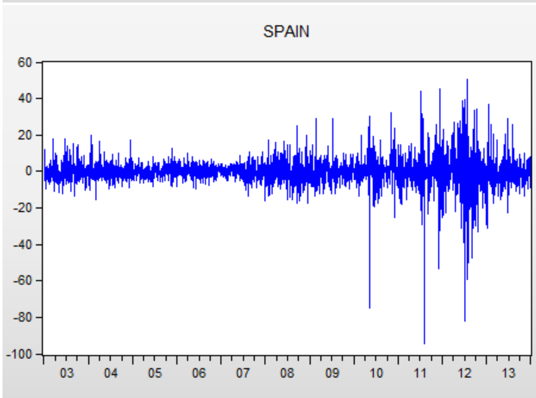







NETHERLAND
40
30
20
10
0
-10
-20
-30
03 04 05 06 07 08 09 10 11 12 13


PORTUGAL
300
200
100
0
-100
-200
-300
03 04 05 06 07 08 09 10 11 12 13


SPAIN
60
40
20
0
-20
-40
-60
-80
-100
03 04 05 06 07 08 09 10 11 12 13

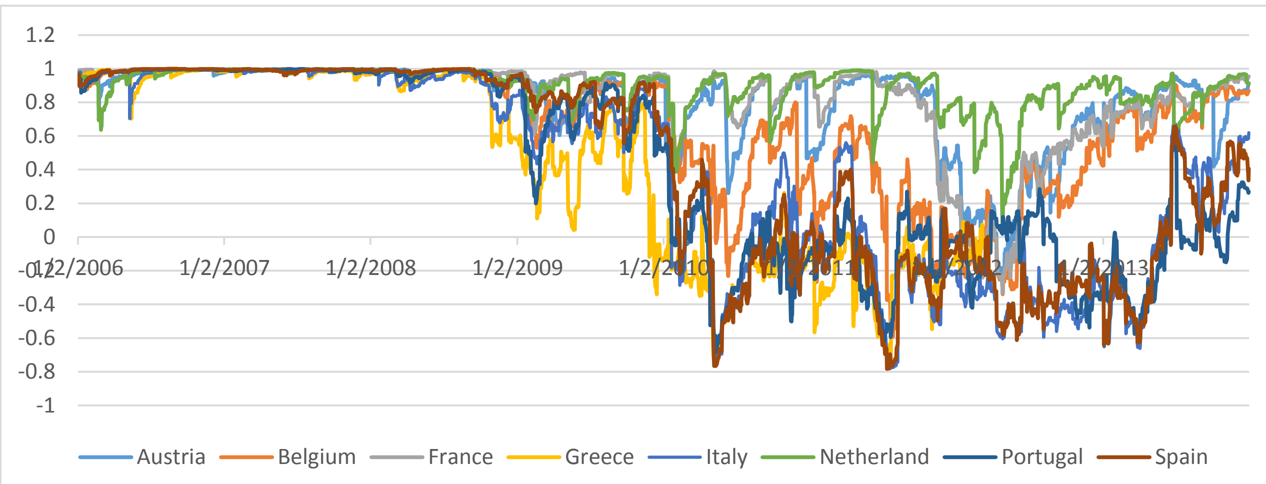
Appendix 3 correlation coefficients between EMU, estimated by EWMA model

We use EWMA method to approximately estimate daily correlation coefficients between base point changes of each two 5 year sovereign bonds as following equation.

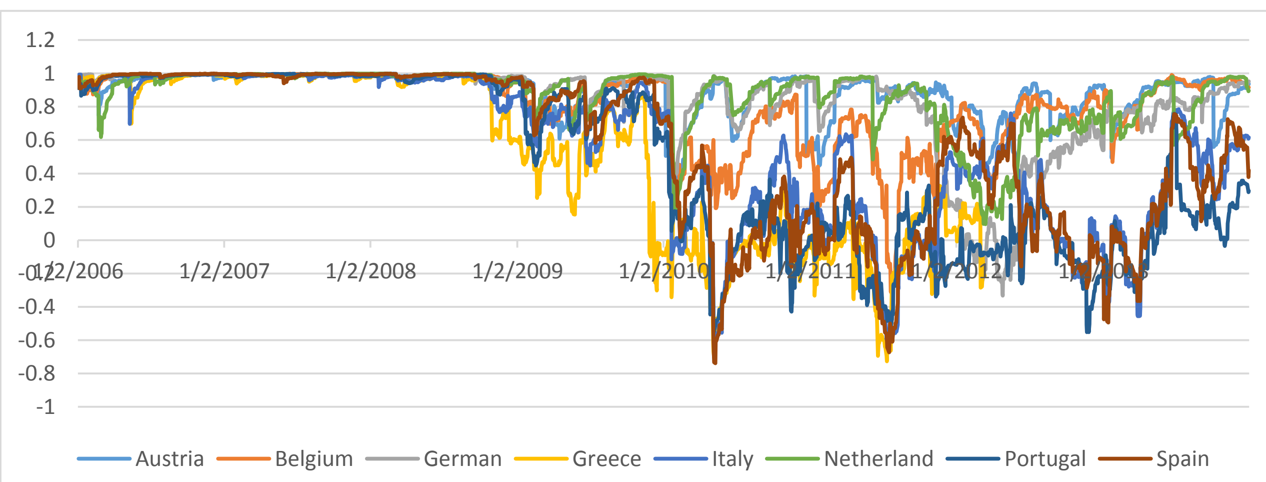
$$\begin{cases} \mathrm{cov}_{i,j,t} = \lambda \mathrm{cov}_{i,j,t-1} + (1-\lambda)\mathrm{bp}_{i,t-1}\mathrm{bp}_{j,t-1} \\ \sigma_{j,t}^2 = \lambda\sigma_{j,t-1}^2 + (1-\lambda)\mathrm{bp}_{j,t-1}^2 \\ \mathrm{bp}_{j,t} \sim \mathrm{i.i.d.}\left(0, \sigma_{j,t}^2\right) \\ \lambda = 0.94 \\ \rho_{i,j,t} = \mathrm{cov}_{i,j,t}/\left(\sigma_{i,t}\sigma_{j,t}\right) \end{cases}$$

where $\mathrm{bp}_{j,t}$ is the base point change of country j's 5 year sovereign bonds at time t; $\mathrm{cov}_{i,j,t}$ is the covariance between base point changes of country i and country j's 5 year sovereign bonds at time t; $\sigma_{j,t}^2$ is the variance of base point changes of country j's 5 year sovereign bonds at time t; $\rho_{i,j,t}$ is the correlation coefficients between base point changes of country i and country j's 5 year sovereign bonds at time t. Graph I depicts the dynamic correlation coefficients between base point changes of German and other EMU countries' 5 year sovereign bonds. And Graph II depicts that correlation coefficients between France and other EMU counties.

Graph I: correlation coefficients between Germany and other countries



Graph II: correlation coefficients between French and other countries



Appendix 4: T tests details of decile VaR group

We include sample period between Apr. 2nd 2006 and Dec. 31st 2011, and form 10 groups by deciles of the ascendingly ranked Greek 5 year sovereign bond market's VaR. As a result, group 1 is the smallest Greek VaR decile, and group 10 is the largest the Greek VaR decile. We execute several t tests to exam whether the mean of correlation coefficients in consecutive groups are equal.

Panel I report the p value of equivalent tests, the null hypothesis of equivalent tests are the variance of those two consecitive are euqal. According to the results of equivalent tests under 5% significant level, we choose between using a pooled t test (for consecutive subgroups with equal variance) or a Welch's t test suggested by Welch (1947)and Satterthwaite (1946) (for consecutive subgroups with unequal variance). And Panel II report the t statistic and p value of t tests.

Panel I: Equality tests of variances

Group	Greece &Italy	Greece &Spain	Greece &France
1&2	4.79%	4.98%	2.77%
2&3	0.00%	0.00%	0.00%
3&4	5.49%	0.03%	26.35%
4&5	0.00%	0.00%	0.00%
5&6	13.45%	0.28%	43.96%
6&7	71.94%	0.00%	3.26%
7&8	3.76%	20.40%	29.69%
8&9	50.46%	0.00%	0.09%
9&10	2.83%	2.45%	0.00%

Panel II: T tests of mean of correlation coefficients

Group	Greece &Italy		Greece &Spain		Greece &France	
	t-statistic	p value	t-statistic	p value	t-statistic	p value
2-1	5.06	(0.00%)	4.36	(0.00%)	0.78	(43.45%)
3-2	-4.14	(0.01%)	-5.10	(0.00%)	-4.75	(0.00%)
4-3	-4.48	(0.00%)	-3.92	(0.01%)	-3.29	(0.11%)
5-4	-1.42	(15.63%)	-3.01	(0.29%)	-1.94	(5.41%)
6-5	-5.09	(0.00%)	-2.37	(1.83%)	-6.17	(0.00%)
7-6	-13.04	(0.00%)	-12.47	(0.00%)	-12.80	(0.00%)
8-7	-4.79	(0.00%)	0.19	(84.84%)	-6.47	(0.00%)
9-8	2.70	(0.74%)	5.82	(0.00%)	7.35	(0.00%)
10-9	-3.12	(0.20%)	-3.17	(0.17%)	-7.75	(0.00%)

Appendix 5: Factor tests in each subsample

We regress the percentage changes of VaR of each EMU sovereign bond market on last three days country specific and global factor respectively in each subsample.

$$\mathrm{VaR}_{j,t}\% = \alpha + \beta_1 X_{t-1}^{+} + \beta_2 X_{t-2}^{+} + \beta_3 X_{t-3}^{+} + \beta_4 X_{t-1}^{-} + \beta_5 X_{t-2}^{-} + \beta_6 X_{t-3}^{-} + \varepsilon_t$$

Where X_{t-1}^{+} equals the percentage changes of the factor X at time t-1 if that factor is positive, and X_{t-1}^{-} equals the percentage changes of the factor X at time t-1 if that factor is negative. Since all the factors are percentage changes, the interpretation of the coefficients (β) is that when the factor X changes 1%, the VaR of individual sovereign bond i changes β% in average. Lag 1 is the first lag of the corresponding factor. In other words, it equals the value of financial factor at time t-1; lag 2 is the second lag of the corresponding factor; and lag 3 is the third lag of the corresponding factor.

$r\_USD/EUR+$ and $r\_USD/EUR-$ are positive and negative components of USD/EUR exchange rates, respectively; r_VIX+ and r_VIX- are positive and negative components of implied S&P 500 volatility, respectively; r_local_index+ and r_local_index- are positive and negative components of local equity index, respectively.

Panel I report the regression results in the Before Crisis subsample between Jan. 1st 2006 [28] and Dec. 31st 2007; Panel II report the regression results in the Subprime Crisis subsample between Jan. 1st 2008 and Sep. 30th 2009; Panel III report the regression results in the Sovereign Bond Crisis subsample between Oct. 1st 2009 and Dec. 31st 2011.*,**, and ***, means t tests are significant at the 10%, 5%, and 1% significant level, respectively.

Panel I: factor test in the Before Crisis subsample

	Austria	Belgium	France	Germany	Greece	Italy	Netherland	Portugal	Spain
r_USD/EUR+									
lag 1	1.35	1.29	1.15	1.45*	1.36*	1.59*	1.20	1.27*	1.40*
lag 2	0.68	0.36	0.57	0.82	0.31	0.70	0.85	0.73	0.62
lag 3	-0.20	-0.23	-0.43	-0.08	-0.09	-0.48	-0.47	-0.40	0.11
r_USD/EUR-									
lag 1	-0.54	-0.35	-0.11	-0.68	-0.29	-0.77	-0.91	-0.93	-0.42
lag 2	-0.49	0.06	-0.23	-0.35	0.28	-0.01	-0.25	-0.16	-0.05
lag 3	0.02	0.08	-0.48	-0.03	-0.06	0.24	-0.28	0.33	-0.30
Constant	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00
r_VIX+									
lag 1	0.12**	0.17**	0.11**	0.12**	0.13**	0.10**	0.13***	0.09*	0.12**
lag 2	0.00	-0.04	-0.05	0.00	-0.02	-0.01	-0.02	-0.02	-0.02
lag 3	0.00	-0.01	-0.01	-0.01	-0.03	-0.02	0.00	0.00	-0.01
r_VIX-									
lag 1	0.00	-0.02	0.00	0.00	0.00	0.01	-0.01	0.00	0.02
lag 2	0.01	0.02	0.01	0.01	0.03	0.01	0.03	0.01	0.02
lag 3	0.02	0.03	0.02	0.02	0.04	0.03	0.01	0.02	0.01
Constant	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
r_local_index+									
lag 1	0.29	0.39	0.61*	0.59*	-0.11	0.18	0.39	0.23	0.47
lag 2	-0.35	-0.26	-0.30	-0.32	-0.25	-0.42	-0.70**	-0.39	-0.22
lag 3	-0.23	-0.34	-0.13	-0.20	-0.49	-0.39	-0.09	-0.48	-0.46
r_local_index-									
lag 1	-1.31***	-1.79***	-1.61***	-2.00***	-0.81**	-1.37***	-1.70***	-1.70**	-1.81***
lag 2	0.07	0.31	0.40	0.38	0.12	0.09	0.42	0.43	0.11
lag 3	0.16	0.44	0.10	0.04	0.35	0.40	0.23	0.01	0.47
Constant	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00

[28] We need several years to stabilize our EWMA model. Thus even though we have data from Jan. 1st 2003, we cannot begin our analysis at that time.

Appendix 5--continued

Panel II: factor tests in the Subprime Crisis sample									
	Austria	Belgium	France	Germany	Greece	Italy	Netherland	Portugal	Spain
r_USD/EUR+									
lag 1	0.89	0.65	1.70***	1.55***	1.69**	1.30***	1.33**	1.21**	1.65**
lag 2	-0.13	0.21	-0.02	-0.02	1.00	0.84	0.27	0.36	-0.11
lag 3	0.70	2.22	0.10	0.09	0.13	0.45	0.24	0.15	0.49
r_USD/EUR-									
lag 1	-0.90*	-0.22	-1.16**	-1.27**	-0.98*	-0.79	-1.12**	-0.93**	-0.69
lag 2	0.34	0.02	0.37	0.46	0.54	0.00	0.35	0.15	0.44
lag 3	0.55	-0.12	0.65	0.60	-0.30	0.14	0.35	0.30	-0.03
Constant	-0.01	-0.01**	-0.01*	-0.01	-0.01**	-0.01**	-0.01**	-0.01**	-0.01
r_VIX+									
lag 1	0.13*	0.12*	0.15**	0.15**	0.10*	0.08	0.15**	0.15**	0.12*
lag 2	-0.04	-0.01	-0.05	-0.07*	0.07	0.02	-0.03	-0.01	-0.04
lag 3	0.04	0.10	0.03	0.04	-0.01	0.03	0.03	0.04	0.05
r_VIX-									
lag 1	-0.10	-0.13*	-0.11*	-0.08	-0.05	-0.06	-0.13**	-0.19*	-0.14**
lag 2	0.03	0.03	0.04	0.05	-0.11	0.00	0.03	0.00	-0.07
lag 3	0.02	-0.02	0.0.1	0.01	-0.01	-0.08	0.00	0.01	0.01
Constant	0.00	-0.01**	0.00	0.00	-0.01**	-0.01**	-0.01*	-0.01**	-0.01*
r_local_index+									
lag 1	0.68*	1.38**	1.17***	1.05**	0.81*	0.79**	1.02***	1.09**	1.05**
lag 2	-0.22	-0.35*	-0.06	-0.21	-0.01	-0.01	0.01	-0.05	-0.06
lag 3	-0.08	-0.28	-0.17	-0.23	-0.16	-0.10	0.05	0.01	-0.18
r_local_index-									
lag 1	-0.32*	-0.76***	-0.82***	-0.81***	-0.36*	-0.37	-0.64***	-0.62***	-0.60***
lag 2	0.13	0.39**	0.12	0.26	-0.04	0.00	0.08	-0.09	0.25
lag 3	0.10	0.23	0.35*	0.31	0.30*	0.33	0.21	0.15	0.03
Constant	-0.01	-0.01	-0.01**	-0.01	-0.01	-0.01	-0.01***	-0.01**	-0.01*

Appendix 5—continued

Panel III: factor tests in the Sovereign Bond Crisis subsample									
	Austria	Belgium	France	Germany	Greece	Italy	Netherland	Portugal	Spain
r_USD/EUR+									
lag 1	-0.04	-0.38	1.39*	1.41**	2.71	0.92	1.18**	0.88	1.56
lag 2	-0.69	-0.08	-0.17	-0.43	-1.55*	-0.69	-0.11	-0.98	1.08
lag 3	0.15	0.73	0.39	-0.28	-1.97***	-1.07*	0.09	-1.47**	-0.83
r_USD/EUR-									
lag 1	-2.18***	-1.90	-1.62**	-3.25***	-1.96*	-3.78**	-2.72***	-0.94	-3.22*
lag 2	0.09	0.45	-0.43	0.70	-0.33	-1.46	0.78	-0.17	-1.17
lag 3	0.47	-0.86	-0.64	-0.43	-0.46	0.45	0.00	0.39	-0.51
Constant	0.00	0.00	-0.01	-0.01**	0.00	-0.01	-0.01	0.01	-0.02*
r_VIX+									
lag 1	0.26***	0.28**	0.30***	0.31***	0.08	0.43***	0.25***	0.04	0.34**
lag 2	0.02	-0.07	0.06	-0.08*	0.02	-0.08	-0.08	0.07	-0.07
lag 3	0.02	0.03	0.08	0.02	0.10	0.12	0.15	0.10	0.20*
r_VIX-									
lag 1	-0.15**	-0.17**	-0.16**	-0.23***	-0.40	-0.37**	-0.19**	-0.23	-0.37*
lag 2	-0.11	0.01	0.00	0.02	0.05	0.23**	0.15	0.08	0.14
lag 3	-0.07	-0.02	-0.01	0.01	0.11	0.07	-0.04	0.04	-0.10
Constant	-0.01**	-0.01	-0.01***	-0.01***	-0.01	-0.01	-0.01***	0.00	-0.01**
r_local_index+									
lag 1	0.25	0.40	0.36	0.96***	1.72*	1.24	0.77***	2.31	1.70*
lag 2	0.24	0.59	-0.29	0.08	-0.11	-0.11	-0.14	-0.34	0.03
lag 3	0.30	0.05	-0.02	-0.46**	-0.43	-0.55*	-0.25	-0.78**	-0.45**
r_local_index-									
lag 1	-1.01**	-1.74***	-1.11***	1.62***	-1.44***	-1.92***	-1.61***	-2.21**	-1.80***
lag 2	-0.04	-0.13	0.21	0.31	-0.67**	-0.47	0.32	-0.16	-0.27
lag 3	-0.16	0.11	-0.16	0.46**	0.21	0.23	0.04	0.16	-0.28
Constant	-0.01**	-0.01**	0.00	-0.01**	-0.02***	-0.01**	-0.01	-0.01	-0.02**