Downside Risk, Portfolio Diversification and the Financial Crisis for the Eurozone

Abstract.

This paper evaluates the value at risk for individual sovereign bond and national equity markets for ten member countries in the euro-zone using four estimation models and three accuracy criteria in addition to the daily capital requirements, for the full sample period and a subperiod that marks the beginning of the recent global financial crisis. The results show that the conditional extreme value theory model under both the normal and Student–t distributions satisfies the four accuracy criteria the best and gives the least capital charges for both periods, while the RiskMetrics gives the worst results. These euro-zone bond and equity markets are also classified into two groups: the PIIGS (Portugal, Italy, Ireland, Greece and Spain) and the Core (Germany, France, Austria, the Netherlands and Finland), and optimal portfolios are constructed for these two groups as well as for the ten euro area as a whole. Given the sample periods, the results show no strong diversification for any of the two groups or for the whole area in any of the bond and equity asset classes or both. The bond and equity portfolios are augmented with commodities and the best grand portfolio is the one that is diversified with the commodities gold, silver and oil, particularly for the subperiod.

Keywords: Value at Risk (VaR) euro-zone, bond benchmarks, stock indices, commodities.

1. Introduction

The euro-zone has been in a sovereign debt crisis and at the risk of a catastrophic breakup since 2009. The crisis has affected its capital markets and economies, leading to mass joblessness and a severe debt predicament. The euro-zone capital markets are highly correlated because of increasing integration and harmonization in this area over time. Thus, the mounting risk and uncertainty have confounded investors, portfolio managers and policy-makers across the euro-zone as well as in other countries of the world.

However, the euro-zone countries are dissimilar. In some countries the problem resulted from bubbles in the real estate markets, while in others it had to do with severe budget deficits or troubles in the banking sector. Some countries have slipped into a severe recession, while others have suffered from sluggish growth. The same comparison applies to their capital markets, particularly their sovereign bond markets. We follow the literature on the classification of the euro-zone member countries and divide those countries into two groups: the Core and the PIIGS. The Core includes Germany, France, Austria, the Netherlands and Finland, while the *PIIGS* consists of Portugal, Italy, Ireland, Greece and Spain. Different levels of interest rates and budget deficit- and debt-to-GDP ratios among the euro-zone countries figure highly in this classification.

More recently, there are encouraging signs of change in this area, showing strengthening euro, improvements in its capital markets and stabilization in its economies.[1] It seems that the survival of the euro-zone is likely and opportunities are looming after these positive developments. If the euro-zone survives, it will not be long before investors and portfolio

[1] We should also caution that there is still the possibility that the austerity policies can lead to a severe deterioration of the economic and political situation, and consequently may cause a social rupture between European countries.

managers will again search the euro-zone's capital markets seeking new investment opportunities.

In the meantime, the deterioration in government finances in the euro-zone and the global financial markets has led investors and portfolio managers to look for other asset classes, particularly commodities as return enhancers and safe havens in their flight to safety. Commodities are real assets and possess intrinsic values that reflect changes in the price level. Moreover, commodities are not income-producing assets as they do not yield an ongoing stream of cash flows as stocks do. There also exists a high degree of heterogeneity among individual commodities (Fabozzi, Füss and Kaiser, 2008; Erb and Harvey, 2006; Kat and Oomen, 2007a, 2007b). On the other hand, similar to stocks, most commodities have positive excess kurtosis which implies a leptokurtic return distribution. This distribution has fatter tails with the higher probability for extreme events, compared to normally distributed returns. However, in contrast to stocks most commodities are positively skewed. This characteristic is beneficial to investors because it implies a lower downside risk and an upward return bias of an investment portfolio. These characteristics distinguish commodities from stocks, particularly from the integrated euro-zone's individual country stock market indices, and give rise to expectations of low correlations with those stock indices.

Researchers, such as McCown and Zimmerman (2006), show that gold has the characteristics of a zero-beta asset that enables investors to hedge against inflation and crises. Capie et al. (2005) also demonstrate that gold protects investors and also show that this yellow metal protects investors' wealth against depreciation in the value of the dollar. Baur and McDermott (2010) also suggest that gold protects investors' equity wealth against shocks in adverse stock markets in major European countries and the United States. Erb and Harvey (2006), Roache and Rossi

(2010) and Elder et al. (2012) also find that silver is counter-cyclical, implying that precious metals other than gold may also protect investors' wealth in the events of adverse conditions in stock markets. Industrial metals may also serve as safe havens, portfolio diversifiers and return enhancers in the events of negative economic conditions that affect bond and equity markets. Hammoudeh et al. (2013) and Hammoudeh et al. (2011) also find oil to be a return enhancer and risk reducer when combined in a diversified portfolio with precious metals.

In such a developing environment, it will be interesting and useful to examine the downside risk in the euro-zone sovereign bond and stock markets and figure out ways to construct portfolios that diversify away risks, protect wealth and augment the risk-adjusted returns in these capital markets with asset classes from other major markets such as commodities. It will also be particularly important to estimate market risks and construct portfolios over a long period and in the period since the onset of the recent economic down turn which has made financial risk management strategies more challenging.

The primary objective is to calculate the value at risk (VaR) for the stock and sovereign debt markets in the ten individual euro-zone countries and assess the individual countries' downside risks under the full sample and the subperiod that marks the 2007/2008 global financial crisis. We also aim to evaluate the VaR estimation models against well-known accuracy criteria and compute the capital requirements for the individual countries for both periods. Our next goal is to construct optimal portfolios for stocks and bonds for both the PIIGS and Core groups for both periods. Finally, we diversify these portfolios with commodity to enhance the benefits of more diversified portfolios for the two periods. Finally, we rank these portfolios based on the VaR risk and returns. Although the financial markets of euro-zone countries are not performing well, our hope is that our research will help in exploring future profitable opportunities in the euro-zone which can be exploited when normal conditions prevail.

We should emphasize that the results of the paper are related to the whole period which is affected by the confluence of several factors and to the subperiod that covers the recent crises and their aftermath. Therefore, the full period and the subperiod present general and special results but they should be considered in those contexts. The results should not be robust with smaller subperiods because we use a window of 1,000 observations in backtesting.

2. Literature review

The research on the stock markets in euro-zone and Europe is well diversified. Earlier strands examine issues such as downside risk, optimal portfolios, regime switching, among other subjects. However, in the last few years this type of research has concentrated on reasons and implications of the recent sovereign debt crisis. It has dealt with issues related to relationships between stock, government bond and sovereign CDS markets for low and high risk countries in the Economic and Monetary Union (EMU) and euro-zone. We here provide a literature review of studies that examine bonds, stocks and commodities in relation to the EMU and euro-zone countries.

With the advent of the European financial crisis, the research has focused on the sovereign markets. Using a panel VAR, Vaca, Corzo-Santamaria, and Lazcana-Benito (2011) examine the lead-lag relationships between the sovereign bond, CDS and stock markets for eight European countries over the period 2007-2010. The countries are Greece, Ireland, Portugal, UK, France and Germany. The results show a leading role for the stock markets over the sovereign CDS markets for the full period. But when the turbulent 2010 is isolated from the rest of the data, the evidence suggests that the CDS markets lead the stock markets, translating the credit risk to the private companies. Norden and Weber (2009) find that stock markets lead both CDS and bond markets and that the CDS markets Granger-cause the bond markets for a higher number of firms. This paper did not include the crisis periods.

The research on sovereign bond markets during the debt crisis deals with the dynamics of this bond market in the euro-zone, the influence of global financial conditions between this market and the CDS market. Lane (2012) attributes the origin and propagation of the euro-zone sovereign debt crisis to the flawed original design of the euro. He argues that the incremental multi-country crisis management responses "on the fly" were a destabilizing factor and offers reforms to improve resilience to future shocks. Allen and Ngai (2012) argue that attempts to contain the sovereign deficits and debts through the Stability and Growth Pack failed, and that the austerity programs have induced downward spirals in growth. On the other hand, Haidar (2011) argues that a 'fiscally weak country' is better off to stay within the euro-zone than exiting it.

Maltritz (2012) applies the Bayesian Model Averaging (BMA) to a panel data for ten EMU countries to analyze the basic determinants of the sovereign yields of these EMU member countries. He finds that fiscal country specific drivers and global financial conditions influence the sovereign spreads. Additionally, applying a semi-parametric time-varying coefficient model, Bernoth and Erdogan (2012) examine the determinants of sovereign yield spreads for ten EMU countries before and after 2006. The results show that macroeconomic fundamentals determine the sovereign differentials before 2006, while after 2006 there was a shift in investors' risk aversion which contributed to alerting in risk pricing. Fong and Wong (2012) uses the CoVaR methodology to study the tail risk relationships among European sovereigns markets and provide important information for policymakers to help identify which countries should undergo close scrutiny during the current debt crisis.

Calice et al. (2013) use a time-varying vector autoregression framework to establish the credit and liquidity spread interactions over the euro-zone crisis period. The authors find substantial variations in the transmission patterns between maturities and across countries.

The review of the equity literature does not produce many studies that apply the various VaR estimation methods to the euro-zone and European stock markets, whether as individual assets, equity portfolios and/or equity portfolios diversified with other asset classes. Commodities offer an effective hedge against both expected and unexpected inflation, as explained in the introduction.

Cotter (2004) applies the extreme value theory, among others, to measure the downside risk for five European equity indices from the beginning of 1998 to the end of April 1999. Cotter's results show that the EVT-VaR dominates alternative approaches such as the variance/covariance and Monte Carlo methods in the tail estimation for those equity indices. Allen (2005) assesses five models which estimate the VaR thresholds for an equally-weighted portfolio comprising three European equity indices, *CAC 40* (France), *FTSE 100* (UK) and Swiss Market Index *(SMI)*, and the *S&P 500* index. Allen finds the Portfolio-Spillover GARCH model (PS-GARCH) (see McAleer and Veiga, 2008 for more information) provides the best result in terms of meeting the requirement of the Basel Accord among the five models considered. Billio and Pelizzon (2000) use a multivariate regime-switching (RS) model to estimate the VaRs for 10 individual Italian stocks and also for a portfolio based on these stocks. They find the *RS* approach outperforms the RiskMetrics and GARCH(1,1) models both in the single asset VaR forecasts and the portfolio VaR estimation.

In the context of optimal portfolio selection, many studies generally focus on using the VaR as an alternative risk measure to the traditional measures of risk that rely on the standard deviation (or variance). The literature includes: Jansen, Koedijk and Vries (2000); Basak and Shapiro (2001); Gaivoronski and Pflug (2005); Palmquist and Krokhmal (1999); and Campbell, Huisman and Koedijk (2001). Campbell et al. (2001) solve for the optimal portfolios based on a Sharpe-like portfolio performance index, using the VaR from the historical distribution as the risk measure. The optimal portfolio they find is the one which maximizes the expected return subject to the specified levels of VaR constraints. Gaivoronski and Pflug (2005) provide a method to calculate the mean-VaR efficient frontier using a smoothed VaR estimation. Their experimental results show that the mean-VaR efficient portfolios differ substantially from the mean-variance efficient portfolios.

The literature on equity portfolio diversification in Europe and euro-zone focuses on comparing diversification over countries with diversification over industries. In 1990 and before the creation of the euro-zone, some studies find that diversification over countries yields more efficient portfolios than diversification over industries (see Heston and Rouwenhorst, 1995). This result has been attributed to the unification process and the harmonization of economic policies in euro-zone. In the 2000s, the literature finds evidence of increasing consequences for the industry factors in driving asset returns in European financial market but the dominance remained for the country factors (see Rouwenhorst, 1999; Carrieri, Errunza and Sarkissian, 2004; Ge´rard et al., 2002; Adjaoute´ and Danthine, 2001; 2004). This result has been aided by the information technology/internet ‘‘bubble’’ (known as IT-hype). Adjaoute and Danthine (2001) find that diversification opportunities within the 15 member euro-zone at that time have been reduced. More recently, by employing the mean–variance approach and using recent data, Moerman (2008) finds strong evidence that diversification over industries yields more efficient portfolios than diversification over countries even when the IT-hype is accounted for. Therefore, the evolution of the literature on euro-zone equity market diversification increasingly supports diversification within industries instead of across national markets.

We also explore in this study diversification among euro-zone national stock markets and commodities since as indicated earlier the correlations with commodities are much lower than between the euro-zone national stock indices. The literature on diversification with commodities is rising in importance because this diversification can enhance returns and/or reduce risk. Satyanarayan and Varangis (1996) and Idzorek (2007) detect diversification benefits, analyzing the shift of the efficient frontier when the investment universe is extended to a commodity index. Georgiev (2001) and Gibson (2004) constitute portfolios with different commodity allocations and compare their risk-return characteristics in the mean-variance space. You and Daigler (2010) detect the diversification benefits of commodity futures by employing the mean-variance and Sharpe optimization models. The good performance of metals (especially gold) during the economic downturns, on one hand, and the recent European sovereign-debt crisis, on the other hand, presents for this study a strong motivation to examine the diversification benefits of individual commodities in portfolios of the euro-zone bond and stock markets.

3. Data and descriptive statistics

3.1. The full period

Table 1 summarizes the notation and the exchanges for the ten country equity and sovereign bond indices under consideration.

We use daily percentage log returns based on the closing spot values for all of the series. We select the full sample period from March 31, 1999 to November 20, 2012, which yields a total of 3,559 observations of percentage log returns, $r_t = 100(lnp_t - lnp_{t-1})$. We also examine the subperiod ranging from July 2, 2007 to November 20, 2012 which is marked by spikes in financial stress indicators such as TED which is the difference between LIBOR and short term Treasury securities rate.[2]

The descriptive statistics for bonds, stocks and commodities under consideration are provided in Table 2 for the full sample period. In Table 2-Panel A, the Netherlands' 10-year government benchmark bond has the highest average daily return, while the one for Greece has the lowest return. The bonds of all countries except Greece, Ireland and Portugal have positive average daily return. The un-weighted average return for the Core countries is 0.007, while the average for the PIIGS countries is -0.006. These numbers reflect the burden of the sovereign debt in the highly indebted euro-zone countries.

In terms of bond volatility as defined by the standard deviation, the Greek sovereign bonds have the highest volatility, while the Finnish 10-year bond has the lowest over the sample period. This is not surprising because Finland has one of the highest per capita incomes while Greece has one of the lowest in the euro-zone. High bond volatility also goes across both euro-zone groups, particularly for the PIIGS. The un-weighted average bond volatility for the Core countries is 0.34, while that for the PIIGS is 0.68.

The results for the skewness test are also mixed across the two bond groups: all countries in the Core group have negative skewness, which means the mass of the distribution of returns is concentrated on the right part. With the exception of Portugal, all countries in the PIIGS group

[2] http://www.crisishelper.com/world_economic_crisis/Financial_crisis_of_2007-2009.html

have positive skewness. All the bond series have a Kurtosis value higher than 3 which means their distributions are more peaked than the normal distribution. The Jarque-Bera statistic suggests a rejection of the normality hypothesis for all the distributions of all the series.

The descriptive statistics for stock market indices are given in Table 2-Panel B. The Austrian Traded Index (*ATX*) has the highest average return among the ten equity indices, while the Greek Composite Share Price Index (*ATHEX*) yields the lowest over the sample period. Note that only two countries have positive average daily stock returns which are Austria and Germany. Austria had the highest economic growth while Germany is the largest and most prosperous economy in the euro-zone. The un-weighted average return for the Core countries is 0.0006, while that for the PIIGS is -0.018.

The Finnish *OMXH* has the highest equity volatility, while the Portuguese *PSI* has the lowest. Higher equity volatility also goes across both groups over the sample period. The un-weighted average volatility for the Core countries is 1.62, while that for the PIIGS is 1.47. This implies that the equity volatility is much higher than that of the bonds for both groups.

The results for the skewness test are mixed across the groups in the sense that some markets have negative skewness, while others have positive skewness. All the series have a kurtosis value higher than 3 and the Jarque-Bera statistic suggests a rejection of the normality hypothesis for all the distributions of all the series.

Considering the commodities in Panel C of Table 2, all series have positive average daily returns. Oil has the highest average daily return, followed by silver and gold. At the same time, it has the highest standard deviation which reflects the high rate of fluctuations in the energy markets over this sample period. All commodities have a negative skewness statistic. All the

Kurtosis statistics for the commodities are greater than 3. Moreover, all the results for Jarque-Bera normality tests reject the normality null hypothesis for the commodities.

3.2. The subperiod

We consider the descriptive statistics for the subperiod which ranges from July 2, 2007 to November 20, 2012, which contains 1407 observations, in Table 3.[3] Panel A of this table shows the descriptive statistics of bonds for this subperiod which has less volatility than the full period. All of the bonds of the Core countries have much higher average returns in the subperiod than in the full period. Not surprisingly, the highest average return in this sub-period belongs to Germany and the lowest to Greece. On average, the bond market of the Core countries yields almost three times higher returns in the subperiod than in the full period, partly due to quantitative easing by central banks. On the other hand, the average return of the PIIGS bonds is three times worse than in the full period. Similar to the full period, the Greek bond has the highest volatility, while the Finish bond has the lowest. Although the average daily bond returns are much higher for the Core countries in this subperiod than the full period, the skewness is positive for all of them except Austria. Also, except for Portugal, the daily bond return distributions for the PIIGS countries are skewed positively. Again in this subperiod like the full period, all the series have a Kurtosis value higher than 3 and the Jarque-Bera statistic suggests a rejection of the normality hypothesis for all the distributions of all the series.

The stock market descriptive statistics of Table 3-Panel B shows that the average daily returns of all countries' equity indices are negative during this period. The German *DAX* index has the lowest negative average return which means highest average return and the Greek

[3] The Inclán and Tiao, 1994 (1994) structural break tests show that most of the series have breaks during 2007 and beginning of 2008. The results of these tests can be available upon request.

ATHEX composite share price index yields the lowest return. Here like the full period the *ATHEX* has highest volatility and Portuguese PSI has the lowest. The skewness of the Dutch *AEX*, the Austrian *ATX* and the Irish *ISEQ* are negative and the rest of them are positive. All the series have a Kurtosis value higher than 3 and the Jarque-Bera statistic suggests a rejection of the normality hypothesis for all distributions of all the series.

Table 7 shows the descriptive statistics of commodities during this sub-period. The average returns of silver, gold and palladium increase, while those for oil and platinum decrease significantly and the average return of copper approaches zero. The skewness of all of those returns except the return of oil is negative. The positive skewness of oil when coupled with a low average return implies a week performance of this commodity in this sub-period compared to the full period. As in the full period, all series have a Kurtosis value higher than 3 and the Jarque-Bera statistic suggests a rejection of the normality hypothesis for all distributions of those series.

4. Methodology

In this section, we briefly explain the models that we use to compute the VaR forecasts and the capital charges in this paper for the ten sovereign bond benchmark, equity index and commodity returns. We follow the methodology used in Hammoudeh et al. (2013). The VaR estimation methods are the RiskMetrics, the DPOT, the CEVT-n and the CEVT-sstd models.[4] These methods fit normal and non-normal distributions including extreme distributions. Cotter (2004) for example shows that the EVT-VaR dominates alternative approaches such as the variance/covariance and Monte Carlo methods, in the tail estimation for those equity indices.

[4] We are aware that there are other VaR estimation methods but we use the most popular ones and also subject them to four evaluation criteria. Space is also a constraint in this lengthy paper.

This section addresses the VaR estimation methods, the accuracy criteria and evaluative tests used in backtesting and the portfolio optimization.

4.1. VaR estimation

A portfolio's value-at-risk in mathematical terms is defined to be the quantile of the portfolio's profit and loss distribution, i.e.,

$$VaR_t(\alpha) = -F^{-1}(\alpha|\Omega_t)$$

where $F^{-1}(.|\Omega_t)$ represents the quantile function of the profit and loss distribution which changes over time as the conditions and the composition of the portfolio change. The negative sign means a normalization that quotes VaR in terms of positive money amounts.

4.1.1. *RiskMetrics*

Under the RiskMetrics approach which is developed by J.P. Morgan (1996), the variance is calibrated using the following Integrated GARCH model:

$$h_t = (1-\lambda)\varepsilon_{t-1}^2 + \lambda h_{t-1} \qquad (1)$$

where h_t is the forecast of conditional volatility, λ is set to 0.94 for daily data, and $\varepsilon_{t-1}$is the last period’s residual. Assuming that the standardized residuals are normally distributed, the VaR measure for this method is given by

$$VaR^{RM}{}_{t|t-1}(\text{p}) = Z_p\sqrt{h_t} \qquad (2)$$

where Z_p represents the p-quantile of a standard normal random variable.

4.1.2. *Conditional extreme value theory (CEVT)*

This approach is a hybrid of a time-varying volatility model and a Peaks-Over-Threshold (POT) method suggested by the Extreme Value Theory (for details about the POT method, see Embrechts et al., 1997). Following Diebold et al. (1998) and McNeil and Frey (2000), we follow a two-step process to forecast the VaRs. We first fit an AR(1)-GARCH(1,1) framework with the index return data, estimate $\hat{\mu}_{t+1|t}$ and $\hat{\sigma}_{t+1|t}$ and calculate the implied residuals; in the second step, we obtain the p-quantile value for the residual distribution by applying the POT method based on the EVT. Although the normal innovations can filter the majority of clustering, it may still generate a misspecified model. In order to accommodate this misspecification, we also use the filter with skewed Student's-t distribution.

The one-day-ahead VaR forecast of the CEVT method is calculated with the following equation:

$$\widehat{VaR}_{t+1|t}^{CEVT}(p) = \hat{\mu}_{t+1|t} + \hat{\sigma}_{t+1|t}\hat{z}_p \tag{3}$$

where $\hat{\mu}_{t+1|t}$ is the estimated conditional mean, $\hat{\sigma}_{t+1|t}$ is the estimated conditional standard deviation, which are obtained from the AR(1)-GARCH(1,1) process. Moreover, the quantile $\hat{z}_p$ for the probability level p is obtained through a Peak-Over-Threshold procedure.

4.1.3. Duration-based peaks over threshold (DPOT)

The POT method is based on the excesses over a high threshold, u, and on the Pickands-Balkema-de Haan Theorem (see Balkema and de Haan, 1974; and Pickands, 1975). For distributions in the maximum domain of attraction of an extreme value distribution, this theorem states that when u converges to the right-end point of the distribution, the excess distribution $[P[X - u|X > u]$ converges to the Generalized Pareto Distribution (GPD):

$$G_{\gamma,\sigma}(y)=\begin{cases}1-(1+\gamma y/\sigma)^{-1/\gamma}, & \gamma\neq 0\\ 1-\exp(-y/\sigma), & \gamma=0,\end{cases} \tag{4}$$

where $\sigma > 0$, and the support is $y \geq 0$ when is $\gamma \geq 0$ and $0 \leq y \leq -\sigma/\gamma$ when is $\gamma < 0$. Smith (1987) proposes a tail estimator based on a GPD approximation to the excess distribution. Inverting this estimator gives an equation to calculate the VaR forecast. With financial time series, a relation between the excesses and the durations between excesses is usually observed. Araújo-Santos and Fraga-Alves (2012b) propose using this dependence to improve the risk forecasts with duration-based POT models (DPOT). For estimation, these models use the durations, at time of excess i, as the preceding v excesses ($d_{i,v}$). At time t, $d_{t,v}$ denotes the duration until t as the preceding v excesses.

The DPOT model assumes the GPD for the excess Y_t above u, such that

$$\boldsymbol{Y_t \sim GPD(\gamma, \sigma_t = \alpha/(d_{t,v})^c)}, \tag{5}$$

where γ and α are parameters to be estimated. The proposed DPOT model implies, for $\gamma < 1$, a conditional expected value for the excess, and for $\gamma < 1/2$, a conditional variance, both of which are dependent on $d_{t,v}$:

$$\boldsymbol{E[Y_t] = \frac{\sigma_t}{1-\gamma} \quad (\gamma < 1), \quad VAR[Y_t] = \frac{(\sigma_t)^2}{(1-2\gamma)} \quad (\gamma < 1/2)}. \tag{6}$$

Inverting the tail estimator based on the conditional GPD gives the equation to calculate the DPOT VaR forecast:

$$\boldsymbol{\widehat{VaR}_{t|t-1}^{DPOT(v,c)}(p) = u + \frac{\hat{\alpha}}{\hat{\gamma}(d_{t,v})^c}\left(\left(\frac{n}{n_x p}\right)^{\hat{\gamma}} - 1\right)}, \tag{7}$$

where n_x denotes the sample size, n the number of excesses, $\hat{\gamma}$ and $\hat{\alpha}$ are estimators of γ and α, respectively. We choose v=3 and $c = 3/4$, as values of c close or equal to 3/4 have been shown to exhibit the best results (see Araújo-Santos and Fraga-Alves, 2012b).

4.1.4. Basel capital requirements

In 1996 the Basel Committee on Banking Supervision (BCBS) issued an Amendment to Basel I Capital Accord, in which the financial institutions are required to calculate their market risk Minimum Capital Requirements (MCR) based on their own VaR models by using the following formula: $m_c = 3 + k$

$$MCR_{t+1} = \max(\frac{m_c}{60}\sum_{i=1}^{60} VaR_{t-i+1}; VaR_t) \quad (8)$$

where $m_c = 3 + k$ and $k \in [0,1]$. The MCR is the maximum between the previous day's VaR and the average of the last 60 daily VaRs increased by the multiplier m_c . The multiplier m_c is determined by the backtesting results for the internal VaR models. Essentially, the greater the number of the violations when the actual loss exceeds the daily VaR forecast during the last 250 trading days, the higher the value of the multiplier m_c. The details of this three-zone approach are *included* in Table 6.

4.2. VaR backtesting

Backtesting helps determine the accuracy of a VaR model by reducing problem to determining whether the hit sequence, which tallies the history of whether or not a loss in excess of the reported VaR has been realized, satisfies the following properties. The first property is the unconditional coverage which deals with the probability of realizing a violation as a result of the realized VaR exceeds the VaR reported by the model. The second property is the independence property which places a restriction on how often VaR violations may occur and also places a strong restriction on the ways in which these violations take place. In other words, it deals with the independency of violations from each other (clustering of violations).

The property tests that are used in backtesting are the following. Kupiec Unconditional Coverage (UC) test which focuses exclusively on the property of unconditional coverage, the Maximum-Median independence (MM) test which examines the independence property, and the Conditional Coverage (CC) test which considers jointly the unconditional coverage and the serial independence of VaR estimates.

4.3. Portfolio optimization

Daily returns are used in order to find the optimal portfolio at the point where the return-risk ratio S(P) is maximized. The risk-return ratio equation is given by

$$max_P\, S(P) = \frac{(r(P)-r_f)}{(\varphi(p,P))}, \tag{9}$$

where P is the optimal portfolio, $\varphi(p,P) = W(0)r_f - \mathrm{V}a\mathrm{R}(p,P)$ is the performance measure for risk, W(0) is the amount invested, r_f is the 3-mounth Treasury rate available on the last day of the sample period which is November 20, 2012. The VaR for $1000 held in the portfolio is given for a daily time horizon and a 99% confidence level, where the historical distribution is used to estimate the VaR.

5. Empirical results

We explain the empirical results of the accuracy evaluation properties for the VaR forecasts generated by the four VaR estimation methods for the individual sovereign bond and stock indices for the ten countries in the Core and PIIGS groups of the euro-zone during the full period and the subperiod which we opt to start on July 2, 2007. The results of the properties for combined portfolios of the national stock and bond indices will also be discussed for those two periods. The U.S. *S&P 500* index, industrial commodities and oil will be included to augment the performance of the bond and equity portfolios of the euro-zone.

The properties include the percentages of violation, unconditional coverage, conditional coverage, independence and the Basel capital requirements. These properties evaluates the forecasts of the four estimation methods in terms of their number of violations, the extent of predictability of the pattern of violations and their implication for incorporating the changes in market risks and the reflection of the according adequacy of the institutions' funding.

The RiskMetrics generally performs the worst and the CEVT-sstd achieves the best results when it comes to the overall VaR properties for the individual countries in the full period. This suggests that this RiskMetrics estimation method would systematically understate the actual risk level. It would also suggest that this method gives rise to a general inadequacy in the reported VaR as it allows previous VaR violations to presage future violations. This finding also signals a lack of responsiveness in the reported VaR measure to incorporate and react quickly to changing market risks, thereby making successive VaR violations more likely. This implies that market risk capital requirements are underfunded for protracted periods during episodes of increased risks. These bad results of the RiskMetrics are consistent with other studies such as Cotter (2004), and Billio and Pelizzon (2000). It is interesting to note that for the bond indices, the normal and skewed-Student CEVT methods perform much better than the other methods for the Core countries group but not for the PIIGS countries group. This implies that it takes more sophisticated methods to get the accuracy properties satisfied for the PIIGS countries. Moreover, some methods give better results for stocks than bonds. Additionally, we only include the efficient frontiers for the most informative portfolios for different combinations of asset classes of stock, bond and commodities for the two groups and the euro-zone as a full. We will first present the results of the full period followed by those for the subperiod.

5.1. Sovereign bond benchmarks

Table 4 shows the backtesting results for the individual bonds for the countries in both groups for the full period. The null hypothesis for the unconditional coverage (UC) property states that the expected proportion of violations, or days when the actual loss exceeds the VaR(0.01), is equal to 1%. A rejection of the null hypothesis means that the model is not adequate. For both the Core and PIIGS groups, the RiskMetrics gives the highest percentage of violations followed by the DPOT, while the CEVT-n and CEVT-sstd yield significantly lower percentages for the full period under consideration. The CEVT-sstd percentage of violation is generally lower or equal to that of the CEVT-n. While the magnitude of this violation does not exceed 2% for the Core countries, it is more than 2% for the PIIGS. Within the Core, Germany has the lowest percentage of violation, while Finland has the highest. The heavily indebted Italy has the lowest violation percentage in the PIIGS. For Greece and Portugal in the PIIGS, this percentage almost reaches 2.5%. In the subperiod which includes the euro-zone debt crises, the percentage of violations is higher for the PIIGS countries' sovereign bonds while it is generally lower for the Core countries than in the full period. This is not surprising because the euro-zone debt crisis started and persisted with the PIIGS countries.

The results of the likelihood ratio test of Kupiec (1995) known as the unconditional coverage test, which assesses the accuracy of the interval forecasts by monitoring the hit sequence, are also given in Table 4-Panel A for the full period. The RiskMetrics approach performs very poorly with respect to this property, giving a rejection of the UC hypothesis for all the hit sequences of the Core and PIIGS countries at the 1% level, which suggests that the expected percentage of violations are higher than 1% in all countries. This result underlines the evolving nature of volatilities in the bond markets. On the other hand, while the DPOT method improves the UC results over the RiskMetrics for all Core countries, it does not improve the results for the PIIGS countries (Panel B). In contrast, both the normal and skewed-Student CEVT models provide more reliable results in terms of this property than the RiskMetrics and DPOT methods for all bonds in the Core group only. This is not the case for the PIIGS's bonds since the UC hypothesis is rejected at the 5% level for all countries in this group except Spain. This implies that for the sovereign bonds of the Core countries the application of the extreme value theory in approximating the tail distributions of the returns can help improve the accuracy of the VaR forecasts significantly. Under the subperiod, none of the methods rejects this property for any of the sovereign bonds of the Core countries, with the only exception is for DPOT in the case of France. Thus, these methods do better in the subperiod than in the full period for the Core group. For the PIIGS group, there is also an overall improvement for all the methods except for DPOT which shows an improvement for only one country in the subperiod relative to the full period.

The results of the maximum median (MM) test proposed by Araújo-Santos and Fraga-Alves (2012a), which assesses the independence hypothesis alone and is suitable for detecting clusters of violations, are included for the full period in Table 4. The RiskMetrics and both CEVT methods pass the MM test. However, the DPOT method fails this test for all countries except Austria in the Core and Portugal in the PIIGS. This result implies that the DPOT method is more likely to fail to satisfy the independence hypothesis and detect the cluster of violations which signals a lack of responsiveness in the reported VaR measure to incorporate and react quickly to changing in market risks. Under the subperiod, DPOT performs much better in terms of the MM property for both groups than in the full period.

The results for the conditional coverage (CC) test proposed by Christoffersen (2009), which considers jointly the unconditional coverage and serial independence of the hit sequence, are also presented in Table 4 for the full period. The RiskMetrics method again performs very poorly for both groups as is the case for the earlier properties. Under this method, the CC hypothesis is rejected for all the hit sequences of the Core and PIIGS countries at the 1% significance level, which suggests that the percentage of violations are higher than 1% in all cases. On the other hand, the DPOT, CEVT-n and CEVT-sstd methods–increasingly–satisfy the CC property in this sequence for the Core countries only, compared to RiskMetrics. However, applying the more sophisticated methods of DPOT and the two CEVT's doesn't improve the CC property for the four PIIGS countries except Spain. The CC property is rejected for Greece, Ireland and Portugal at the 10% significance level for all four methods. Under the subperiod, RiskMetrics satisfy the CC property with no rejections for all Core countries and the other methods also maintain their good performance in terms of this property for this group. There has been an improvement for all the methods in the PIIGS countries.

We present the daily capital requirements results for the ten individual sovereign bond benchmarks for the full period in Table 5. These requirements are relevant for determining the share of tier 1 capital in total assets but the relatively safe assets in this tier yield lower returns. We also present the number of days in the red zone in Table 5. Under the Basel II Accord, the VaR forecasts of banks must be reported to the regulatory authority on daily basis. These forecasts are utilized to compute the amount of capital requirements used as a cushion against adverse market conditions. The Basel Accord stipulates that the daily capital charges must be set at the higher of the previous day's VaR or the average VaR over the last 60 business days, multiplied by a factor k (see Table 6).

Results for the number of days in the red zone show that the two CEVT methods are more reliable than the DPOT and RiskMetrics methods under the full period. The CEVT-sstd has a zero number of days in the red zone for all countries and whereas the CEVT-n has one violation for Portugal. It is interesting to note that while the RiskMetrics method gives rise to the lowest average daily capital charges for all Core countries, the CEVT-sstd yields the lowest average daily capital charges for the PIIGS. Still, financial institutions will find it difficult to use the RiskMetrics method because of its high number of days in the red zone. The DPOT method tends to give the highest average daily capital charges for the Core countries, while the CEVT-n yields the highest charges for the PIIGS except for Spain. In terms of the capital requirements under the subperiod the RiskMetrics and CEVT-n tend to give the lowest amount of capital requirements. The DPOT forecasts for the VaR have considerable number of days in the red zone for Greece, Portugal and Spain.

5.2. National stock indices

As is the case for the sovereign bonds, Table 4 also shows that the RiskMetrics method when applied to the ten national stock indices in both groups of the euro-zone yields the highest number of violations for the full period. On the other hand, the DPOT method performs better for the stock indices than for bonds for both groups. Except for Greece and Ireland, the DPOT method gives the lowest percentage of violations. The CEVT-n and CEVT-sstd yield almost the same violation percentages and they come in the middle between the RiskMetrics and the DPOT methods. In the Core group, generally France's *CAC* index has the lowest number of violations, while the Netherlands's *AEX* has the highest. In the PIIGS, Ireland's *ISEQ* and Italy's *MIB* have the lowest and highest number of violations, respectively. For the subperiod, all models except DEPOT yield higher a percentage of violations for the stock indices of the Core countries, but a lower percentage for the PIIGS countries, compared to the full period.

The unconditional coverage (UC) hypothesis is rejected for all national equity indices of the countries in both groups for the RiskMetrics method, questioning the accuracy of the interval forecasts under this method as was the case for the sovereign bonds under the full period. In contrast, applying the DPOT and the two CEVT methods can improve the UC property significantly for all indices in both groups for this full period, which is different than the case for bonds of the PIIGS. For the Core countries, the CEVT-sstd shows the best performance, while the CEVT-n and DPOT methods rank second and third, respectively, which has also been the case for the Core countries' sovereign bonds. However, for the PIIGS, the DPOT method yields better results than the other methods for only Ireland and Portugal, among all equity indices of this group. Under the subperiod, RiskMetrics still does poorly in terms of the UC property and there is also not much improvement in performance for the other methods for both groups, compared with the full period.

As indicated in the sovereign bonds case, the UC test focuses only on the frequency of the violations of VaR forecasts, but it does not consider the case of clustering for zeros and ones in the hit sequence. As a remedy and as we did for the bond case, we conduct the conditional coverage (CC) test as in Christoffersen (2009) for equities, by accounting for the dynamics of the exceptions by jointly testing for the unconditional coverage and the serial independence of the hit sequence for the full period. Again like what we have for bonds, the RiskMetrics method does not satisfy the CC property for the national equity indices of all ten euro-zone countries. In contrast, by applying the more sophisticated methods the DPOT and the two CEVT's, one can develop the CC property in the equity VaR predictions for all countries in the two groups. While the two CEVT methods show a higher level of significance than the DPOT method for all sovereign bond benchmarks, they are not the best methods when it comes to the national equity indices. The two methods show higher level of significance for this property, compared to the DPOT method, and the exceptions are France's *CAC* and Germany's *DAX*. Under the subperiod, there is some improvement in the performance of the RiskMetrics and DPOT methods, while the two CEVT methods maintain their good performance as in the full period.

Moreover, the RiskMetrics and CEVT methods pass the MM test for the independence property for both groups in the full period, while the DPOT fails to pass this test for France's *CAC*, Greece's *ATHEX* and Spain's *IBEX*. The DPOT performance is better for the equity than the bond indices for the MM test. Under the subperiod, RiskMetrics does not do as well for the Core countries as in the full period while its performance for the PIIGS countries do not change much compared to the full period. For the other methods, the performance stays basically the same.

The daily capital requirements for the ten individual stock indices for the full period are shown in Table 5. The RiskMetrics method computes the lowest average daily capital charges for all Core and PIIGS equities, except for Italy. This is also the case for the Core bonds but is not true for PIIGS bonds. It is worth noting that the DPOT method computes the highest average daily capital charges for all countries except Portugal. The better performance of the CEVT models with respect to this property is obvious from the number of days in the red zone. While the computations by the RiskMetrics and the DPOT methods sometimes exceed 100 days in the red zone, the CEVT-n has one violation which is for Spain, and the CEVT-sstd has zero days in the red zone. In terms of the capital requirements under the subperiod the RiskMetrics gives lowest capital charges for most of the stock indices in both the PIIGS and the Core. The exceptions are Italy, Spain and Finland. DPOT gives us the highest number without exceptions. We must add that lower capital requirements coupled with high number of entries in the red zone does not help the reputation of the financial institution.

5.3. Optimal combined bond and stock index portfolios for full period

In this section, we apply the VaR approach to optimal portfolio selection of the sovereign bond and stock indices for the full period, using the forecast VaR as the measure of the portfolio risk. Following the approach developed in Campbell (2001), we maximize the return-VaR risk ratio. For this purpose, we minimize the VaR risks for each given amount of portfolio return. We use these minimum risks along with their returns to sketch the portfolio efficient frontier that is shown in Figures 1-6 for the full period.

5.3.1. Optimal bond portfolios

Our initial strategy is to first construct an optimal sovereign bond portfolio for each of the two euro-zone groups, and then combine the two groups into one larger bond portfolio to find the best weight combination of the national indices in the total portfolio. Table 7 shows the best weight combination of these portfolios. The efficient frontier for the five Core bond benchmarks portfolio (Portfolio 1) is depicted in Figure 1. The Netherlands, Austria and Germany individually have an optimal weight of 61%, 30% and 6% of this bond portfolio, respectively. Historically, the Netherlands has the highest average daily return, followed by Austria and Germany which both have the same average return like the *S&P 500* index. The German sovereign bond index has a modest share in this portfolio despite its economic and political dominance in the euro-zone because this index falls relatively short on the return side of performance scale relative to that of the Netherlands.

The best portfolio combination for the five bond indices in the PIIGS (Portfolio 2 and Figure 2) is overwhelmingly dominated by Italy's sovereign bond benchmark, with very negligible weights for the other four members in the group. Italy has the highest historical average bond return and the second lowest volatility in this group. Interestingly, the Sharpe ratio of the PIIGS bond portfolio is significantly lower than that of Core. Moreover, by comparing Figures 1 and 2, it is obvious that the bond portfolio of the Core performs much better in terms of both risk and return than that of the PIIGS.

Portfolio 3 which is shown in Figure 3 is the optimal weight combination of the augmented ten bond benchmarks. The best combination of this grand 10-sovereign bond portfolio is dominated by the Core countries. Adding the five PIIGS bond indices to the portfolio of the five Core bond indices almost doesn't affect the risk and return scale in terms of the Sharpe ratio. Thus, the augmented ten bond portfolio is still dominated by the Core countries particularly by the Netherlands, Austria and Germany. However, by comparing Figures 1 and 3 we can see that diversifying the Core bond portfolio with the PIIGS bonds moves the entire efficient frontier towards the left, although the Sharpe ratios for the best combinations for the two portfolios are very similar.

We also investigate the diversification effect of the U.S. bond benchmark on the grand portfolio of the 10 euro-zone bond indices. The thresholds for both portfolios of the grand 10 euro-zone bond indices and the augmented ten euro-zone bond and U.S. bond indices are shown in Figure 3. As can be seen, the U.S. bond benchmark shifts the threshold to the left. This means that at any given average daily return, diversifying the portfolio of the ten euro zone bond indices with the U.S. bond benchmark, which has as much historical average return as Austria and Germany but higher volatility than Spain, does decrease the risk, thereby improves the performance of the more diversified euro-zone-U.S. portfolio.

5.3.2. Optimal stock portfolios

As indicated earlier, all historical average daily returns of the national stock indices of the PIIGS countries are negative for the full period. Therefore, we do not examine the equity portfolio of this group separately. Instead, we first investigate the Core stock indices (Portfolio 4) and then add the PIIGS's five stock indices to the augmented equity portfolio that includes the Core equity portfolio. Adding the PIIGS stock indices to the Core stock portfolio does not affect the performance of the latter's portfolio. Portfolio 5 is the optimal weight portfolio in Figure 4 for the combined Core and PIIGS equity indices portfolio. The weights of all PIIGS's stock indices are zero and the grand equity portfolio is dominated by the Austrian *ATX*. The Sharpe ratio of this portfolio for the ten stock indices is much lower than the Sharpe ratio for the 10 bond index portfolio. Figure 4 shows this result. Although adding the PIIGS stock to the portfolio doesn't affect the portfolio's risk and return scale for a higher amount of the average return, it shifts the efficient frontier towards left.

Merging the two portfolios of the bond and stock indices of the ten euro-zone countries into a 20 asset portfolio increases the performance significantly over the separate bond and equity portfolios. Portfolio 6 depicts the optimal weight combination of this portfolio (Figure 5). Adding the ten stock indices to the portfolio of the ten bond indices increases the return and lowers the risk for the 20 bond and equity index portfolio, thereby raising the Sharpe ratio and increasing the performance of the larger portfolio. Thus, adding the ten stock indices to the portfolio of the ten bond benchmarks can also move the efficient frontier towards left, decreasing risk for each level of return.

5.3.3. The optimal combined bonds, stocks and commodity portfolios

To investigate the diversification benefits of adding commodities to the bond and equity portfolios, we add the oil, gold, silver, platinum, palladium and copper individually and separately to both the portfolios of the national stock indices and the bond benchmarks. Diversifying portfolios by adding commodities improves the Sharpe ratio of both the stock and bond portfolios significantly. However, the mechanism is different for the two groups. For the equity portfolio (Portfolio 7), the diversification contributes to the portfolio gains by enhancing both the average daily return and reducing the risk. However, this is not the case for the bond portfolio, where diversification with commodities only contributes to the return but also increases the risk; still netting out gains and leading to higher performance.

Portfolio 8 which has the highest Sharpe ratio amongst these portfolios is the optimal weight combination of three asset classes of bonds, equity indices and commodities (Figure 6). As depicted in Table 7, the weights of the equity indices are zero for the best combination. Therefore, the best portfolio in terms of the Sharpe ratio is the one that combines bonds and commodities. This implies that the bond benchmarks play the role of reducing the risk, while the commodities play the role of increasing the returns and the stock indices do not add value to this portfolio. Another interesting point is that the weight of the highly volatile palladium is zero in all the portfolios which contain commodities. As can be seen in Figure 6, diversifying the portfolio of bonds and stocks with commodities can improve its performance in terms of both risk and return and it shifts the efficient frontier towards lower risk for given returns.

5.4. Optimal portfolios of the subperiod

For the subperiod that ranges from July 2, 2007 to November 20, 2012, we examine the diversification benefits for the augmented portfolios for bonds and stocks, as well as for commodities. The best combination for the five Core bond benchmark portfolio (Portfolio 9) is dominated by Germany's benchmark with a weight of 81%, followed by Austria which has 9% of total weight of the portfolio. Portfolio 10 consists of the PIIGS group's bond benchmarks. The best combination in this portfolio is dominated by Italy's benchmark (93%) and Ireland's (7%). Portfolio 11 includes all bond benchmarks. The weight of the PIIGS bond benchmarks are zero in the best combination. This combination is the same as Portfolio 9. As all average daily returns for the stock indices are negative during this subperiod, we do not do the optimal portfolio analysis on this asset class separately. Portfolio 12 consists of all of the bond benchmarks and stock indices and the weights for this portfolio are the same as for Portfolios 9 and 11 as the stock indices have zero weights in the best combination. Portfolio 13 in Table 8 shows the optimal weight combination for the Core and PIIGS bond benchmarks augmented with commodities in this subperiod. Germany and Austria have the first and second highest weights of 0.27 and 0.22, respectively. The Sharpe ratio for this larger bond portfolio is much higher than its equivalent one in the full period, thereby highlighting the better performance of the bonds as safe havens during this subperiod.

When we investigate the diversification benefits of adding oil and other commodities to the bond and equity portfolios, we pay attention to the different possible gains from adding these diverse commodities. Portfolio 14 shows the optimal combination of the portfolio of the 10 stock indices and the six commodities. It turns out that the combination of German *DAX* with gold and silver gives us the highest Sharpe ratio in this portfolio that consists of two different asset classes (the weight of the other commodities are zero). This is consistent with the results of Baur and

McDermott (2010), Erb and Harvey (2006), Roache and Rossi (2010) and Elder et al. (2012) which highlight the importance of those precious metals as safe havens and stores of value during the crises and economic downturns. It is interesting to note that the weight of 12% for *DAX* is relatively considerable, compared to those of the stock indices in the equivalent portfolio of the full period (Portfolio 7).

Portfolio 15 which has the highest Sharpe ratio amongst the portfolios in the subperiod is the optimal weight combination of the three asset classes of the bonds, equity indices, and commodities. It turns out that among all commodities under consideration only gold and silver contribute diversification gains to the bond portfolios. It seems that the gains in this portfolio for this subperiod are augmented by commodities (gold and silver) that claim the highest safe haven status among the considered commodities. The pro-cyclical industrial commodities copper and platinum do not do well in the bond portfolios for this subperiod and they also do not improve the portfolio efficient frontier and gains. This result contradicts the finding of Agyel-Ampomah et al. (2012) which argue that these metals have potential diversification benefits because of their negative VAR correlations with the sovereign debt. Our analysis shows that copper and platinum are negatively correlated with all sovereign bonds except for Greece, Ireland and Italy during this subperiod. However, this does not mean that they do well together in augmented bond portfolios. Our portfolio optimization analysis shows that the pro-cyclical copper and platinum do not add value to the diversified portfolio during the subperiod. This may be attributed to the bad performance of these metals that was realized during this subperiod. Comparing Tables 2 and 3, we find that the historical copper and platinum returns decrease significantly during this subperiod, while their historical volatility as measured by standard deviation increases. The correlation analysis shows that gold and silver have positive correlations with all bond benchmarks except the Portuguese bond benchmark, but these precious metals still improve the portfolio performance. Therefore, we can conclude that the risk-return performance of the commodities themselves is more important than their correlations with the sovereign bonds, and this seems what determines the performance of the bond portfolio diversified with commodities. This is also the case with oil which also doesn't add to the value of the bond portfolio in this subperiod. This may also be caused by the oil low return compared to its high volatility in this subperiod. In the subperiod like in the full period, diversifying the Core and PIIGS bonds with commodities (this time just gold and silver) would increase the Sharpe ratio. However, by adding commodities to the portfolio of bonds, the changes in the average daily return and its efficient frontier (Figure 7) are not as significant as in the full period because the bonds are doing very well in terms of both the risk and return after 2007. The optimal portfolio as shown in Table 8 consists of 21% in gold, 0.06% in silver, 18% in Austria's bond benchmark and almost 10% of each of Finland's, France's and Ireland's benchmarks. It is interesting to note that the total weight of the commodities decreases from 51% in the full period to 0.27% in this subperiod. Moreover, the Sharpe ratio is higher than that of the full period.

5.5. Ranking optimal portfolios

In terms of ranking the portfolios over the full period, the most diversified portfolio (Portfolio 8) which combines the ten bonds, ten indices and all five commodities is ranked # 1 based on the VaR Risk-return ratio, followed by Portfolio 7 which consists of the ten stocks and the five commodities (see Table 9). Over the subperiod , similarly the most diversified portfolio (Portfolio 15) of all bonds and indices and the commodities gold and silver ranks first, followed by portfolio of bonds and commodities. Ranking in both periods follows the same diversification sensitive pattern except for portfolio 14 which includes stocks and commodities which is not performing very well in the subperiod due to the collapse of commodity prices (and stock market). It is also worth mentioning that in both periods the portfolios that contain the PIIGS bond benchmarks are the worst in terms of return to risk ratio based ranking.

5.6. Backtesting and daily capital charges for the best portfolios for both periods

It would be interesting to discern how the four methods of RiskMetrics, DPOT and the two CEVT's perform for portfolios of different asset classes. In this regard, we perform the analysis on the best portfolios of the two periods for both periods. The best combination under the full period for optimal Portfolio 8, which is the most diversified, encompasses 48% of the bond benchmarks which are all in the Core, while 52% are all commodities. However, under the subperiod the best combination for Portfolio 15, which is equivalent to Portfolio 8 for the full period, includes bonds from the two groups, a stock index from the Core and commodities. The optimal weight for the bonds in the Core countries is 58%, while the bond of Ireland in the PIIGS accounts for 10%, Germany's equity index *DAX* for 5% and commodities for 27%. The results for Portfolio 8 are shown in Tables 10 and 11 (for Portfolio 15 results are available upon request). For both periods, the DPOT has the lowest percentage of violations while RiskMetrics predicts the lowest amount of capital requirements. The percentage of violations of the DPOT and CEVT-sstd models for this portfolio is almost 1% which is much better than performance of these models for the individual bonds. The RiskMetrics and CEVT-n have the percentage of violations to be almost 2% and 1.3% respectively; thereby they do not perform well for this best portfolio. The UC and CC properties are achieved under the DPOT and both CEVT models but not under the RiskMetrics. As in the case of individual bonds, the RiskMetrics and CEVT-n models perform well in terms of the MM property for the best portfolio. The CEVT-sstd and the DPOT fail in this case.

Table 11 shows the daily capital charges for the best portfolio for the full period. The number of days in the red zone is zero for all models except in the case of the RiskMetrics. RiskMetrics has the lowest prediction for capital charges while DPOT has the highest for both portfolios.

6. Conclusions

This essay examines the downside risks in the sovereign bond and stock markets for ten euro-zone countries and discerns ways to construct portfolios that diversify away risks for the full period and a subperiod that recognizes the 2007/2008 global financial crisis. The selected euro-zone countries are divided into two groups the Core and the PIIGS, taking into consideration the sizes of budget deficits and the debt to GDP ratio. The Core includes Austria, Finland, France, Germany and the Netherlands, while the PIIGS consists of Greece, Ireland, Italy, Portugal and Spain. We investigate three asset classes which include the individual country sovereign bond benchmarks, national stock indices and commodities. We estimate the VaRs for the individual country bond benchmarks and equity indices and evaluate their accuracy properties. We also construct optimal portfolios of the bond benchmarks and the equity indices and further augment them with oil, precious metals and three industrial commodities to enhance the diversification gains. We use four major VaR estimation methods: The RiskMetrics, DPOT, CEVT-n and CEVT-sst. We evaluate those methods in terms of four VaR properties which include unconditional coverage (UC), conditional coverage (CC), independence (MM) and minimum capital requirements as stipulated by the Basel II accord.

The results show that the RiskMetrics method fails to satisfy most of the evaluative properties particularly the UC and CC properties and tends to give the highest number of entries in the red zone for the individual countries over the full period. However, this method gives better results in terms of all properties for the subperiod. It seems to perform better during high volatility. Its performance is still questionable because using it may hurt the reputation of financial institutions as it gives the greatest number of entries in the red zone.

The two CEVT methods produce the best results with respect to these two properties, while the DPOT method comes in between over the full period. While those two CEVT methods maintain their good performance during the subperiod, the DPOT performs worse in terms of all properties than it does in the full period. DPOT may not perform well in periods of high volatility.

Regarding the two euro-zone groups, the VaR estimation methods with the exception of RiskMetrics produce satisfactory results in terms of meeting the four evaluative properties for the case of the sovereign bonds of the Core group but not for the PIIGS bond group which may require more sophisticated VaR estimation methods for both the two periods. In terms of the national stock indices, the VaR methods satisfy the four properties well for both euro-zone groups but still they perform better for the Core than for the PIIGS. The high risk in the PIIGS countries is a challenge for the VaR estimation models.

The bond portfolio optimization shows that the Sharpe ratio of the PIIGS bond portfolio is significantly lower than that of the Core, ranking the Core better than the PIIGS for this asset class over the full period. This result cannot be obtained for the subperiod because all the returns of the bonds for the PIIGS are negative. Therefore, the augmented ten bond portfolio is still dominated by the Core countries particularly by the Netherlands (52%), Austria (26%) and Germany (18%). At any given average daily return, diversifying the group portfolio of the ten euro zone bond indices with the U.S. bond benchmark, which has as much historical average return as Austria and German but higher volatility than Spain, does decrease the risk, thereby improves the performance of the more diversified euro-zone-U.S. bond portfolio for the full period. Merging the two portfolios of the bond and stock indices of the ten euro-zone countries into a 20 asset portfolio increases the performance significantly over the separate bond and equity portfolios for both periods.

Our analysis shows that in the full period, gold which is known as a hedge and a safe haven shows good diversification benefits when added to portfolios that include stock and bonds for the full period and the subperiod, respectively. Moreover, adding silver, copper, platinum, and oil to the portfolios of stock and bond indices that include gold improves the Sharpe ratio significantly giving the best combination for the full period. For the subperiod, the best combination can be achieved by adding only gold and silver to the portfolio that contains the 20 stocks and bonds. However, the commodity diversification benefit mechanism is different for the portfolios of those two asset classes of stocks and bonds. For the equity portfolio, the commodity diversification contributes to the portfolio gains by enhancing both the average daily return and reducing risk. However, this is not the case for the bond portfolio, where commodity diversification contributes only to the return but also increases the risk; still netting out more gains than risks and leading to higher performance.

Therefore, the gains in the bond and stock portfolios for the subperiod are more pronounced when those portfolios are augmented by the commodities that claim the highest safe haven status (i.e., gold and silver) among the considered commodities. On the other hand, the pro-cyclical industrial commodities copper and platinum do not do well in the bond portfolios for this subperiod and they also do not improve the portfolio efficient frontier. This underscores the cyclical nature of the industrial commodities during a stagnation period.

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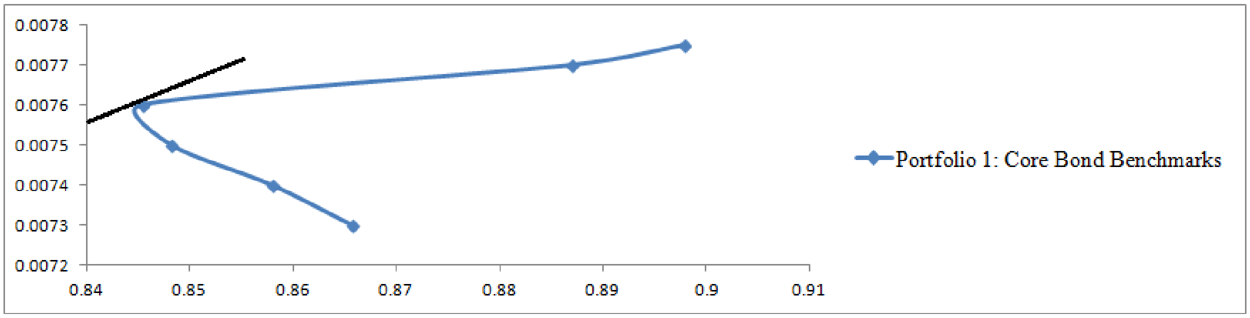
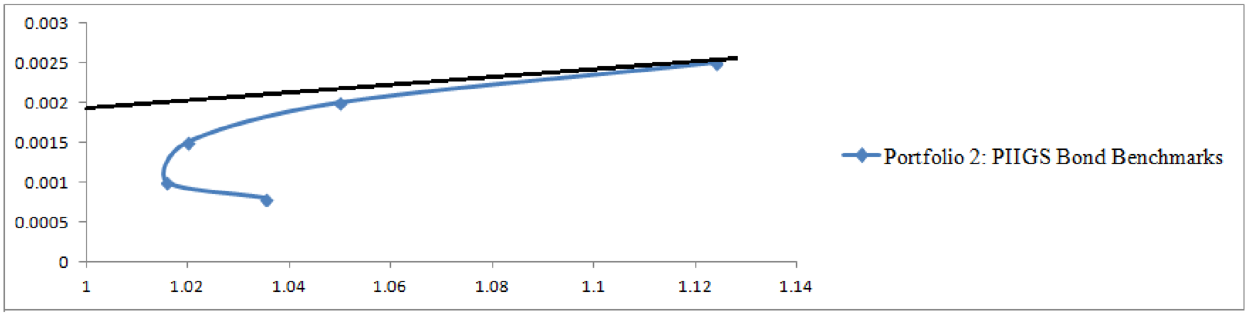
Figure 1: Efficient VaR Frontier for Optimal Bond Portfolio 1 (Full Period)



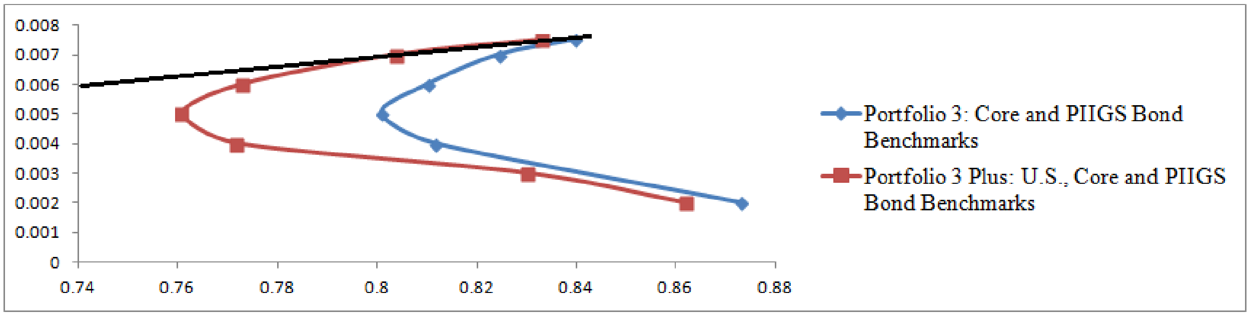
Notes: Portfolio 1 includes the Core countries' sovereign bond benchmarks. In the best combination, which is the tangency point between the efficiency frontier and the capital line, the bond benchmarks for the Netherlands, Austria and Germany have the highest weights which are 61%, 30% and 6%, respectively.

Figure 2: Efficient VaR Frontier for Optimal Bond Portfolio 2 (Full Period)



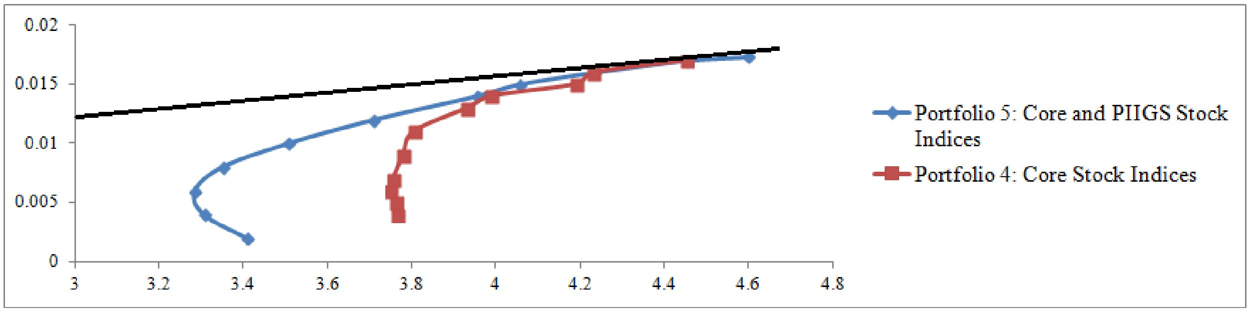
Notes: Portfolio 2 includes the PIIGS countries' sovereign bond benchmarks. The best combination (the tangency point) here is dominated by Italy's bond benchmark.

Figure 3: Efficient VaR Frontier for Portfolio 3 (Full Period)



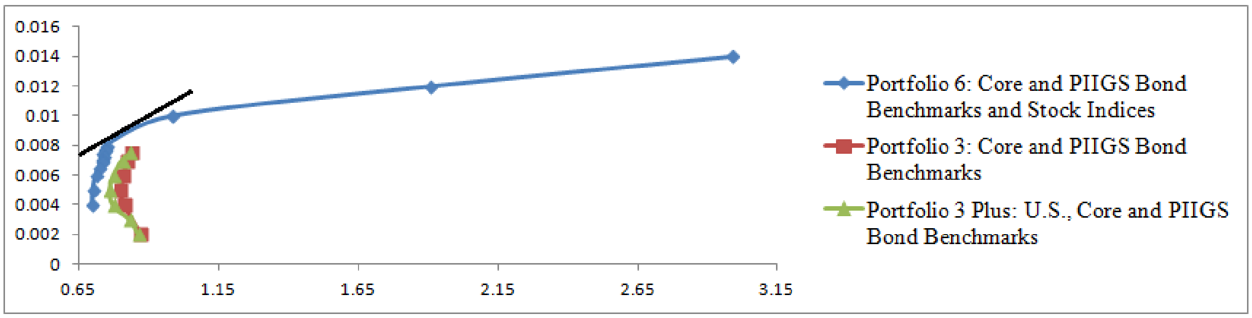
Notes: Portfolio 3 includes the Core and the PIIGS countries' sovereign bond benchmarks. In the best combination (the tangency point) the Netherlands, Austria and Germany have the highest weights which are, 52%, 26% and 18%, respectively, while the weights of the PIIGS bonds are zero. Portfolio 3 Plus includes the U.S. Bond benchmark in addition to Portfolio 3.

Figure 4: Efficient VaR Frontiers for Optimal Portfolios 4 and 5 (Full Period)



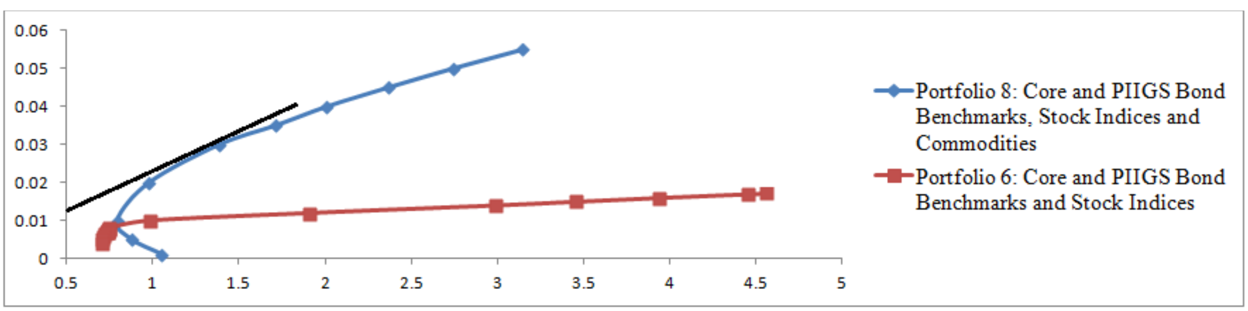
Notes: Portfolio 4 includes the Core equity indices while Portfolio 5 includes the Core and the PIIGS equity indices. For the best combination (the tangency point) which is the same for these two portfolios, Austria's equity Index *ATX* has 96% of the portfolio, while Germany's equity *DAX* accounts for 4%.

Figure 5: Efficient VaR Frontier for Optimal Portfolio 6 (Full Period)



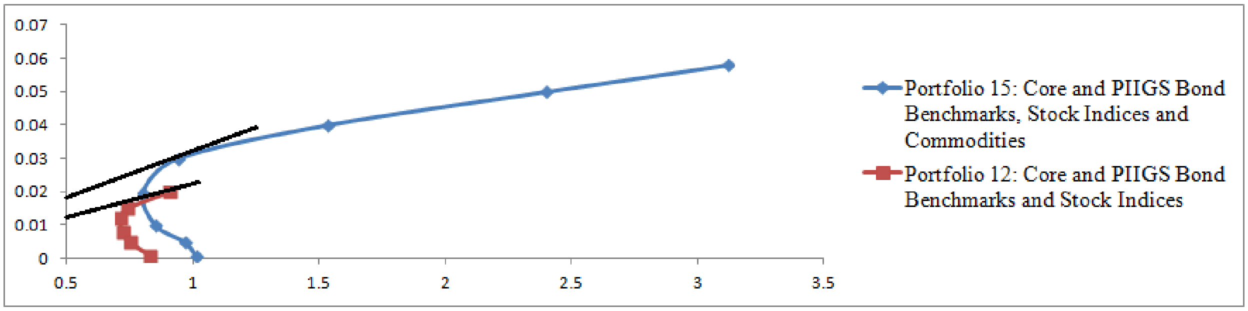
Notes: Portfolio 6 includes the bond benchmarks and the stock indices of the Core and PIIGS countries. In the best combination (the tangency point) the bond benchmarks of the Netherlands, Germany and Austria have the 46%, 27% and 9%of the weight, respectively, while that of the Austrian Traded Index (*ATX*) is 18%.

Figure 6: Efficient VaR Frontier for Optimal Portfolio 8 (Full Period)



Notes: Portfolio 8 includes the ten bond benchmarks, the ten stock indices and all commodities (copper, gold, oil, platinum and silver). For the best combination (the tangency point) the weights of Germany's bond benchmarks, copper, gold, oil, platinum and silver returns are 34%, 11%, 13%, 11%, 7% and 9%, respectively.

Figure 7: Efficient VaR Frontiers for Optimal Portfolios 12 and 15 (Subperiod)



Notes: Portfolio 12 contains bond benchmarks and stock indices of Core and PIIGS countries. In the best combination (the tangency point) Germany's and France's and Austria's bond benchmarks have 81%, 10 % and 9% of the weight of the portfolio. Portfolio 15 includes bond benchmarks, stock indices of the Core and PIIGS groups, along with the commodities gold and silver only. In the best combination, which is the tangency point between the efficiency frontier and the capital line, bond benchmarks of Austria, the Netherlands, Finland, France, Ireland and Germany have the weights 18%, 12%, 11%, 10%, 10% and 7% of the total portfolio, respectively, while gold, silver, Germany's DAX have 21% , 6% and 5% of the total portfolio. The figures for the efficient frontier for Portfolios 9, 10, 13 and 14 are available upon request.

Table 1: List of Stock and Sovereign Bond Market Indices

Country	Stock market indices			Bond Benchmarks (BMXX)
	Symbol	Name	Description	Symbol
Netherlands	*AEX*	Amsterdam Exchange Index	This market capitalization weighted index is composed of a maximum of 25 of the most actively traded[5] securities on the exchange.	BMNL
Greece	*ATHEX*	ATHEX Composite Share Price Index	This market capitalization weighted index is composed of the 60 largest[6] companies that traded in the Big Cap category of the Athens stock exchange.	BMGR
Austria	*ATX*	Austrian Traded Index in EUR	This market capitalization weighted index comprises the 20 with the highest liquidity and market value.	BMOE
France	*CAC*	*CAC 40*	This market capitalization weighted index composes the 40 largest equities measured by free-float market capitalization and liquidity companies listed on Euronext Paris equity market.	BMFR
Germany	*DAX 30*	Deutscher Aktien Index	This market capitalization weighted index composes the 30 largest equities measured by free-float market capitalization and liquidity companies listed on Frankfurt Stock Exchange.	BMBD
Italy	*FTSE*	*MIB* (Milano Italia Borsa)	This index consists of the 40 most-traded stock classes on the exchange..	BMIT
Spain	*IBEX*	*IBEX 35*(Iberia Index)	This index is composed of the 35 most liquid securities traded on the Spanish Market	BMES
Ireland	*ISEQ*	*ISEQ* overall index	This index is composed of the 20 companies with the highest trading volume and market capitalization liquid securities traded on the Irish Stock Exchange.	BMIT
Finland	*OMXH*		*OMX* Helsinki (*OMXH*) – Finland	BMFN
Portugal	*PSI*		Portugal PSI General	BMPT

Notes: All data are obtained from DataStream. BMXX are series in DataStream where XX stands for the country code.

[5] The selection is made on an annual review date in March. It is based on the share turnover over the previous year.
[6] The companies are ranked on the basis of their Trading Value excluding blocks.

Table 2. Descriptive Statistics [Full Period]

Panel A. Sovereign Bond Benchmarks

Bonds	Core Countries					PIIGS Countries					US
	Austria	Finland	France	Germany	Netherlands	Greece	Ireland	Italy	Portugal	Spain	
Mean	0.0074	0.0064	0.0064	0.0074	0.0077	-0.0356	-0.0003	0.0025	-0.0024	0.0008	0.0076
Median	0.0	0.0014	0.0	0.0093	0.0	0.0	0.0029	0.0005	0.0	0.0	0.0
Maximum	1.7784	1.9299	2.3048	2.2473	1.8664	29.2276	8.3540	5.9299	11.3648	6.5039	4.0529
Minimum	-2.1020	-1.2229	-2.0162	-1.5231	-1.3920	-21.6688	-5.0876	-3.6878	-11.6271	-2.6395	-2.8735
Std. Dev.	0.3388	0.3289	0.3571	0.3518	0.3364	1.2888	0.5495	0.4315	0.7249	0.4429	0.4999
Skewness	-0.2273	-0.0468	-0.1209	-0.0713	-0.1202	1.0118	0.5062	1.1419	-0.4606	1.2832	-0.0356
Kurtosis	5.1821	4.3878	5.8865	4.5997	4.2275	146.5786	33.3905	27.5416	61.3925	22.9790	5.5964
Jarque-Bera	736.7482	286.9064	1244.212	382.4847	232.0036	3057613.	137111.1	90088.16	505753.5	60168.71	1000.451
Prob.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel B. National Stock Market Indices

Stock	Core Countries					PIIGS Countries					US
	AEX	*ATX*	*CAC*	*DAX*	*OMXH*	*ATHEX*	*IBEX*	*ISEQ*	*MIB*	*PSI*	*S&P500*
Mean	-0.0140	0.0173	-0.0054	0.0108	-0.0056	-0.0409	-0.0063	-0.0138	-0.0260	-0.0015	0.0021
Median	0.0023	0.0123	0.0	0.0425	0.0	0.0	0.0213	0.0203	0.0116	0.0095	0.0161
Maximum	10.0282	12.0210	10.5946	10.7974	14.5631	13.4311	13.4836	9.7331	10.8769	10.1110	10.9572
Minimum	-9.5903	-10.2526	-9.4715	-8.8746	-17.4037	-10.2140	-9.5858	-13.9636	-8.5981	-10.6505	-9.4695
Std. Dev.	1.5293	1.4672	1.5354	1.5868	1.9826	1.7824	1.5292	1.4420	1.5245	1.0926	1.3173
Skewness	-0.0728	-0.3062	0.0275	-0.0061	-0.3154	0.0263	0.1143	-0.5639	-0.0570	-0.1850	-0.1561
Kurtosis	8.9691	10.6718	7.6895	7.2316	9.3787	7.2304	8.1397	10.6242	7.9093	12.7080	10.5531
Jarque-Bera	5286.795	8783.678	3261.571	2655.382	6092.749	2654.349	3925.154	8808.664	3575.948	13996.14	8474.466
Prob.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel C. Commodity Returns

Commodities	Copper	Gold	Oil	Palladium	Platinum	Silver
Mean	0.0488	0.0512	0.0633	0.0159	0.0412	0.0530
Median	0.0	0.0164	0.0	0.0	0.0580	0.0
Maximum	11.7259	7.0059	40.4634	11.5235	10.0419	18.2786
Minimum	-10.3579	-7.9718	-36.4014	-16.9984	-9.6731	-18.6926
Std. Dev.	1.7964	1.1451	2.3261	2.1699	1.4817	2.1230
Skewness	-0.1530	-0.0807	-0.2851	-0.4007	-0.4832	-0.5459
Kurtosis	7.0560	7.9253	61.2444	7.0258	8.2306	13.1680
Jarque-Bera	2453.545	3601.232	503115.4	2498.7090	4195.626	15508.41
Prob.	0.00	0.00	0.00	0.00	0.00	0.00

Note: All data for bond benchmarks are obtained from DataStream and data for commodities are obtained from Bloomberg. The time span is between March 31, 1999 to November 20, 2012.

Table 3. Descriptive Statistics [Subperiod]

Panel A. Sovereign Bond Benchmarks

Bonds	Core Countries					PIIGS Countries					US
	Austria	Finland	France	Germany	Netherlands	Greece	Ireland	Italy	Portugal	Spain	
Mean	0.0192	0.0190	0.0179	0.0216	0.0196	-0.0976	0.0006	0.0064	-0.0080	-0.0016	0.022508
Median	0.0174	0.0166	0.0124	0.0179	0.0050	-0.0179	0.0100	0.0	-0.0013	-0.0050	0.015294
Maximum	1.7784	1.9299	2.3047	2.2473	1.8663	29.2276	8.3539	5.9299	11.3648	6.5038	4.052948
Minimum	-2.1020	-1.2228	-2.0161	-1.5231	-1.3919	-21.6688	-5.0875	-3.6877	-11.6271	-2.6395	-2.873543
Std. Dev.	0.3863	0.3791	0.3905	0.4121	0.3804	2.0166	0.7837	0.5854	1.0732	0.5987	0.588466
Skewness	-0.1194	0.0623	0.0498	0.0875	0.0210	0.7608	0.4667	1.2138	-0.3214	1.3775	0.106617
Kurtosis	5.2085	3.9242	5.3391	4.1836	3.9844	62.0029	20.2555	20.1656	32.0079	16.9976	5.385502
Jarque-Bera	289.2870	50.9906	321.3514	83.93417	56.9249	204230.0	17506.87	17619.90	49354.94	11931.60	336.2783
Prob.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel B. National Stock Market Indices

Stock	Core Countries					PIIGS Countries					US
	AEX	*ATX*	*CAC*	*DAX*	*OMXH*	*ATHEX*	*IBEX*	*ISEQ*	*MIB*	*PSI*	*S&P500*
Mean	-0.0369	-0.0564	-0.0397	-0.0078	-0.0512	-0.1261	-0.0461	-0.0750	-0.0718	-0.0482	-0.0056
Median	0.0	0.0	0.0	0.0274	0.0	0.0	0.0	0.0	0.0	0.0	0.0347
Maximum	10.0282	12.0210	10.5945	10.7974	8.8499	13.4310	13.4836	9.7330	10.8769	10.1109	10.9572
Minimum	-9.5903	-10.2526	-9.4715	-7.4334	-7.9239	-10.2140	-9.5858	-13.9635	-8.5981	-10.6505	-9.4695
Std. Dev.	1.6819	2.0216	1.7660	1.6665	1.7276	2.2100	1.8590	1.9208	1.9086	1.4154	1.6095
Skewness	-0.1031	-0.1047	0.1392	0.1333	0.0679	0.1436	0.2236	-0.4054	0.0467	-0.0556	-0.2440
Kurtosis	9.3003	6.9241	7.7575	8.3569	5.6015	5.6075	7.7600	7.7304	6.4911	10.3926	10.1676
Jarque-Bera	2329.5	905.3	1331.4	1686.5	397.8	403.4	1340.0	1350.4	715.0	3204.6	3025.7
Prob.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel C. Commodity Returns

Commodities	Copper	Gold	Oil	Palladium	Platinum	Silver
Mean	0.0008	0.0696	0.0259	0.0392	0.0151	0.0691
Median	0.0	0.0585	0.0	0.1043	0.1143	0.0396
Maximum	11.7259	6.8414	40.4634	9.5310	10.0418	18.2785
Minimum	-10.3212	-7.9718	-36.4014	-16.9984	-9.6731	-18.6926
Std. Dev.	2.1410	1.3463	2.5431	2.2208	1.6512	2.6822
Skewness	-0.1568	-0.2270	0.4364	-0.5973	-0.6464	-0.3415
Kurtosis	5.5888	6.4973	84.2865	7.4452	8.0234	10.2375
Jarque-Bera	398.6841	729.1650	387409.2	1242.1320	1577.3880	3098.2240
Prob.	0.00	0.00	0.00	0.00	0.00	0.00

Note: The time span is between July 2, 2007 to November 20, 2012.

Table 4: Back-testing Results for Sovereign Bonds and Stock National Indices (Full Period)

Panel A: Core countries

Austria	% of viol.		Kupiec uc		MM ind		Christ. cc	
	Bond	*ATX*	Bond	*ATX*	Bond	*ATX*	Bond	*ATX*
RiskMetrics	0.0175	0.0191	12.1305(0.00***)	17.0596(0.00***)	2.1501 (0.20)	1.4993 (0.30)	13.7215(0.00***)	17.0823(0.00***)
DPOT	0.0121	0.0105	1.0823(0.30)	0.0771(0.78)	3.3025(0.11)	-0.2194(0.77)	1.8217(0.40)	1.1976(0.55)
CEVT-n	0.0117	0.0101	0.7274(0.39)	0.0066(0.93)	2.3134(0.18)	-0.1816(0.72)	1.4429(0.48)	0.5409(0.76)
CEVT- sstd	0.0117	0.0105	0.7274(0.394)	0.0771(0.781)	2.1891(0.19)	0.0561(0.70)	1.4191(0.492)	0.6543(0.721)

Finland	% of viol.		Kupiec uc		MM ind		Christ. cc	
	Bond	*OMXH*	Bond	*OMXH*	Bond	*OMXH*	Bond	*OMXH*
RiskMetrics	0.0187	0.0191	15.7627(0.00***)	17.0596(0.00***)	1.4236 (0.28)	0.4836(0.54)	17.6165(0.00***)	17.0822(0.00**)
DPOT	0.0128	0.0070	1.9858(0.15)	2.5368(0.11)	4.8051(0.04**)	-1.1660(0.96)	2.5716(0.27)	2.7859(0.24)
CEVT-n	0.0125	0.0086	1.5024(0.22)	0.5341(0.46)	1.3246(0.32)	-0.2991(0.76)	2.3182(0.31)	0.9129 (0.63)
CEVT- sstd	0.0125	0.0086	1.5024(0.22)	0.5340 (0.46)	1.3246(0.32)	-0.2991(0.76)	2.3182(0.31)	0.9129 (0.63)

France	% of viol.		Kupiec uc		MM ind		Christ. cc	
	Bond	*CAC*	Bond	*CAC*	Bond	*CAC*	Bond	*CAC*
RiskMetrics	0.0164	0.0179	8.9058(0.00***)	13.2973(0.00***)	0.5945(0.48)	-0.6401(0.84)	10.2874(0.00***)	14.5613(0.00***)
DPOT	0.0121	0.0085	1.0822(0.29)	0.5340(0.46)	8.3495(0.00***)	7.0053(0.01***)	1.8224(0.40)	0.9129(0.63)
CEVT-n	0.0117	0.0085	0.7274(0.39)	0.5340(0.46)	0.7426(0.45)	1.2100(0.36)	1.4190(0.49)	2.3007(0.31)
CEVT- sstd	0.0113	0.0085	0.4400(0.50)	0.5340(0.46)	1.3189(0.37)	1.2100(0.36)	1.0847(0.58)	2.3007(0.31)

Germany	% of viol.		Kupiec uc		MM ind		Christ. cc	
	Bond	*DAX*	Bond	*DAX*	Bond	*DAX*	Bond	*DAX*
RiskMetrics	0.0160	0.0199	7.9262(0.00***)	19.7773(0.00***)	0.1565(0.65)	0.1792(0.63)	9.2742(0.01***)	19.7978(0.00***)
DPOT	0.0117	0.0085	0.7274(0.39)	0.5340(0.46)	5.6097(0.02**)	1.7414(0.26)	1.5524(0.46)	0.9129(0.63)
CEVT-n	0.0102	0.0105	0.0066(0.93)	0.0771(0.78)	0.8874(0.43)	2.5959(0.18)	0.5409(0.76)	1.1976(0.55)
CEVT- sstd	0.0102	0.0102	0.0066(0.93)	0.0066(0.93)	0.8874(0.43)	2.0980(0.20)	0.5409(0.76)	1.2397(0.53)

Netherlands	% of viol.		Kupiec uc		MM ind		Christ. cc	
	Bond	*AEX*	Bond	*AEX*	Bond	*AEX*	Bond	*AEX*
RiskMetrics	0.0168	0.0207	9.9337 (0.00***)	22.6552(0.00***)	1.5336(0.30)	0.1885(0.63)	11.4180(0.00***)	25.0458(0.00***)
DPOT	0.0148	0.0093	5.2901 (0.0***)	0.1019(0.75)	8.9230 (0.00***)	2.8248(0.13)	7.6011(0.02**)	1.5840(0.45)
CEVT-n	0.0113	0.0109	0.4400(0.50)	0.2224(0.63)	1.4231(0.35)	-0.9204(0.91)	1.1078(0.57)	0.8441(0.65)
CEVT- sstd	0.0113	0.0105	0.4400(0.50)	0.0770(0.78)	1.4231(0.35)	-0.8840(0.93)	1.1078(0.57)	0.6542(0.72)

Table 4: (Full Period) cont'd

Panel B: PIIGS countries

Greece	% of viol.		Kupiec uc		MM ind		Christ. cc	
	Bond	*ATHEX*	Bond	*ATHEX*	Bond	*ATHEX*	Bond	*ATHEX*
RiskMetrics	0.0254	0.0195	42.9804(0.00***)	18.3980 (0.00***)	1.0489 (0.38)	0.5934 (0.47)	47.7565 (0.00***)	19.2798(0.00***)
DPOT	0.0207	0.0125	22.6552(0.00***)	1.5024 (0.22)	18.7775(0.00***)	6.5737 (0.01***)	47.3022 (0.00***)	2.1621 (0.33)
CEVT-n	0.0175	0.0097	12.1305(0.00***)	0.0138 (0.90)	3.1471 (0.10)	2.2196 (0.23)	12.1985 (0.00***)	0.5068 (0.77)
CEVT- sstd	0.0195	0.0097	18.3980 (0.00***)	0.0138 (0.90)	3.5213 (0.06*)	2.2196 (0.23)	21.2723(0.00***)	0.5068 (0.77)

Ireland	% of viol.		Kupiec uc		MM ind		Christ. cc	
	Bond	*ISEQ*	Bond	*ISEQ*	Bond	*ISEQ*	Bond	*ISEQ*
RiskMetrics	0.0230	0.0183	32.1921(0.00***)	14.5083(0.00***)	3.2538 (0.08**)	-0.5329 (0.83)	33.7787 (0.00***)	17.9271(0.00***)
DPOT	0.0144	0.0109	4.5164 (0.03*)	0.2224 (0.63)	7.9042 (0.00***)	-0.1745 (0.71)	6.9891 (0.03*)	9.0691 (0.01***)
CEVT-n	0.0148	0.0074	5.2901 (0.02*)	1.8821 (0.17)	3.0989 (0.09*)	0.6473 (0.57)	7.6011 (0.02*)	2.1613 (0.33)
CEVT- sstd	0.0148	0.0074	5.2901 (0.02*)	1.8821 (0.17)	3.0989 (0.09*)	0.6473 (0.57)	7.6011 (0.02*)	2.1613 (0.33)

Italy	% of viol.		Kupiec uc		MM ind		Christ. cc	
	Bond	*MIB*	Bond	*MIB*	Bond	*MIB*	Bond	*MIB*
RiskMetrics	**0.0199**	**0.0257**	19.7773 (0.00***)	44.8918(0.00***)	0.1553(0.64)	-1.0107(0.92)	21.8726(0.00***)	44.9758(0.00***)
DPOT	0.0148	0.0085	5.2901(0.02*)	0.5340(0.46)	3.3162(0.08*)	0.6092(0.50)	5.5828(0.06*)	2.3007(0.31)
CEVT-n	0.0144	0.0121	4.5164(0.03*)	1.0822(0.29)	1.1794(0.38)	-0.9449(0.93)	4.8581(0.08*)	1.8217(0.40)
CEVT- sstd	0.0144	0.0113	4.5164(0.03*)	0.4400(0.50)	1.1794(0.38)	-0.8782(0.92)	4.8581(0.08*)	1.3569(0.50)

Portugal	% of viol.		Kupiec uc		MM ind		Christ. cc	
	Bond	*PSI*	Bond	*PSI*	Bond	*PSI*	Bond	*PSI*
RiskMetrics	0.0242	0.0207	37.4374(0.00***)	22.6552(0.00***)	1.3256(0.29)	0.5232 (0.53)	40.5155 (0.00***)	23.3032(0.00***)
DPOT	0.0164	0.0101	8.9058 (0.00***)	0.0066(0.93)	1.6515(0.25)	2.7152 (0.14)	16.9112 (0.00***)	0.5409(0.76)
CEVT-n	0.0168	0.0113	9.9337 (0.00***)	0.4400(0.50)	3.1926 (0.10)	2.8857 (0.15)	11.5427 (0.00***)	1.3569(0.50)
CEVT- sstd	0.0175	0.0117	12.1305 (0.00***)	0.7274(0.39)	2.9298(0.12)	2.8518 (0.12)	13.5037(0.00***)	1.5524(0.46)

Spain	% of viol.		Kupiec uc		MM ind		Christ. cc	
	Bond	*IBEX*	Bond	*IBEX*	Bond	*IBEX*	Bond	*IBEX*
RiskMetrics	0.0211	0.0187	24.1522 (0.00***)	15.7627 (0.00***)	0.5814 (0.48)	0.3646 (0.54)	24.1935 (0.00***)	15.7915(0.00***)
DPOT	0.0160	0.0078	7.9262 (0.00***)	1.3335 (0.24)	7.4417 (0.00***)	4.6115 (0.05*)	9.7958 (0.00***)	1.6443 (0.40)
CEVT-n	0.0128	0.0101	1.9858 (0.15)	0.0066 (0.93)	2.1834 (0.21)	3.0997 (0.11)	2.8543 (0.24)	0.5409 (0.76)
CEVT- sstd	0.0136	0.0093	3.1352 (0.07*)	0.1019 (0.74)	2.1246 (0.22)	3.0720 (0.11)	3.5889 (0.16)	0.5552 (0.75)

Notes: Numbers in the parentheses show the p values. (***), (**) and (*) represent the 1% , 5% and 10% significance level, respectively.

Table 5: Daily Capital Charges for Sovereign Bonds and Stock National Indices (Full Period)

Panel A: Core countries

Austria	Number of days in the red zone		Mean of Daily Capital Charges		Maximum of Daily Capital Charges		Minimum of Daily Capital Charges	
	Bond	*ATX*	Bond	*ATX*	Bond	*ATX*	Bond	*ATX*
RiskMetrics	63	50	2.394	11.778	5.022	42.952	1.335	4.480
DPOT	0	0	2.783	12.687	5.648	31.460	1.673	4.398
CEVT - n	0	0	2.541	12.036	5.049	42.005	1.484	5.691
CEVT - sstd	0	0	2.490	11.808	5.153	41.469	1.507	5.708

Finland	Number of days in the red zone		Mean of Daily Capital Charges		Maximum of Daily Capital Charges		Minimum of Daily Capital Charges	
	Bond	*OMXH*	Bond	*OMXH*	Bond	*OMXH*	Bond	*OMXH*
RiskMetrics	63	53	2.384	10.567	4.282	27.350	1.186	5.018
DPOT	0	0	2.823	12.118	5.046	23.485	1.598	6.710
CEVT - n	0	0	2.478	11.098	4.181	28.113	1.481	5.800
CEVT - sstd	0	0	2.421	10.992	4.265	27.628	1.498	5.779

France	Number of days in the red zone		Mean of Daily Capital Charges		Maximum of Daily Capital Charges		Minimum of Daily Capital Charges	
	Bond	*CAC*	Bond	*CAC*	Bond	*CAC*	Bond	*CAC*
RiskMetrics	63	0	2.380	9.828	5.191	28.210	1.375	4.729
DPOT	0	110	2.821	11.679	5.510	25.457	1.698	5.919
CEVT - n	0	0	2.523	10.522	5.123	33.862	1.578	4.949
CEVT - sstd	0	0	2.492	10.372	5.149	33.012	1.600	4.912

Germany	Number of days in the red zone		Mean of Daily Capital Charges		Maximum of Daily Capital Charges		Minimum of Daily Capital Charges	
	Bond	*DAX*	Bond	*DAX*	Bond	*DAX*	Bond	*DAX*
RiskMetrics	3	73	2.484	10.045	4.554	34.161	1.378	4.602
DPOT	0	0	3.051	11.497	5.398	24.320	1.716	5.173
CEVT - n	0	0	2.655	10.327	4.532	35.481	1.742	5.004
CEVT - sstd	0	0	2.605	10.234	4.384	31.675	1.764	4.969

Netherlands	Number of days in the red zone		Mean of Daily Capital Charges		Maximum of Daily Capital Charges		Minimum of Daily Capital Charges	
	Bond	*AEX*	Bond	*AEX*	Bond	*AEX*	Bond	*AEX*
RiskMetrics	3	0	2.400	9.516	4.449	36.770	1.318	3.658
DPOT	8	105	2.906	11.235	5.156	27.113	1.689	4.872
CEVT - n	0	0	2.545	9.995	4.685	41.507	1.532	4.500
CEVT - sstd	0	0	2.509	9.723	4.406	35.847	1.555	4.489

Table 5: (Full Period) cont'd

Panel B: PIIGS countries

Greece	Number of days in the red zone		Mean of Daily Capital Charges		Maximum of Daily Capital Charges		Minimum of Daily Capital Charges	
	Bond	*ATHEX*	Bond	*ATHEX*	Bond	*ATHEX*	Bond	*ATHEX*
RiskMetrics	215	0	7.869	12.406	40.834	30.566	1.371	4.869
DPOT	376	104	7.346	13.953	31.568	31.528	1.628	5.085
CEVT - n	0	0	9.190	12.772	60.686	29.103	1.776	5.819
CEVT - sstd	0	0	7.499	12.494	63.627	28.000	1.834	5.976

Ireland	Number of days in the red zone		Mean of Daily Capital Charges		Maximum of Daily Capital Charges		Minimum of Daily Capital Charges	
	Bond	*ISEQ*	Bond	*ISEQ*	Bond	*ISEQ*	Bond	*ISEQ*
RiskMetrics	131	192	4.088	10.610	14.249	36.360	1.271	3.485
DPOT	8	0	4.307	12.577	12.831	35.858	1.652	4.214
CEVT - n	0	0	4.408	11.874	15.180	40.173	1.650	5.462
CEVT - sstd	0	0	4.012	11.950	13.730	41.347	1.710	5.423

Italy	Number of days in the red zone		Mean of Daily Capital Charges		Maximum of Daily Capital Charges		Minimum of Daily Capital Charges	
	Bond	*MIB*	Bond	*MIB*	Bond	*MIB*	Bond	*MIB*
RiskMetrics	73	133	2.956	11.119	9.530	32.904	1.358	3.780
DPOT	0	0	3.315	11.869	9.321	25.782	1.620	4.865
CEVT - n	0	0	3.339	11.072	12.572	32.969	1.516	4.481
CEVT - sstd	0	0	3.042	10.981	9.669	33.017	1.526	4.205

Portugal	Number of days in the red zone		Mean of Daily Capital Charges		Maximum of Daily Capital Charges		Minimum of Daily Capital Charges	
	Bond	*PSI*	Bond	*PSI*	Bond	*PSI*	Bond	*PSI*
RiskMetrics	191	192	4.976	7.889	21.694	28.679	1.323	2.258
DPOT	117	1	4.731	8.325	17.663	18.859	1.666	2.048
CEVT - n	75	0	5.517	8.511	27.611	30.586	1.758	2.891
CEVT - sstd	0	0	4.620	8.076	20.457	27.642	1.824	2.871

Spain	Number of days in the red zone		Mean of Daily Capital Charges		Maximum of Daily Capital Charges		Minimum of Daily Capital Charges	
	Bond	*IBEX*	Bond	*IBEX*	Bond	*IBEX*	Bond	*IBEX*
RiskMetrics	68	16	3.218	10.217	9.645	30.174	1.364	3.740
DPOT	97	0	3.394	11.437	10.163	27.418	1.896	4.921
CEVT - n	0	16	3.187	11.142	8.486	33.652	1.767	4.573
CEVT - sstd	0	0	2.983	10.875	8.134	34.093	1.833	4.425

Note: In the Basel accord, the red zone represents the number of violations that are equal to or greater than 10 days for the last 250 trading days, the yellow zone for 5-9 days and the green zone for 0-4 days.

Table 6. Basel Accord Penalty Zones

Zone	Number of Violations	k
Green	0 to 4	0.00
Yellow	5	0.40
	6	0.50
	7	0.65
	8	0.75
	9	0.85
Red	10+	1.00

Note: The number of violations is accumulated for the last 250 trading days.

Table 7. Estimated VaR-Optimal Portfolios (Full Period)

Portfolio 1. Core-Bond Benchmarks

AU	*FI*	*FR*	*GE*	*NL*	VaR ($)	Return	Return-Risk ratio
30%	2%	1%	6%	61%	0.84	0.0076	0.0077

Portfolio 2. PIIGS-Bond Benchmarks

IR	*IT*	VaR ($)	Return	Return-Risk ratio
2%	98%	1.12	0.0025	0.00155

Portfolio 3. Core and PIIGS - Bond Benchmark

AU	*FR*	*GE*	*NL*	VaR ($)	Return	Return-Risk ratio
26%	2%	18%	52%	0.84	0.0075	0.007743

Portfolio 4. Core-Stock Indices

ATX	*DAX*	VaR ($)	Return	Return-Risk ratio
96%	4%	4.45	0.0170	0.0038

Portfolio 5. Core and PIIGS-Stock Indices

ATX	*DAX*	VaR ($)	Return	Return-Risk ratio
96%	4%	4.45	0.0170	0.0038

Portfolio 6. Core and PIIGS-Bond Benchmarks and Stock Indices

ATX	*AU*	*GE*	*NL*	VaR ($)	Return	Return-Risk ratio
18%	9%	27%	46%	0.81	0.0090	0.0098

Portfolio 7. Core and PIIGS-Stock Indices and Commodities

ATX	*DAX*	Copp	Gold	Oil	Plat	Silver	VaR ($)	Return	Return-Risk ratio
1%	1%	14%	33%	32%	9%	8%	3.007	0.0541	0.0157

Portfolio 8. Core and PIIGS-Bond Benchmarks, Stock Indices and Commodities

AU	*FN*	*FR*	*GE*	*NL*	Copp	Gold	Oil	Plat	Silver	VaR ($)	Return	Retun-Risk ratio
4%	2%	3%	34%	5%	11%	13%	11%	7%	9%	1.38	0.03	0.02

Notes: *AU* stands for sovereign bonds for Austria, *FI* for Finland, *FR* for France, *GE* for Germany, *NL* for the Netherlands, *IR* for Ireland, *IT* for Italy and , The optimal portfolio is obtained at the point where the risk-return trade-off equation (9) is maximized.

Table 8. Estimated VaR-Optimal Portfolios (Subperiod)

Portfolio 9: Core-Bond Benchmarks					
AU	*FR*	*GE*	VaR ($)	Return	Return-Risk ratio
9%	10%	81%	0.93	0.0212	0.02255

Portfolio 10: PIIGS-Bond Benchmarks				
IT	*IR*	VaR ($)	Return	Return-Risk ratio
93%	7%	1.47	0.0062	0.0041

Portfolio 11:Core and PIIGS - Bond Benchmarks					
AU	*FR*	*GE*	VaR ($)	Return	Return-Risk ratio
9%	10%	81%	0.93	0.0212	0.02255

Portfolio 12: Core and PIIGS – Bond Benchmarks and Stock Indices					
AU	*FR*	*GE*	VaR ($)	Return	Return-Risk ratio
9%	10%	81%	0.93	0.0212	0.02255

Portfolio 13: Core and PIIGS - Bond Benchmarks and Commodities									
GE	*AU*	*FI*	*FR*	*NL*	Gold	Silver	VaR ($)	Return	Return-Risk ratio
27%	22%	6%	2%	16%	21%	6%	0.97	0.0283	0.028

Portfolio 14: Core and PIIGS-Stock Indices and Commodities					
DAX	Gold	Silver	VaR ($)	Return	Return-Risk ratio
12%	73%	15%	3.29	0.0615	0.0179

Portfolio 15: Core and PIIGS-Bond Benchmarks, Stock Indices and Commodities											
DAX	*AU*	*FI*	*FR*	*GE*	*IR*	*NL*	Gold	Silver	VaR ($)	Return	Return-Risk ratio
5%	18%	11%	10%	7%	10%	12%	21%	6%	0.96	0.0305	0.03

Notes: see notes under Table 7.

Table 9. Ranking of Portfolios over the full period and subperiod

Rank	Full period of 1999-2012	Subperiod of 2007-2012
1	Portfolio 8 (10 bonds + 10 stocks + commodities)	Portfolio 15 (10 bonds + 10 stocks + commodities)
2	Portfolio 7 (10 stocks + commodities)	Portfolio 13 (10 bonds+commodities)
3	Portfolio 6 (10 bonds + 10 stocks)	Portfolio 12 (10 bonds+10 stocks)
4	Portfolio 3 (10 bonds)	Portfolio 11 (10 bonds)
5	Portfolio 1 (Core bonds)	Portfolio 9 (Core bonds)
6	Portfolio 5 (10 stocks)	Portfolio 14 (10 stocks + commodities)
7	Portfolio 4 (Core stocks)	Portfolio 10 (PIIGS bonds)
8	Portfolio 2 (PIIGS bonds)	

Notes: commodities in the portfolios under the full period include copper, gold, oil, platinum and silver, while under the subperiod they include just gold and silver.

Table 10: Back-testing Results for Portfolio 8

Portfolio 8	% of viol.	Kupiec uc	MM	cc
RiskMetrics	0.0195	18.3981(0.00***)	0.9847 (0.37)	21.2723(0.00***)
DPOT	0.0094	0.10191(0.75)	6.7339 (0.02**)	1.5840 (0.45)
CEVT-n	0.0133	2.53071(0.11)	3.6701 (0.07*)	5.5369 (0.06*)
CEVT- sstd	0.0105	0.0771(0.78)	8.3653 (0.00***)	1.1976 (0.55)

Notes: Portfolio 8 includes Core and PIIGS bond benchmarks, stock indices and commodities.

Table 11: Daily Capital Charges for Portfolio 8

Portfolio 8	Number of days in the red zone	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	22	1.904	4.544	1.124
DPOT	0	2.295	4.864	1.253
CEVT - n	0	2.014	4.844	1.183
CEVT - sstd	0	2.004	4.681	1.249

Notes: Portfolio 8 includes Core and PIIGS bond benchmarks, stock indices and commodities.