Three Essays on Economic and Financial Risks in Different Asset Classes and Diverse Regions

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Essay 1: Downside Risk, Portfolio Diversification and the Financial Crisis in 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.

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 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

[1] I 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.

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]

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

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[3] securities on the exchange.	BMNL
Greece	*ATHEX*	ATHEX Composite Share Price Index	This market capitalization weighted index is composed of the 60 largest[4] 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.

[3] The selection is made on an annual review date in March. It is based on the share turnover over the previous year.
[4] The companies are ranked on the basis of their trading values excluding blocks.

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.

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 the data for commodities are obtained from Bloomberg. The time span is between March 31, 1999 to November 20, 2012.

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 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.[5] 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

[5] 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.

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.

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.

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 *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.[6] These methods fit normal and non-normal distributions including extreme distributions. Cotter (2004)

[6] 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.

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. 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:

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

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

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

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):

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

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

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

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 $d_{t,v}$:

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

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

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

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: $m_c = 3 + k$

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

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.

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 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.

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.

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

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.

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.38

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.

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

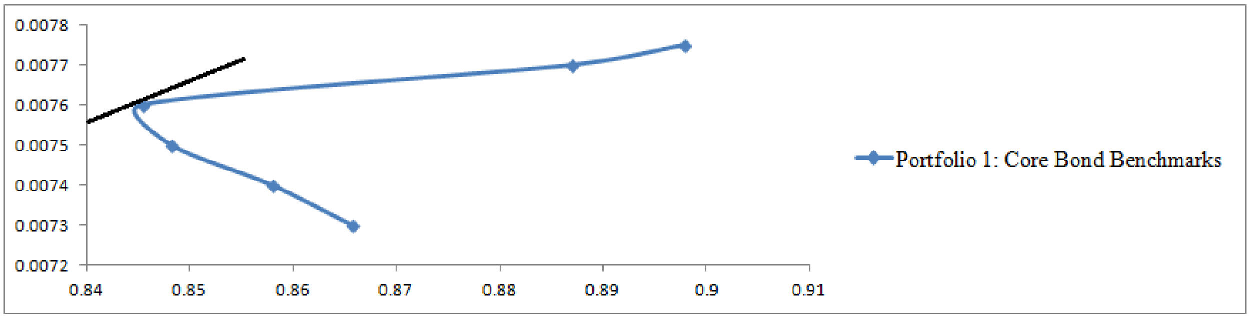
ATX	*DAX*	Copp	Gold	Oil	Plat	Silver	VaR ($)	Return	Return-Risk ratio
1%	1%	14%	33%	32%	9%	8%	3.007	0.0541	0.0157

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. The risk-free return is the last available data of Treasury 3-month Bill (T-Bill) rate obtained from Fred data base. 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. The Sharpe ratio is the return/risk ratio.

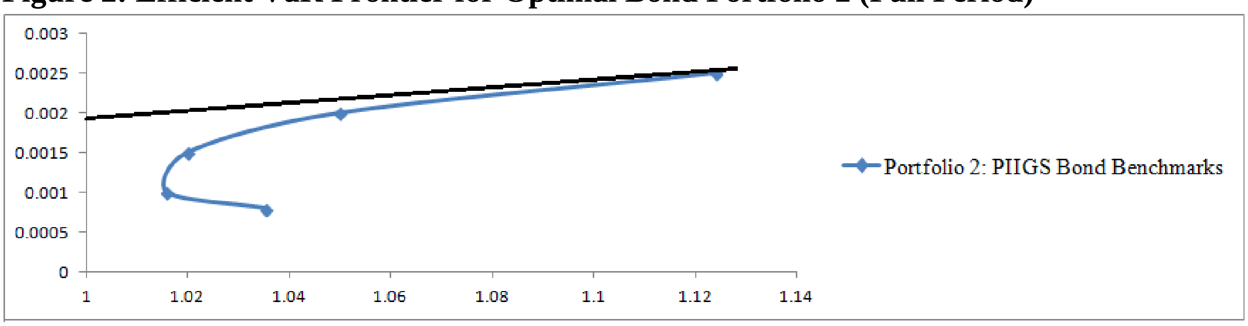
Figure 1: Efficient VaR Frontier for Optimal Bond Portfolio 1 (Full Period)



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.

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.

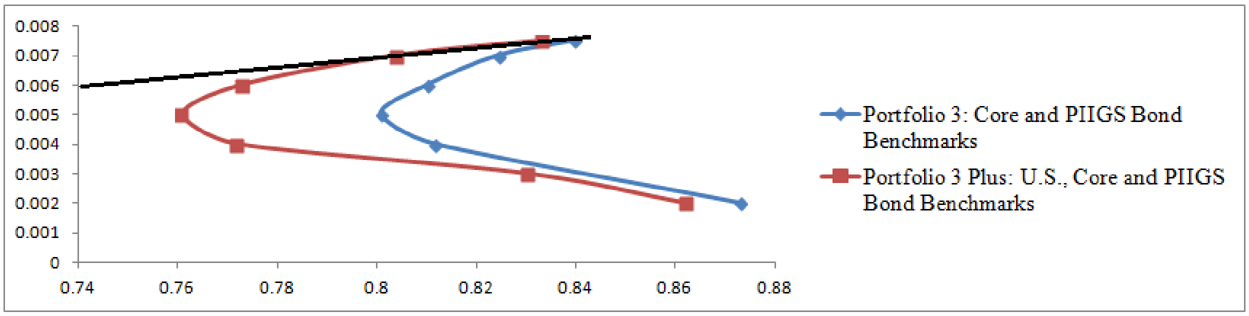
Figure 2: Efficient VaR Frontier for Optimal Bond Portfolio 2 (Full Period)



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

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.

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



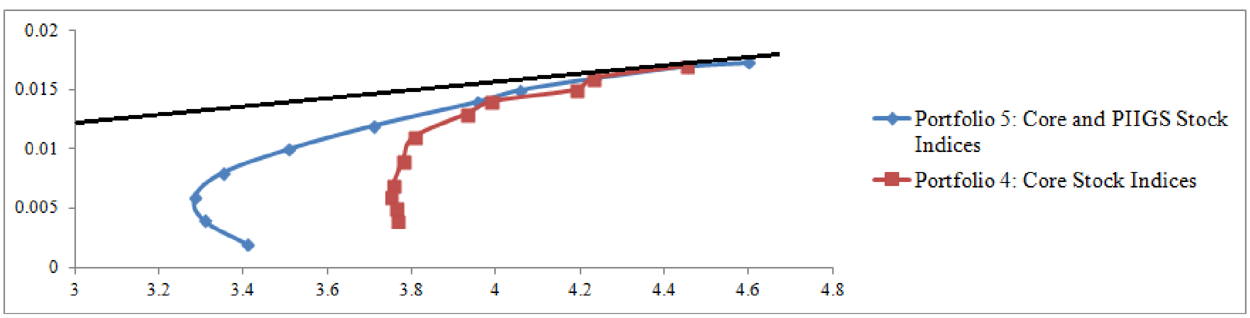
Notes: Portfolio 3 includes the Core and the PIIGS countries' sovereign bond benchmarks. In the best combination (the tangency point) the Netherlands, Austria and Germany have the highest weights which are, 52%, 26% and 18%, respectively, while the weights of the PIIGS bonds are zero. Portfolio 3 Plus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

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.

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

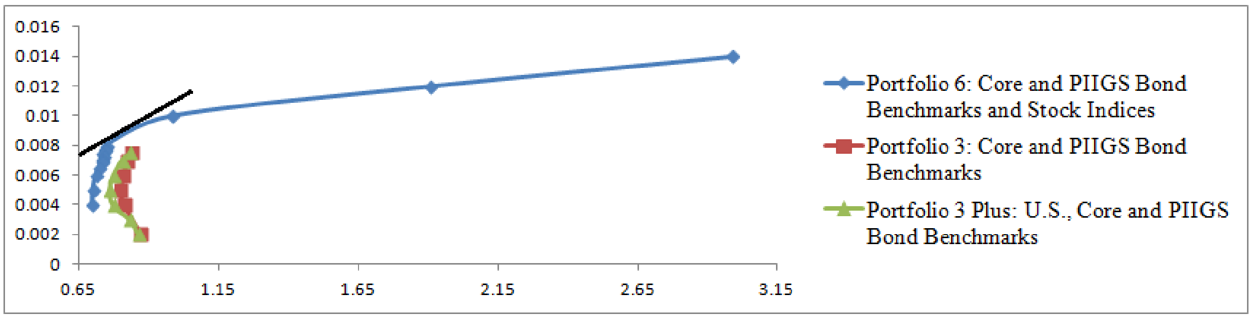


Notes: Portfolio 4 includes the Core equity indices while Portfolio 5 includes the Core and the PIIGS equity indices. For the best combination (the tangency point) which is the same for these two portfolios, Austria's equity Index *ATX* has 96% of the portfolio, while Germany's equity *DAX* accounts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

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.

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



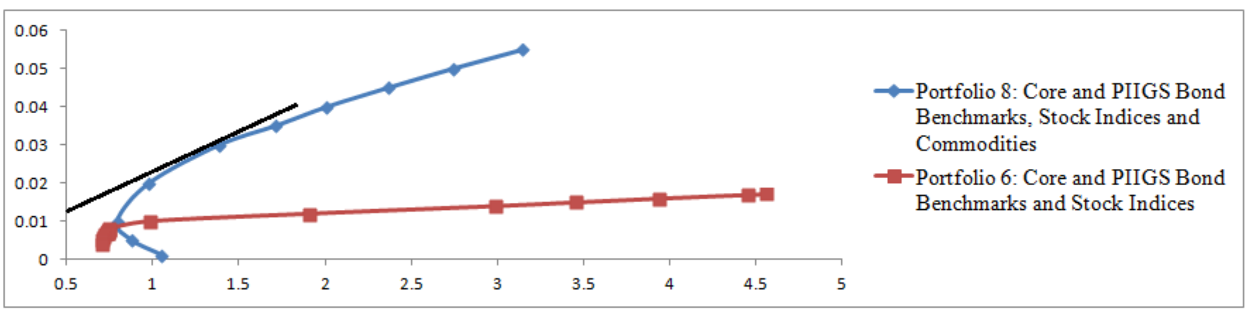
Notes: Portfolio 6 includes the bond benchmarks and the stock indices of the Core and PIIGS countries. In the best combination (the tangency point) the bond benchmarks of the Netherlands, Germany and Austria have the 46%, 27% and 9%of the weight, respectively, while that of the Austrian Traded Index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

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.

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.

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.

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

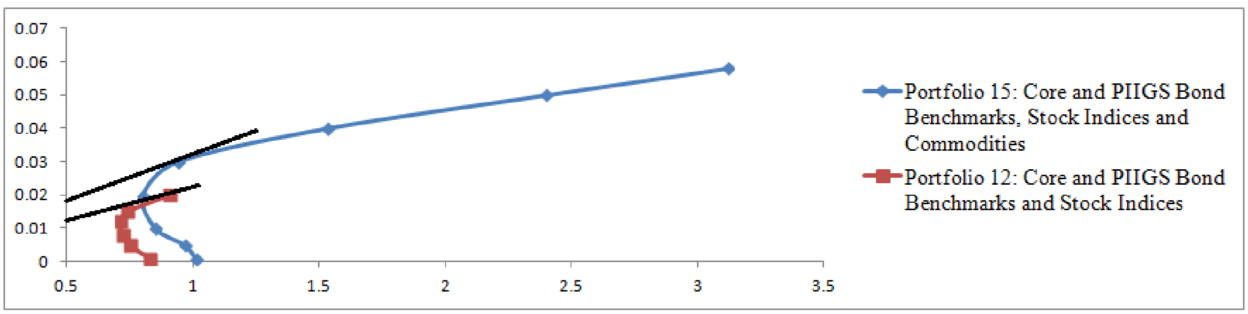
<table>
<tr><th colspan="12">Portfolio 10: PIIGS-Bond Benchmarks</th></tr>
<tr><td colspan="2">IT</td><td colspan="4">IR</td><td colspan="2">VaR ($)</td><td colspan="2">Return</td><td colspan="2">Return-Risk ratio</td></tr>
<tr><td colspan="2">93%</td><td colspan="4">7%</td><td colspan="2">1.47</td><td colspan="2">0.0062</td><td colspan="2">0.0041</td></tr>
<tr><th colspan="12">Portfolio 11:Core and PIIGS - Bond Benchmarks</th></tr>
<tr><td colspan="2">AU</td><td colspan="2">FR</td><td colspan="3">GE</td><td colspan="2">VaR ($)</td><td colspan="2">Return</td><td>Return-Risk ratio</td></tr>
<tr><td colspan="2">9%</td><td colspan="2">10%</td><td colspan="3">81%</td><td colspan="2">0.93</td><td colspan="2">0.0212</td><td>0.02255</td></tr>
<tr><th colspan="12">Portfolio 12: Core and PIIGS – Bond Benchmarks and Stock Indices</th></tr>
<tr><td colspan="2">AU</td><td colspan="2">FR</td><td colspan="3">GE</td><td colspan="2">VaR ($)</td><td colspan="2">Return</td><td>Return-Risk ratio</td></tr>
<tr><td colspan="2">9%</td><td colspan="2">10%</td><td colspan="3">81%</td><td colspan="2">0.93</td><td colspan="2">0.0212</td><td>0.02255</td></tr>
<tr><th colspan="12">Portfolio 13: Core and PIIGS - Bond Benchmarks and Commodities</th></tr>
<tr><td>GE</td><td>AU</td><td>FI</td><td colspan="2">FR</td><td colspan="2">NL</td><td>Gold</td><td>Silver</td><td>VaR ($)</td><td>Return</td><td>Return-Risk ratio</td></tr>
<tr><td>27%</td><td>22%</td><td>6%</td><td colspan="2">2%</td><td colspan="2">16%</td><td>21%</td><td>6%</td><td>0.97</td><td>0.0283</td><td>0.028</td></tr>
<tr><th colspan="12">Portfolio 14: Core and PIIGS-Stock Indices and Commodities</th></tr>
<tr><td colspan="2">DAX</td><td>Gold</td><td colspan="2">Silver</td><td colspan="3">VaR ($)</td><td colspan="2">Return</td><td colspan="2">Return-Risk ratio</td></tr>
<tr><td colspan="2">12%</td><td>73%</td><td colspan="2">15%</td><td colspan="3">3.29</td><td colspan="2">0.0615</td><td colspan="2">0.0179</td></tr>
<tr><th colspan="12">Portfolio 15: Core and PIIGS-Bond Benchmarks, Stock Indices and Commodities</th></tr>
<tr><td>DAX</td><td>AU</td><td>FI</td><td>FR</td><td>GE</td><td>IR</td><td>NL</td><td>Gold</td><td>Silver</td><td>VaR ($)</td><td>Return</td><td>Return-Risk ratio</td></tr>
<tr><td>5%</td><td>18%</td><td>11%</td><td>10%</td><td>7%</td><td>10%</td><td>12%</td><td>21%</td><td>6%</td><td>0.96</td><td>0.0305</td><td>0.03</td></tr>
</table>

Notes: see notes under Table 7.

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.

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.

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.

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.

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 Table 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 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 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.

Table 11: Daily Capital Charges for Portfolio 8

Portfolio 8	Number of days	Daily Capital Charges

	in the red zone	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.

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.

Essay 2: Interactions between Conventional and Islamic Stock Markets in the US, Europe and Asia: A Hybrid Threshold Analysis and Forecasting

Abstract

This study investigates the linkages between the Islamic stock market defined based on the Dow Jones stock universe and three major global conventional stock markets that include the United States, Europe and Asia. We employ a nonlinear framework by using threshold models to capture asymmetric, nonlinear and time-varying relationships between the four markets. There is evidence that the Islamic market has a positive and stimulating effect on the three conventional markets, which contradicts the dichotomy hypothesis between these markets. The global financial crisis has, however, a lower negative effect on the Islamic market than on the other markets, giving some relevance to the Sharia principles-based restrictions during crises. Finally, the integration of nonlinearity and regime-switching hypotheses can help to improve the modelling and forecasting of the markets' future return dynamics and linkages over the linear benchmark model. These results have important policy implications for investors, policymakers and econometricians.

1. Introduction

The 2007/2009 global financial crisis has exerted enormous negative impacts on conventional financial institutions and markets, whether they are banking, financial services, credit or stock markets. The conventional financial system is viewed as a structure characterized by excessive lending, high leverage and a lack of an adequate market discipline, which have created the background for the global crisis. A need has risen for a renovation of the conventional financial systems through creating viable alternatives that afford opportunities to reduce investment risks, increase returns, enhance financial stability and reassure investors and financial markets. One of the new alternatives that embody innovations in the world's financial system is the creation of Islamic banks, and stock and sukuk (bond) markets[7]. These markets follow the *Sharia* rules, and thereby operate differently from their conventional counterparts. Consequently, assets in the Islamic finance markets have grown rapidly in certain regions of the

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[7] See Barnett and Jawadi (2013) for other forms of alternative finance.

world, rising from 1.22 trillion in 2011 to \$1.46 trillion in 2012 (Vizcaino, 2013), and are predicted to reach US\$6.5 trillion by 2020.[8]

The failure of conventional finance and the severe impacts of the crisis have renewed interest in Islamic finance as a more viable financial system that can endure financial crises better than the conventional system and can also be used as a diversification vehicle to reduce the risk in conventional portfolios. In essence, Islamic finance may offer products and instruments that are fortified by greater social responsibility, ethical and moral values and sustainable finance. In this paper, we are interested in examining Islamic stock markets and their connections to major global stock markets, taking into account specific characteristics the financial series.

In theory, Islamic stock markets are not supposed to transfer risks to and from conventional stock markets because both markets differ in several ways (Dridi and Hassan, 2010; Chapra, 2008; Dewi and Ferdian, 2010). First, Islamic markets prefer growth and small cap stocks, but conventional markets opt for value and mid cap stocks. Second, Islamic finance restricts investments in certain sectors (e.g. alcohol, tobacco, rearms, gambling, nuclear power and military-weapons activities, etc.). Third, unlike conventional finance, Islamic finance also restricts speculative financial transactions such as financial derivatives, which have no underlying real transactions like futures and options, government debt issues with a fixed coupon rate, and hedging by forward sale, interest-rate swaps and any other transactions involving items not physically in the ownership of the seller (e.g., short sales). Accordingly, the related recent literature argues that Islamic finance is less cost effective (i.e., less efficient) but that Islamic banks are better capitalized and have a higher asset quality and greater intermediation ratio

[8] For more details, see Kuwait Finance House Research Ltd at http://www.kfhresearch.com/ .

(Beck et al., 2013)[9]. Therefore, those studies contend that Islamic stock markets have low correlations and limited long-run relationships with the conventional markets, whereby they can provide financial stability and diversification. The more recent literature compares the sensitivity of each type of those stock markets to global factors, particularly those representing economic policy uncertainty in the United States and the sovereign debt markets in Europe. It underlines the superiority of Islamic stock investing in outperforming conventional investment particularly under the recent global financial crisis (Jawadi *et al.,* 2013).

In this paper, we examine the relationships between global stock indices representing four global stock markets. We investigate risk transfer between the Dow Jones Islamic Market World Index (*DJIM*), and each of the U.S. S&P500 Index (*SPUS*), the S&P Europe index (*SPEU*), and the S&P Asia 50 index (*SPAS*). The selection of *DJIM* is justified by the fact that it is the most widely used, the most comprehensive representative of Islamic stocks, and has the most adequate time series for the sharia-based stocks. The global S&P indices have also the advantage to be the largest conventional indices covering several activities and sectors around the globe.

Accordingly, this study has two main objectives. The first is to investigate comovements and adjustment dynamics between the Islamic and major conventional stock markets during tranquillity and crisis periods. The second is to examine the crisis effect on those conventional and Islamic markets. Interestingly, this study uses recent econometric techniques associated with threshold (TAR) models to capture these linkages while taking further asymmetry and nonlinearity in the data into account. Indeed, this framework allows stock price interactions to vary according to the business cycle phase (expansion, recession), in order to capture rapid changes in the market index dynamics and reproduce time-varying comovements.

[9] See Jawadi *et al.* (2015) for a recent empirical investigation of the efficiency hypothesis for conventional and Islamic stock markets in the short and long terms.

Our findings show significant linkages between the Islamic and the three major conventional stock markets that evolve according to the prevailing regimes, suggesting that the relationships between these two types of investments are regime-dependent. Interestingly, our modelling contributes by specifying the presence of discontinuous and asymmetrical bidirectional spillover effects between the Islamic and the major conventional stock markets.

The paper is organized as follows. Section 2 presents a review of the literature. Section 3 provides the empirical methodology and Section 4 discusses the main empirical results. Concluding remarks and policy and economic implications are summarized in Section 5.

2. Literature review

The literature on Islamic finance can be divided into four categories. These include the characteristics of Islamic finance, the relative performance of this financial system in comparison to that of other socially responsible and faith-based investments, possible links between Islamic banks and markets and their conventional counterparts, and the potential performance between the two business systems during the global crisis and the shrinking gap between them. Therefore, this review is conducted on the basis of these four themes, while our paper belongs to second category.

The early literature deals with the unique characteristics of the Islamic financial system, particularly the prohibitions against the payment and receipt of interest. It also deals with the Islamic industry screens that restrict investment in economic activities related to sharia-forbidden activities indicated earlier. In this regard, it uses Islamic funds or indices that concentrate on these industries: technology, telecommunications, steel, engineering, transportation, health care, utilities, construction and real estate (Abd Rahman, 2010). Bashir (1983) draws a contrast between the Islamic financial and conventional systems by highlighting that Islamic finance is asset-based and asset-driven, while the conventional system is interest-based and debt-driven. Robertson (1990), Usmani (2002), and Iqbal and Mirakhor (2007) discuss the *Riba* or the premium that must be paid along with the principal by the borrower to the lender as a condition or an extension of the loan under conventional finance.

The more recent and second strand of the literature investigates the links between Islamic and conventional financial markets in terms of relative returns and relative volatility. The comparison also focuses on the relative performance during the recent global financial crisis and relies on some characteristics of Islamic markets. These markets are represented by indices from different regions where some are a subset of the Dow Jones indices, while others belong to the FTSE indices, among others. The indices that are related to individual Muslim countries are not comprehensive and short in length. The literature also uses different methodologies to achieve the stated goals, ranging from the traditional linear autoregressive models to more sophisticated nonlinear models and tests (Ajmi *et al.,* 2013). Using bivariate and the trivariate models, Hakim and Rashidian (2002) examine the dynamic correlation and the short- and long-run (cointegeration) relationships between the Dow Jones Islamic market index (*DJIM*), the U.S. three-month Treasury bill rate and the U.S. Wilshire 5000 Index, which is the broadest index for the U.S. stock market and has about 75% of its companies not in DJIM. The authors find no statistically significant bivariate links between the DJIM and any of the two U.S. variables, suggesting that the later do not explain the changes in DJIM in the trivariate model. Those authors conclude that investors in the *DJIM* are relatively more immune from the turmoil of the stock markets than those who invest in the U.S. broad index.

More recently, Dania and Malhotra (2013) find evidence of a positive and significant return spillover from the conventional market indices in North America, European Union, Far East, and Pacific markets to their corresponding Islamic index returns. They also find similar evidence for volatility spillover, and that the volatility is asymmetric with significant news effects. Krasicka and Nowak (2012) compare Malaysian Islamic and conventional security prices and their responses to macroeconomic factors. Their results suggest that Islamic and conventional bond and stock prices are driven by common factors. Moreover, Islamic banks particularly in recent years have responded to economic and financial shocks in the same way as conventional banks have, which suggests that the gap between Islamic and conventional financial practices is diminishing. On the other hand, Sukmana and Kholid (2012) examine the risk performance of the Jakarta Islamic stock index (JAKISL) and its conventional counterpart Jakarta Composite Index (JCI) in Indonesia using GARCH models. Their result shows that investing in the Islamic stock index is less risky than investing in the conventional counterpart.

Hassan *et al.* (2005) compare the investment performance of an Islamic ethical portfolio with that of a conventional benchmark portfolio to discern the impacts of the sharia-based screens on ethical investments. The results indicate that the application of Islamic ethical screens do not necessarily have an adverse impact on investment performance. Hoepner *et al.* (2011) analyze both the financial performance and investment style of 265 Islamic stock mutual funds from twenty countries. The authors find that Islamic funds' investment style is somewhat tilted towards growth stocks and that the funds from predominantly Muslim economies show a clear preference for small caps. They also find their results to be consistent over time and robust to time-varying market exposures and capital market restrictions. Girard and Hassan (2008) compare the differences in return performance between Islamic and non-Islamic indices and find that Islamic indices are growth and small-cap oriented, while conventional indices are relatively more value and mid-cap focused. After controlling for the firm, market and global factors, the authors do not find significant differences in terms of performance between these types of investments. Forte and Miglietta (2007) determine whether Islamic mutual funds as faith-based investments (i.e., FTSE Islamic indices) can be included into the category of socially responsible mutual funds, or they would be more fittingly grouped in a separate investment family. The results show that Islamic investments exhibit peculiar and interesting portfolios' differences in terms of econometric profile, compared to conventional and socially responsible indices. Hashim (2008) examines the effect of adopting Islamic screening rules on stock indices' returns and risk, using monthly data from FTSE Global Islamic index. The results show that the performance of the FTSE Global Islamic is superior to that of the well diversified socially responsible index, the FTSE4Good. They also assure the appropriateness of the rules adopted in managing the Islamic index.

As indicated earlier, the literature also explores the potential importance of Islamic finance, particularly during the recent global financial crisis. Chapra (2008) indicates that excessive lending, the high leverage on the part of the conventional financial system and the lack of an adequate market discipline have created the background for the global crisis. This author contends that the Islamic finance principles can help to introduce better discipline into the markets and preclude new crises from happening. Dridi and Hassan (2010) compare the performance of Islamic banks and conventional banks during the recent global financial crisis in terms of the crisis impact on their profitability, credit and asset growth and external ratings. Those authors find that the two business models are impacted differently by the crisis. Special factors related to the Islamic banks limit the adverse impact of the crisis on their profitability compared to that of conventional banks, while factors related to weakness in their risk management practices highlight their larger relative profit vulnerability. On the other hand, Islamic banks fare better in terms of credit and deposit growth, and the external rating agencies' re-assessment of risk is generally more favorable for these banks than for conventional banks during the crisis.

Dewi and Ferdian (2010) also argue that Islamic finance can be a solution to the financial crisis because it prohibits the practice of *Riba*. Ahmed (2009) claims that the global financial crisis has revealed the misunderstanding and mismanagement of risks at institutional, organizational and product levels. This author also suggests that if institutions, organizations and products had followed the principles of Islamic finance they would have prevented the current global crisis from happening.[10] More recently, Jawadi *et al.* (2014) measure financial performance for Islamic and conventional stock indexes for three regions (the U.S., Europe and the World) before and after the subprime crisis and point to attractiveness of performance of Islamic stock returns particularly after the subprime crisis. Arouri *et al.* (2013) pursue a different approach. While comparing the impacts of the financial crisis on Islamic and conventional stock markets in the same three global areas and finding less negative effects on the former than the latter, the authors examine diversified portfolios in which the Islamic stock markets outperform the conventional markets. They demonstrate that diversified portfolios of conventional and Islamic investments lead to less systemic risks.

[10] There is also a growing literature on Islamic banks (see for example, Cihak and Hesse, 2010; Abd Rahman, 2010; Hesse *et al.,* 2008). Sole (2007) also presents a "good" review of how Islamic banks have become increasingly more integrated in the conventional banking system.

As can be seen from this extended review, there is no consensus in the literature on the directional relationship between Islamic and conventional markets and on whether the spillover between the markets is symmetric or asymmetric which has received much less attention than the linear case. Moreover, it seems that interactions between both types of stock markets evolve over time and vary according to the market, data and period under consideration.

Our purpose in this paper is to use more appropriate nonlinear techniques associated with threshold models, which have the advantage of specifying asymmetrical relationships having time-varying parameters, to study the interactions between different stock markets under consideration. The industry restrictions imposed on the Islamic stock markets and the prohibition of using hedging instruments against different kinds of risks lay the groundwork for different performances in up and down markets.

Our study fits the strand of the literature that examines the spillovers between the DJIM market and the three global conventional stock markets, but with concentration on the asymmetric and nonlinear aspects of their dynamic relationships. It also provides a complete and robust framework to investigate abrupt transitions between the two types of stock markets during tranquility and turmoil regimes. The Islamic literature is poor in this area.

3. Econometric Methodology

The econometric methodology focuses on the threshold autoregressive (TAR) models.[11] The popular linear VAR models only reproduce linear linkages. However, this procedure is rather inappropriate if the series under consideration exhibit asymmetry, nonlinearity and time-variation. The Islamic market is a candidate for asymmetry because of the effects of the sharia-

[11] We have carried out the analysis for the Islamic and conventional markets using the linear Vector Autoregressive (VAR) model. The modelling and the results are not provided in this paper to save space but can be available upon request.

based restrictions and prohibitions on investments. To take into account the nonlinearity in the relationships, we use the nonlinear models that characterize the threshold effect.

3.1. Threshold models

We focus in this study on a particular class of nonlinear models, which is known as the threshold models. These models have recently been applied widely in economics and finance, and thereby have gained strong attention. They extend the linear model by allowing for nonlinear relationships among the variables, a characteristic that is particularly interesting because it allows for capturing asymmetry, structural breaks and nonlinearity in time series dynamics[12]. As financial data often exhibit abrupt changes in the aftermath of crises, this type of modelling obviously makes the threshold specifications a more realistic representation of financial data-generation processes. As for our case, this study focuses on linkages between Islamic and conventional stock market indices, while also allowing for formally testing the influence of the Islamic indices on the conventional stock markets. Thus, the threshold models are warranted in order to explore the time-varying and asymmetry properties of the stock market reactions that may vary according to the type of the prevailing regime.

Formally, threshold models include the Markov-switching[13] (MS) models (Hamilton, 1994), the Smooth Transition Autoregressive (STAR) models (Granger and Teräsvirta, 1993), and the Threshold Autoregressive (TAR) models (Tong and Lim, 1980). The MS models, which are also called probabilistic processes, imply the presence of different relationships for which their realizations are determined by an unobserved conditional probability, while the transition between regimes in the STAR models is determined by a known and deterministic rule

[12] See Zapata and Gauthier (2003) for a brief note on threshold models and their applications, and Guégan (1994) for more details about threshold models and their statistical properties.

[13] We are not using Morkov-switching because it did not give us good results.

(transition variable). Moreover, the STAR models can be considered as a generalization of the TAR models which assume that the transition is abrupt rather than smooth as is the case for the STAR models.

Among the threshold models, we focus on the TAR models to investigate the comovements and dynamics between the Islamic and conventional stock markets in context of asymmetry and nonlinearity. Furthermore, the TAR models have two main advantages. First, they describe relationships that are linear per regime but that are nonlinear over the whole period. Second, the property of abrupt transitions between regimes allows one to capture the rapid changes in dynamics between the variables in order to reproduce time-varying comovements that can evolve according to the prevailing regimes. This model is also preferred in our study to the STAR model because it provides a pertinent specification that helps capture jumps and abrupt linkages related to the recent global financial crisis.

3.2 . Univariate TAR modeling

3.2.1. TAR models

The TAR models are introduced by Tong and Lim (1980) and are extensively discussed in Tong (1990). They are particularly appropriate to reproduce asymmetry in business cycles through the specification of different regimes that are activated according to a certain threshold. Thus, a TAR model implies a relationship that is nonlinear over the whole period but is linear per regime. It is piecewise linear as it defines a linear autoregressive model in each regime.

Formally, a simple two-regime TAR model, denoted TAR(2,p,S_t), corresponds to this system:

$$
\begin{aligned}
Y_t &= \alpha_{10} + \sum_{i=1}^{p} \alpha_{1i}\, Y_{t-i} + \sum_{j=1}^{p} \beta_{1j}\, X_{1t-j} + \sum_{k=1}^{p} \delta_{1k}\, X_{2t-k} + \varepsilon_{1t} \quad \textit{if} \;\; S_t \le c \\
Y_t &= \alpha_{20} + \sum_{i=1}^{p} \alpha_{2i}\, Y_{t-i} + \sum_{j=1}^{p} \beta_{2j}\, X_{1t-j} + \sum_{k=1}^{p} \delta_{2k}\, X_{2t-k} + \varepsilon_{2t} \quad \textit{if} \;\; S_t > c
\end{aligned} \qquad (1)
$$

where S_t represents the transition variable which can refer to the lagged endogenous variable given by Y_{t-d}, the subscript d is the delay parameter. The coefficient c refers to the threshold parameter for the regimes, p the maximum lag number and (a_{10}, a_{1i}, b_{1j}, d_{1k}).

A TAR specification is required to reproduce several nonlinear features (i.e., the limit cycle, amplitude dependent frequencies, jump phenomena, etc.). However, according to Enders and Granger (1998) and Caner and Hansen (2001), the stationarity and ergodicity for the TAR models are not rejected if some conditions on the TAR estimators are checked. A TAR model is also useful to reproduce the asymmetry and periodic behavior between regimes where the transition between those regimes is expected to be abrupt. Alternativelly, a more general specification defining the Smooth TAR (i., e., STAR) models (Teräsvirta and Anderson, 1992) makes regime- switching smooth rather than abrupt as it is carried out through a continuous function[14].

[14] For a recent comparison between the TAR and STAR models based on a simulation exercise for stock returns, see Gibson and Nur (2011). As for our study, the TAR models are preferred to STAR models because in context of the recent severe crisis the transmission between stock markets is expected to be rapid.

For the TAR modeling, the lag number (*p*) can be determined using the information criteria and or autocorrelation functions. The estimation of the TAR model requires the application of sequential conditional least squares only. As in Tong and Lim (1980), the implementation of TAR modeling is carried out in three main steps, which consist in specifying *p*, definining the threshold parameter *c* and the delay parameter *d* (that defines the transition variable) and estimate the two-equation system by the Least Square (LS) method. However, as the values of the threshold *c* and the delay parameter *d* are unknown, the method of Tong and Lim (1980) is rather less applied in the literature. Accordingly, an alternative procedure based on linearity tests has been introduced by Tsay (1989) and Hansen (1996) to estimate the TAR models. Such approach is based on the threshold tests and is conditioned by the estimated values for *c* and *d*. We use this approach in this paper.

3.2.2. Threshold tests

These tests aim to specify the values of *c* and *d*, while testing the null hypothesis of linearity against its nonlinearity alternative. To do this, two linearity tests are applied for several values of d: $1 \leq d \leq p$, and the optimal value should minimize the p-value of the linearity test. In practice, two main linearity test strategies have been introduced: the Tsay (1989) and Hansen

(1996) tests. [15] Tsay (1989) proposes a linearity test that is related to the Portmanteau test of nonlinearity (Petruccelli and Davies, 1986), based on arranged regression and predictive residuals. This test is viewed as a combination of the linearity tests developed by Keenan (1985), Tsay (1986) and Petruccelli and Davies (1986). The test is simple and widely applicable in four main steps. First, we select the autoregressive order p using the partial autocorrelation function (PACF) of Y_t (the model defined in Equation (2)) and the information criteria16, and we retain possible values for the delay parameter d which helps define the threshold variable ($1 \leq d \leq p$). Second, we check the arranged auto-regression for a given p and apply a threshold nonlinearity test, while ordering observations according to the increasing values of the threshold variable. This implies two regressions: The first corresponds to the k observations associated with weak values of the threshold variable, while the second is associated with its higher values. Accordingly, we obtain the following ordering model that corresponds to the model defined by equation (1) for which the threshold parameter is located between the k and ($k+1$) observations:

$$
\begin{aligned}
Y_{(O)} &= \alpha_{10} + \sum\nolimits_{i=1}^{p} \alpha_{1i} \, Y_{(O)t-i} + \sum\nolimits_{j=1}^{p} \beta_{1j} \, X_{(O)t-j} + \varepsilon_{1(O)} \quad \textit{for the k first values of } S_O \\
Y_{(O)} &= \alpha_{20} + \sum\nolimits_{i=1}^{p} \alpha_{2i} \, Y_{(O)t-i} + \sum\nolimits_{j=1}^{p} \beta_{2j} \, X_{(O)t-j} + \varepsilon_{2(O)} \quad \textit{for the next values of } S_O
\end{aligned}
\qquad (2)
$$

[15] We briefly discuss these methods, but for more details about these linearity tests, the reader can consult Ben Salem and Perraudin (2001).
[16] Tsay (1989) prefers PACF over the information criteria as it imposes no penalty on high-order terms. Also, the information criteria could be misleading with presence of nonlinear processes.

where O denotes the ranking of the observation according to increasing values of the threshold variable (S_t).

The arranged autoregression has the advantage to regroup observations in two groups so that all of the observations in a group are described by the same linear AR model. Additionally and interestingly, this separation does not require the precise value of the threshold, as only the number of observations in each group depends on it (Tsay, 1989). The estimation procedure would be simpler if the threshold value is known, but since it is unknown, then its estimation is carried out sequentially. Accordingly, the TAR model is estimated by the recursive method for each value of d and the linearity hypothesis consists of testing the equality between the AR coefficients of the two regimes under consideration (the model in equation 2). From Tsay (1989), we note that the test statistic corresponds to:

$$Q(p) = \frac{\sum_{t=1}^{T} \hat{e}_t^2 - \sum_{t=1}^{T} \hat{u}_t^2}{\sum_{t=1}^{T} \hat{u}_t^2} \frac{T-k-2p-1}{p+1} \qquad (3)$$

where $k = (T/10) + p$, $\hat{e}_t$ denotes normalized error ε_t , $\hat{u}_t$ corresponds to the residuals of the regression of e(o) on (1, $Y'_{(O)}$).

Under the null hypotheis of linearity, this statistic follows a Fisher test noted *F (p+1, T-k-2p-1)*. If linearity is rejected, then the optimal value of *d* should maximize this statistic, and thus we move to the next step. In this third step, the threshold value *c* is determined graphically as the graph can provide useful information on locating the threshold.[17] In particular, while plotting the values of the t-ratios or *the student tests* of recursive estimates of the autoregressive coefficients of model (2) versus the threshold variable, the optimal threshold value should correspond to the first observed structural break. The t-ratios of various coefficients may be examined as long as they are statistically significant. Indeed, the estimated AR coefficients and the t-ratios start changing when the recursion reaches the threshold value. Furthermore, according to Tsay (1989), the estimated threshold value should normally belong to the interval [Min S_t, Max S_t]. Finally, after determining the *c* and *d* parameters, the TAR model is estimated in the last step by the usual LS method.

As for Hansesn (1996), his methodology has the advantage to introduce a more global strategy while suggesting to determine both *c* and *d* according to the Tsay (1989) principle. Accordingly, his linearity test depends on these two parameters. First, we estimate an AR model of *p* order, recuperate its estimated residual $\hat{e}_t$ and consider possible values for *d*. Second, we

[17] The threshold value c is determind in tis study by using a linearity test.

apply to each value of d a Lagrange multiplier linearity test (LM test) and we compute the LM(c) statistics for different values of c following this formula:

$$LM(c) = S(c)'I(c)S(c) \tag{4}$$

where $S(c)$ denotes the estimated model score under the null hypothesis, while $I(c)$ refers to the Fisher matrix of information.

In order to check the power of this test, Hansen (1996) suggests computing different statistics, namely *sup LM(c), exp LM(c)* and *Mean LM(c)*. If linearity is rejected, the optimal value of d should maximize these statistics and then we move to next step. Third, the threshold parameter is estimated, while minimizing the residual variance of the estimated TAR models for different possible values of d. Finally, we estimate the TAR model using the LS method.

Ben Salem and Perraudin (2001) compare these two approaches and suggest that it is difficult to conclude whether one strategy supplants another or not.[18] As for the TAR estimation, ordinary LS method is still useful because TAR model is locally linear.

4. Empirical results

4.1 . Data and descriptive statistics

This study focuses on investigating the linkages between Islamic and three conventional markets. To this end, we use closing daily stock market indices for the Sharia-compliant stocks in the Dow Jones stock index universe and for stocks in three main regions: the United States,

[18] In my study, I check linearity using both Tsay and Hansen tests.

Europe and Asia over the period January 4, 1999 – October 12, 2012. While the selection of regions allows for making an international comparison between global markets, the sample period permits to check linkages between Islamic and international stock indices during calm and turbulent times including the recent financial crisis.

The time series for the four stock market indices are sourced from Bloomberg. The DJIM index measures the global universe of investable equities that have been screened for Sharia compliance. The companies in this index pass the industry and financial ratio screens. The regional allocation for DJIM is classified as follows: 60.14% for the United States; 24.33% for Europe and South Africa; and 15.53% for Asia.

First, we test the null hypothesis of unit roots in the data. Our findings show that all four indices are I(1), which implies that the focus should be on stock returns as provided by the first difference of stock indices.[19]

The descriptive statistics for conventional and Islamic returns of the four stock indices are reported in Table 1. The returns in the mean are positive for all regions except the region represented by European index. This performance also indicates that the stock investment is more attractive for Asia, followed by the Islamic markets and the Unites States. On the other hand, the exposure of these stock investments toward risk is lower for the Islamic market than for the other regions, according to the measure of total risk defined by the historical standard deviation. This suggests that the Islamic investments reduce investors' exposure to financial risk as explained in past research. Moreover, we note a leptokurtic excess as well as an asymmetric effect in the stock return distributions of the indices as can be seen from the skewness

[19] I do not report the results of unit root tests to save space; however results are available upon request.

coefficient. Accordingly, the rejection of normality hypothesis and the negativity of skewness coefficient may suggest nonlinearity in the stock return dynamics.

Table 1. Descriptive Statistics for Stock Returns

Series	**RIF**	**RAS3**	**REU**	**RUS**
Mean	8.54^{E}-05	0.0004	-6.94^{E}-05	4.02^{E}-05
Std. Dev.	0.011	0.014	0.014	0.013
Skewness	-0.278	-0.124	-0.051	-0.141
Kurtosis	9.169	7.891	7.348	10.408
Jarque-Bera	5739.5	3587.9	2830.0	8222.4

Note: RUS, REU, RAS3 denote U.S., European and Asian stock returns respectively, while RIF refers to Islamic stock returns. The number of observations is 5041.

In order to provide more information about the relationships between the Islamic and the three conventional stock returns, we compute the return correlation matrix for the full period and the pre- and post- 2007 subperiods (Table 2). Accordingly, we discern two important results. On one hand, our analysis points out the presence of significant bilateral contemporaneous correlations between the Islamic and conventional stock returns as well as bilateral correlations between the U.S., European and Asian markets, indicating further evidence of co-movements between these markets in the short-run. On the other hand, given the correlations before and after the subprime crisis, we note that the linkages between markets increase after 2007 as shown in Table 2 and in Figure 1.

Table 2. The Stock Return Correlation Matrix

Panel A. Full period: 04-01-1999/12-10-2012

	RIF	RUS	REU	RAS3
RIF	1.00	0.88	0.75	0.42
RUS		1.00	0.57	0.18
REU			1.00	0.38
RAS3				1.00

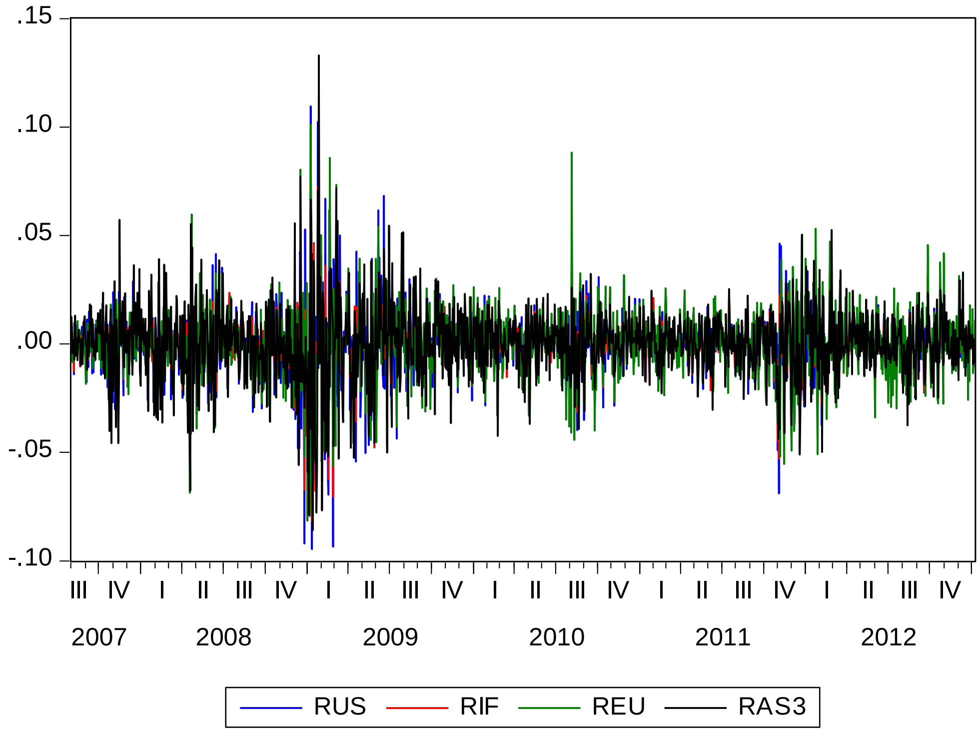
Panel B. First subperiod: 04-01-1999/30-07-2007

	RIF	RUS	REU	RAS3
RIF	1.00	0.88	0.67	0.32
RUS		1.00	0.51	0.12
REU			1.00	0.32
RAS3				1.00

Panel C. Second subperiod: 01-08-2007/12-10-2012

	RIF	RUS	REU	RAS3
RIF	1.00	0.88	0.82	0.51
RUS		1.00	0.64	0.24
REU			1.00	0.44
RAS3				1.00

Figure 1. Stock Return Dynamics for the Four Markets



Note: RUS, REU, RAS3 denote U.S., European and Asian stock returns respectively, while RIF refers to the Islamic stock returns.

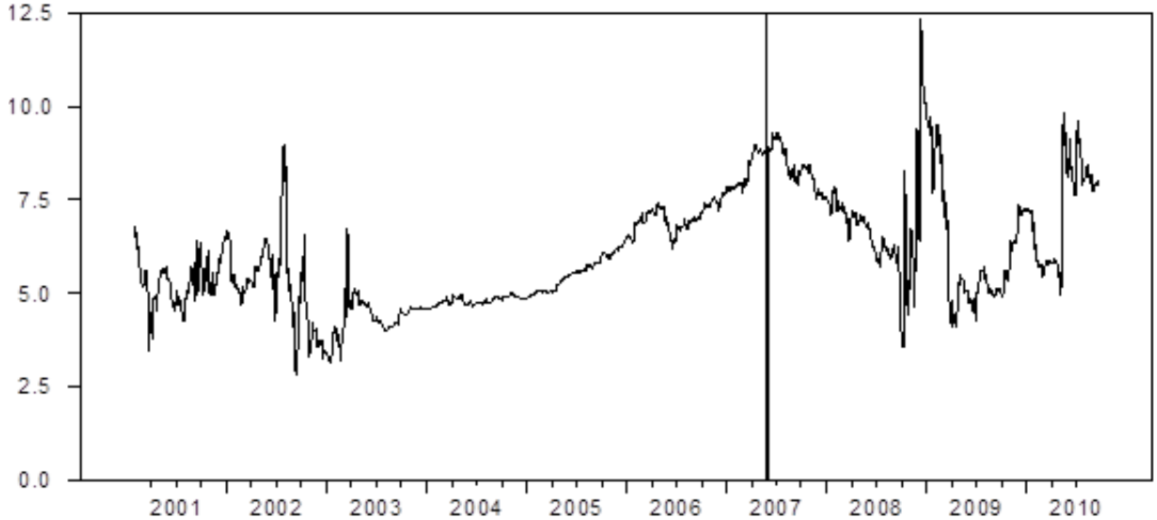
This increase in correlations between these international stock markets after 2007 subperiod has two interesting implications. While this increase does not seem to be coherent with informational efficiency (Fama, 1965), it implies a *priori* evidence of further global integration between these markets and/or an increase in herding behaviour which intensifies during financial stress. However, such analysis is static and is relevant to the short-run. Furthermore, it does not take into account further asymmetric and time-varying relationships.

4.2.Structural break tests

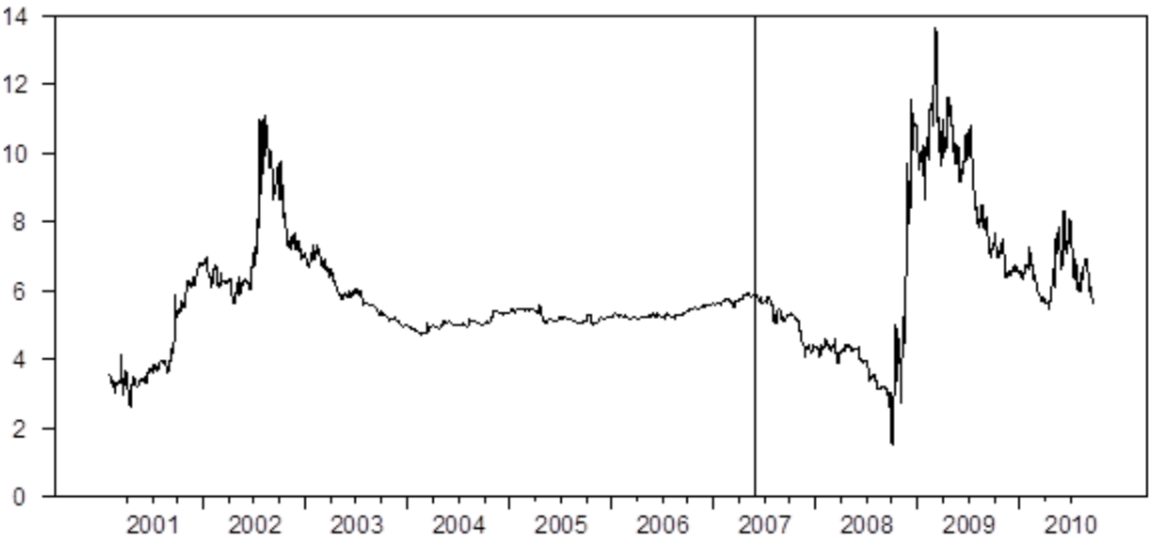
Before moving to the linearity tests, we propose to check for structural breaks in the data. This enables one to check implicitly for more threshold effects in the stock return dynamics. To do so, we apply three types of tests. First, we perform Andrews-Ploberger (1994)'s structural break test. This test is particularly warranted in order to check for a single structural break at an unknown point within the sample. In particular, the generated series of the LM statistics are computed for the breaks at each of the points in the middle range of the data set. This test has however highly non-standard distributions and its asymptotic p-values are thus computed using Hansen (1997)'s approximations. Based on the Andrews-Ploberger breakpoint test's statistics given in Figure 2, we do not reject the presence of a structural break in the middle range of the data. For all indexes, the test result shows that a break seems to occur around the middle of 2007 but with varying intensities for the different markets, the following effect of the subprime crisis. The Great Recession in the United States dates back to December 2007. This result also can be a precursor of the subprime crisis (which occurred in August 2008) and the global financial crisis (occurred in 2008-2009) that had not been publically announced yet.

Figure 2. The Andrews-Ploberger Breakpoint Test

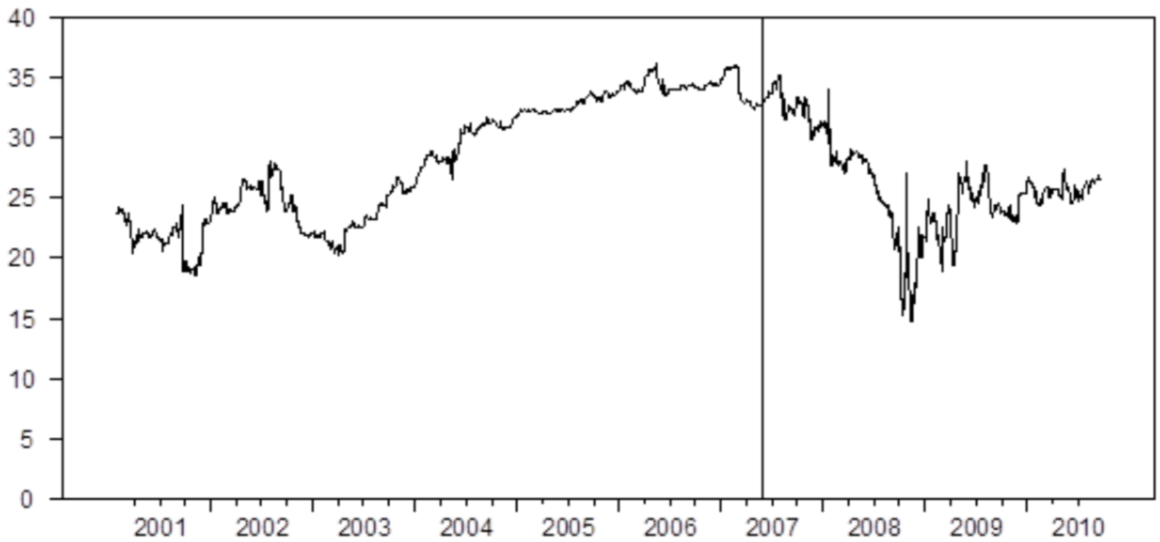
Europe



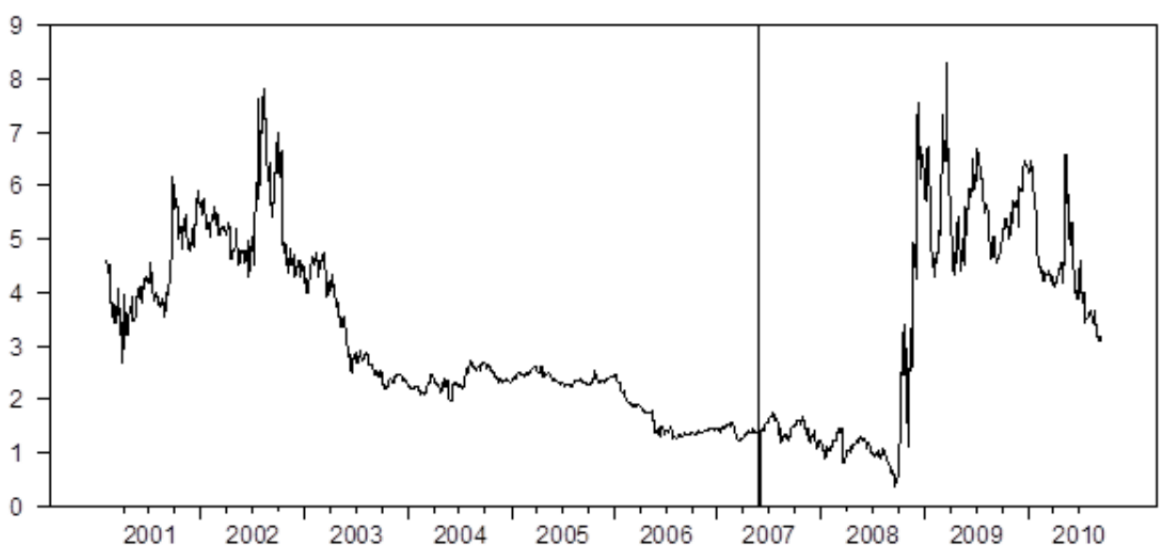
United States



Asia



Islamic Finance Market



Note: The variable on the vertical axis is the test statistic. This test shows that the break point has occurred in May 2007 for all the four markets.

Second, we apply the Bai and Perron (2003) structural break test[20], which has the advantage of checking for multiple breaks and dating them. Our resultspoint to several significant structural breaks[21], particularly in 2008 corresponding to the start of the global financial crisis, which is

[20] See Jawadi and Sousa (2013) for more details on these tests and their properties.
[21] I do not report the results to save space but are available upon request.

coincident with the post *Lehman-Brother* bankruptcy period. Third, we apply another structural test based also on the Bai and Perron (2003) test, but this test uses a threshold variable other than time and also authorizes two possible breaks. Interestingly, our results which are reported in Table 3 suggest further evidence of significant structural breaks in the data for all stock returns under consideration. This table reports the estimated break values for each market which all are negative, suggesting that the breaks occurred when the market is under correction and the trend is negative due to the crisis effect. The break values are however relatively lower for the Islamic stock return, suggesting a lower crisis effect on Islamic returns in relation to the conventional returns. This result is perhaps bearing on the industry restriction and not on the prohibition against using hedging instruments in Islamic finance. It can also be considered as an indication for the presence of the threshold effect. To explicitly check for this effect, we apply more explicit threshold and linearity tests.

Table 3. Estimates of Break Values

Break Values	Europe	U.S.	Asia	Islamic
Break value 1	-0.0672	-0.0631	-0.0676	-0.0529
(p-value)	0.00	0.00	0.00	0.00
Break value 2	-0.0574	-0.0532	-0.0676	-0.0390
(p-value)	0.00	0.00	0.00	0.00

Note: The numbers in this Table refer to the estimated values of the breaks for the four markets. Lower negative values signal lower negative impacts. These break are statistically significant at the 1% level.

4.2.1. Linearity test results

We apply a number of threshold and linearity tests so that we can adequately specify the nonlinearity type such as threshold and structural changes inherited in the data inherited in our data. First, we apply the Hansen (1996) test to check for the threshold effects in the stock return dynamics. Second, we check for nonlinearity through two classes of tests: the Tsay (1989) and Teräsvirta (1994) tests[22]. While the Tsay test is useful to check for abrupt breaks in the stock return dynamics, the Teräsvirta tests are of great interest to examine the smooth transition between stock return regimes. Furthermore, the Teräsvirta tests that are based on a sequence of the Fisher tests and the Taylor development have the advantage to test the null hypothesis of linearity against its alternative of nonlinearity under the presence of a nuisance parameter, due to the fact that the null hypothesis can be defined differently. Indeed, these tests are based on the LM tests, which can help avoid the nuisance or the non-identification parameter problem, as their distribution is known under the null hypothesis of linearity. The LM tests follow a standard χ^2 distribution. Finally, the implementation of the Tsay (1989) test can also help to check for nonlinearity and also optionally check whether a TAR model can be preferred to a STAR model or not.[23]

In practice, if the null hypothesis of linearity is accepted and the threshold effect hypothesis is rejected, then the stock return adjustment dynamics are said to be linear, while a TAR regression is more appropriate under the alternative hypothesis of nonlinearity (H_1).[24] We apply all these tests and report the main results in Table 4. This table reports the p-values of linearity tests against TAR (Hansen and Tsay tests) and against STAR (Teräsvirta tests). Linearity is rejected at the level of 5%, when p-value is less than 0.05.

---

[22] The Teräsvirta (1994) linearity tests check linearity against a STAR nonlinearity type, but these tests can also be used to test for the TAR nonlinearity type.

[23] While the nonlineary form is often unknown and in the econometric literature, there are no tests to test a TAR against a STAR model. However, the choice can be used according to data frequency and also is checked through the misspecification tests. Indeed, the rejection of nonlinearity in residual terms validates the choice of the nonlinearity form.

[24] For more details about these linearity and threshold tests, see Tsay (1989), Teräsvirta (1994), Hansen (1996), and Van Dijk *et al.* (2002).

Table 4. Threshold and Linearity Tests (p-values)

Series				**Hansen (1996)**	**Tsay (1989)**	**Tsay (1989)**[25]	**Teräsvirta (1994) hypotheses**				**Model**
	p_1	**d**	**s_t**				**H_{01}**	**H_{02}**	**H_{03}**	**H_{12}**	
Europe	2	1	REU_{t-1}	0.00[a]	0.00	0.09[b]	0.00	0.00	0.03	0.00	TAR
U.S.	2	1	RUS_{t-1}	0.00[a]	0.00	0.00[b]	0.00	0.00	0.00	0.00	TAR
Asia	1	1	RASt-1	0.00[a]	0.00	0.09[b]	0.52	0.00	0.26	0.01	TAR
Islamic index	1	1	RIFt-1	0.00[a]	0.00	0.03[b]	0.00	0.00	0.00	0.03	TAR

Note: (a) refers to the Bootstrap p-values. (b) refers to the p-values of Fisher statistics for the Tsay test. H_{01}, H_{02}, H_{03} and H_{12} refer to the STAR model differentiation null hypotheses of Teräsvirta (1994)[26].. H_{01}: the fourth-order terms of the Taylor approximation are not significant. H_{02}: under H_{01}, third-order terms of the Taylor approximation are not significant. H_{03}: under H_{02}, second-order terms of the Taylor approximation are not significant. S_t refers to the optimal transition variable. d is the delay parameter and P_1 is the autoregressive order.

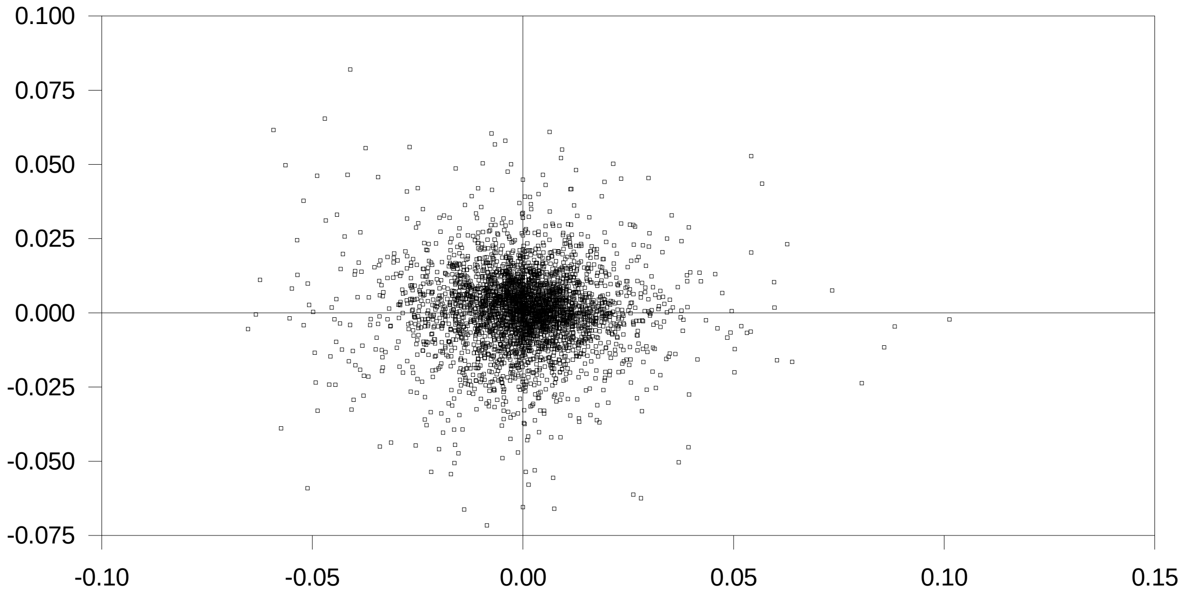
Our findings show strong evidence of asymmetry and nonlinearity in the stock return dynamics of the four markets. Indeed, the Hansen (1996) test that is based on the bootstrap technique checks the null hypothesis of "no threshold" against its alternative of a "Threshold effect". It does not reject the hypothesis of a threshold break for all series at the 1% level. According to the Tsay tests, linearity is strongly rejected against the TAR specification for the whole series. Moreover, linearity is rejected according to the Teräsvirta (1994) tests, confirming the switching-regime hypothesis. However, according to the Tsay (1989) test, the transition is abrupt rather than smooth confirming our intuition that is related to the effect of the global crisis.

[25] The Tsay test checks for neglected non-linearity in an autoregression. Optionally, it is also applied because it can test linearity against nonlinearity of the STAR type.
[26] For more details about linearity tests, see Hansen (1996), Tsay (1989) and Teräsvirta (1994).

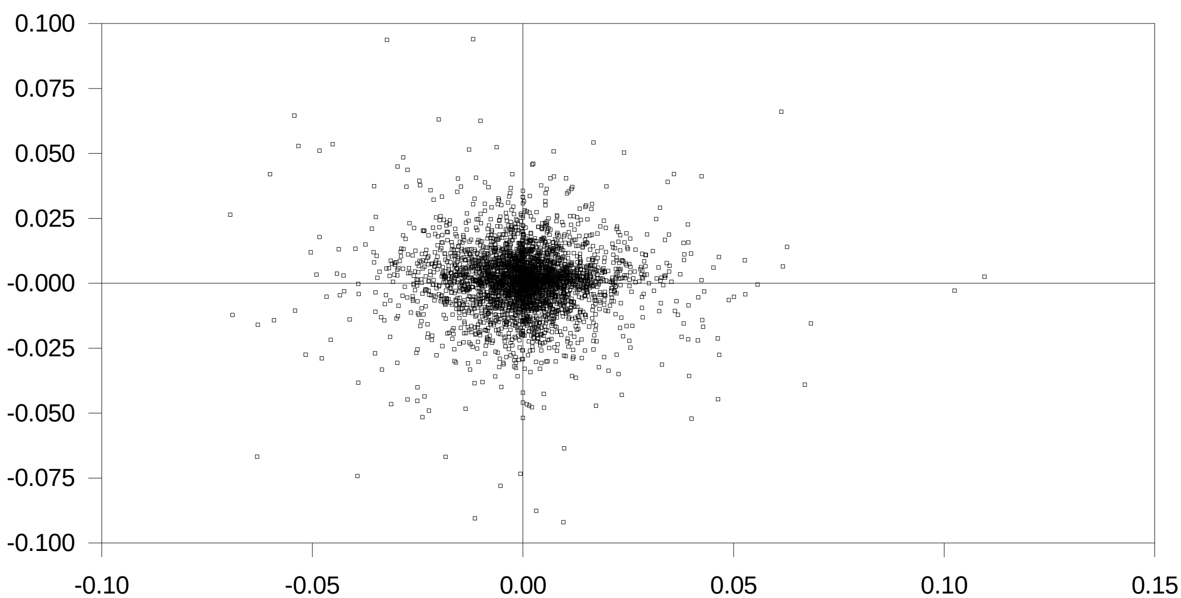
In order to illustrate the importance of nonlinearity in stock return dynamics, we graphically report the results of the Tsay Arranged Autoregression Tests in Figure 3.

Figure 3. The Tsay Arranged Autoregression Test statistic

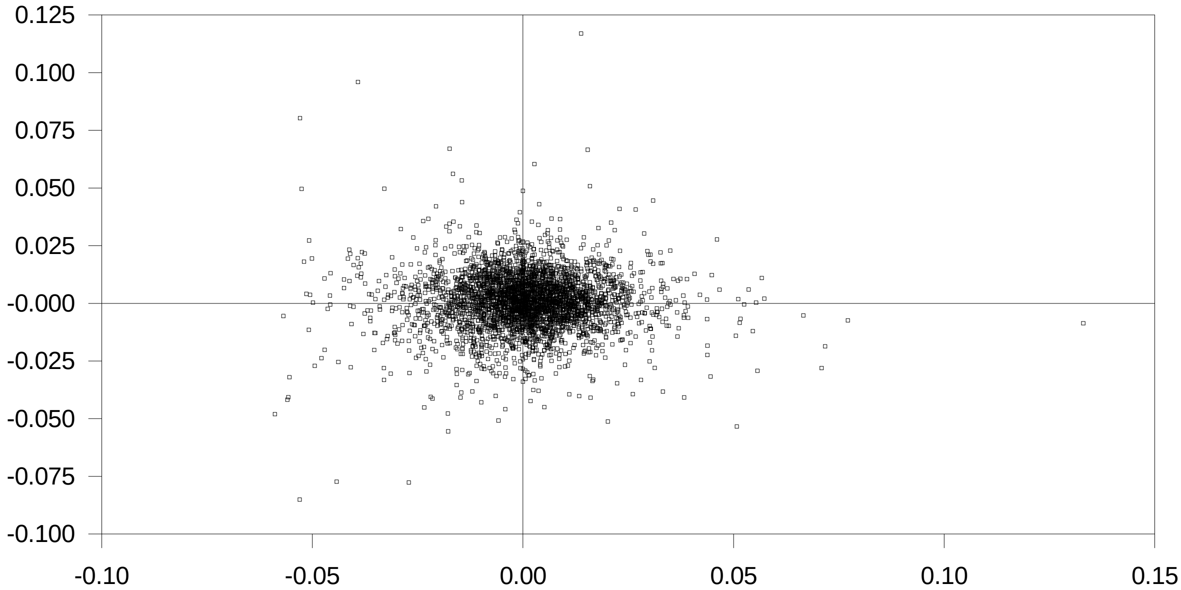
Europe



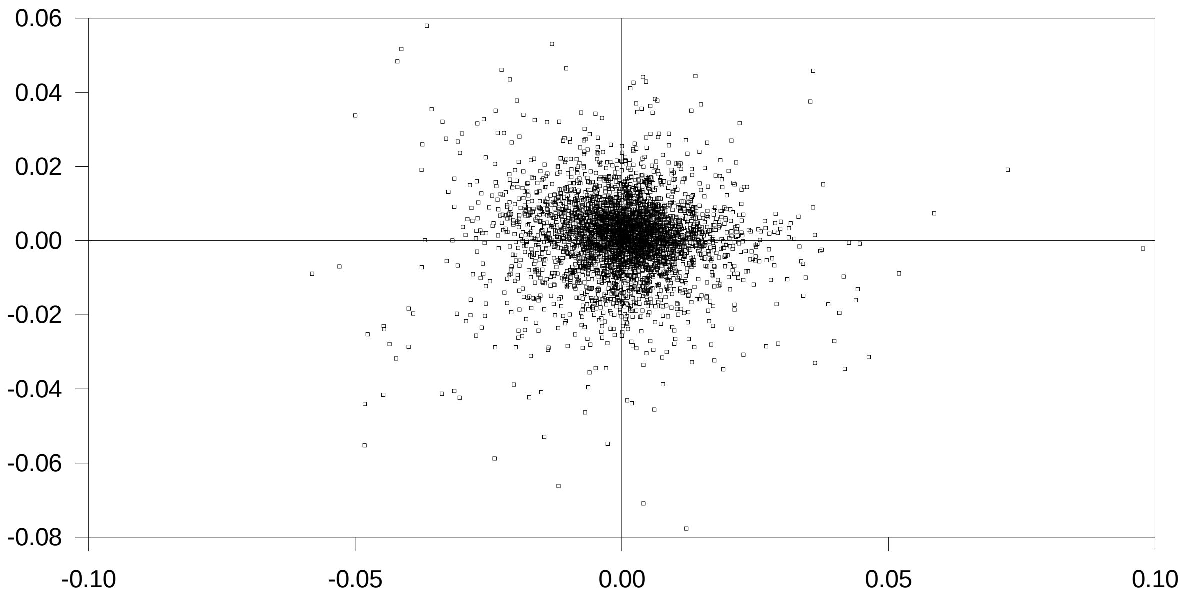
The U.S.



ASIA



Islamic Market



Notes: The vertical axis reports the statistic of the Tsay test against the threshold value placed on the horizontal axis. This test performs an arranged regression test for threshold autoregression. Intuitively, the rejection of threshold effect is associated with less volatile distribution as in the Asian market and vice versa.

As can be seen from these plots, the one-regime hypothesis cannot be accepted since the data are rather dispersed from the mean and volatile, implying further the presence of different regimes. Indeed, the higher the dispersion is lower the probability of the existence of one regime, which implies the rejection of linearity. The dispersion is more marked for the U.S., Europe and Islamic markets than for the Asian market. After pointing to the presence of a significant threshold effect in the data, we next propose to estimate the stock return dynamics using the TAR models which allows one to capture more asymmetry, nonlinearity and multiple regimes and breaks in these data series.

4.2.2. Univariate TAR estimation

We model nonlinearity in the stock return dynamics, using the TAR models under the hypothesis of the presence of two regimes: the lower regime and the upper regime. The TAR modeling has the advantage to capture nonlinearity and asymmetry as well as abrupt structural changes in the data and the dynamics that vary according to regimes. We proceed in two main steps. First, we estimate the univariate TAR, while including only the own lagged endogenous variables as explanatory variables for each series (Equation 6 below). This helps us to specify in particular the timely structural dependency and also to check for persistence and memory effects in the stock return dynamics. Second, we introduce the exogenous control variables such as the Islamic Finance stock return and the stock returns of other indexes (Model 7). Such variables help to control for the contagion effects between the stock markets and the reaction of any market toward the arrival of new Islamic finance investments. Interestingly, such specification is also required to examine the various reactions according regimes.

A benchmark univariate two-regime TAR model corresponds to:

$$R_t = \beta_{10} + \sum_{i=1}^{p} \beta_{1i} R_{t-i} + \varepsilon_{1t} \ \ if \ \ R_{t-k} \leq c$$
$$R_t = \beta_{20} + \sum_{i=1}^{p} \beta_{2i} R_{t-i} + \varepsilon_{2t} \ \ if \ \ R_{t-k} > c \tag{5}$$

where β_{1i} and β_{2i} refer to coefficients in the first and second regimes, p denotes the number of lags, c represents the threshold parameter, ε_{1t} *and* ε_{2t} are the error-terms of the first and second regimes and R_t refers to the stock return.

In this specification, the transition between regimes is expected to be activated abruptly when the previous stock return exceeds a given threshold c that is endogenously specified. The estimation of this two-regime self-exciting threshold autoregression is carried out according to Hansen (1996), which also allows for computing the asymptotic p-values of the tests for the threshold. As in Equation (5), the univariate regression includes a constant and a set of lags of the dependent variable.

The results associated with the estimation of the Model in Equation (6) offer some findings (Table 5). First, the distribution of the returns between the two regimes for the four markets under consideration is rather asymmetric according to the number of observations per regime, confirming the preliminary analysis. This asymmetry is also illustrated by the fact that the stock return dynamics vary per regime. Second, lag effects are noted, confirming the presence of memory effects in the stock return dynamics of the four indexes, even some of them are not statically significant. Third, the autoregressive estimators are often negative, indicating that the markets are still under correction phases, particularly under regime 1 which is the lower regime.

Table 5. Univariate TAR Estimation

Europe

Tests for threshold effects (p-values)		**SupLM** **ExpLM** **AvecLM**	(0.00)*** (0.00)*** (0.00)***
Regime 1	**Estimators**	**Regime 2**	**Estimators**
$\hat{B}_{10}$	-0.0001*** (0.0002)	$\hat{B}_{20}$	0.0001*** (0.002)
$\hat{B}_{11}$	-0.025** (0.026)	$\hat{B}_{21}$	0.088** (0.05)
$\hat{B}_{12}$	-0.041** (0.036)	$\hat{B}_{22}$	-0.034 (0.105)
c	0.0117	c	0.0117
n	3048	n	539

Table 5 cont'd.

The U.S.

Tests for threshold Effects (p-values)		SupLM ExpLM AvecLM	(0.00) *** (0.00) *** (0.00) ***
Regime 1	**Estimators**	**Regime 2**	**Estimators**
$\hat{B}_{10}$	-0.0015*** (0.001)	$\hat{B}_{20}$	-0.00003*** (0.0002)
$\hat{B}_{11}$	-0.181* (0.08)	$\hat{B}_{21}$	-0.049** (0.034)
$\hat{B}_{12}$	-0.164* (0.078)	$\hat{B}_{22}$	0.020** (0.02)
c	-0.0046	c	-0.0046
n	1020	n	2571

Table 5 cont'd.

Asia

Tests for threshold effects (p-values)		**SupLM** **ExpLM** **AvecLM**	(0.00) *** (0.00) *** (0.00) ***
Regime 1	**Estimators**	**Regime 2**	**Estimators**
$\hat{B}_{10}$	-0.003*** (0.001)	$\hat{B}_{20}$	0.0008*** (0.0003)
$\hat{B}_{11}$	-0.095* (0.08)	$\hat{B}_{21}$	0.044** (0.029)
$\hat{B}_{12}$	-	$\hat{B}_{22}$	-
c	-0.0061	c	-0.0061
n	986	n	2606

Table 5 cont'd.

Islamic Market

Tests for threshold effects (p-values)		SupLM ExpLM AvecLM	(0.00) (0.00) (0.00)
Regime 1	**Estimators**	**Regime 2**	**Estimators**
$\hat{B}_{10}$	-0.004*** (0.001)	$\hat{B}_{20}$	0.0001*** (0.0001)
$\hat{B}_{11}$	-0.066 (0.115)	$\hat{B}_{21}$	0.135** (0.02)
$\hat{B}_{12}$	-	$\hat{B}_{22}$	-
c	-0.0091	c	-0.0091
n	553	n	3039

Note: (***), (**) and (*) refer to the 1% , 5% and 10% significance levels, respectively. *n* denotes the number of observations per regime. The threshold is represented by *c*. Regime 1 is the near equilibrium lower regime which is below the threshold, while regime 2 is the volatile upper regime which adjusts to the equilibrium. The numbers in parentheses correspond to the robust estimators' standard deviations.

4.2.3. Measuring interaction effects with threshold models

We extend the univariate model by introducing control variables and estimating augmented TAR models. For example, for the U.S. market, we introduce the current and lagged for the European, Asian and Islamic returns to capture further interaction effects, and the same applies for the other markets. To specify these effects, we carry out this task in three steps. First, we specify the basic linear model to identify these effects. Second, we allow these effects to vary per regime and check this through linearity tests. Finally, when linearity is rejected, we specify these effects using the threshold models. Accordingly, the extension of Model (5) to a nonlinear context with control variables provides the following TAR specification for which the threshold variable corresponds to the Islamic return.[27]

$$\begin{aligned} R_t &= \beta_{10} + \sum_{i=1}^{p} \beta_{1i} R_{t-i} + \sum_{j=1}^{p} \beta^{EU}{}_{1J}\, REU_{t-J} + \sum_{k=1}^{p} \beta^{AS}{}_{1k}\, RAS_{t-k} + \sum_{l=1}^{p} \beta^{IF}{}_{1l}\, RIF_{t-l} + \varepsilon_{1t} \quad if\ RIF_{t-l} \le c \\ R_t &= \beta_{20} + \sum_{i=1}^{p} \beta_{2i} R_{t-i} + \sum_{j=1}^{p} \beta^{EU}{}_{1J}\, REU_{t-J} + \sum_{k=1}^{p} \beta^{AS}{}_{1k}\, RAS_{t-k} + \sum_{l=1}^{p} \beta^{IF}{}_{1l}\, RIF_{t-l} + \varepsilon_{2t} \quad if\ RIF_{t-l} > c \end{aligned} \qquad (6)$$

The findings of this extended non-linear model given in Equation (6) as well as the linear counterpart imply several interesting conclusions. The main results are summarized in Table 6. Overall, linearity is still rejected for the four markets. In order to clearly discuss these results, we present for each market the findings of the two models.

As for the model specification, the explanatory variables are retained according to the information criteria. Let us start with Europe. First, the linear model shows significant European dependency on the U.S. market and also points to positive and significant interaction effects between the Islamic index and the European market. Second, a nonlinear two-regime TAR specification for the European market fits the data better, and also shows time-varying

[27] Such hypothesis enables one to check whether a change in the Islamic stock market would imply a significant adjustment in the conventional markets or not.

dependency on the U.S. market and the Islamic market index as the U.S. effect varies according to the prevailing regime. Interestingly, when the European market is in its lower (calm) regime, the effect of Islamic market on European market is stronger, and is positive and significant, while in the upper (volatile) regime (when the European market is higher), the effect is still positive and significant but relatively lower. There is no significant dependency for this market on the Asian market by the other markets.

Table 6. Augmented Threshold Model Results

Variable	Europe	U.S.	Asia	Islamic Market
Regime 1				
C	-0.0003**	-0.0001	6.28E-05**	6.28E-05*
REU		-0.2353***	0.1868***	0.1868***
REU(-1)	-0.2197***	0.0449***	-0.0222***	-0.0222***
REU(-2)	-0.0118***	0.0086		
REU(-3)	-0.0075***	0.0207***		
RUS	-0.5944***		0.6464***	0.6464***
RUS(-1)	0.2534***	-0.1367***	0.0174	0.0174
RUS(-2)	0.1010***	0.0076		
RUS(-3)	-0.0183***			
RAS3		-0.2153***	0.1124***	0.1124***
RAS3(-1)				
RIF	1.4070***	1.5602***		
RIF(-1)	-0.0533***		0.0520***	0.0520***
Regime 2				
C	-0.0001**	0.0001	-0.0004*	-0.0004*
REU		0.0181***	0.2204***	0.2204***

REU(-1)	-0.1405***	0.1110**	-0.1007***	-0.1007***
REU(-2)	-0.2643***	0.0256***		
REU(-3)	-0.1319***	0.0073		
RUS	0.3884***		0.4137***	0.4137***
RUS(-1)	0.5182***	-0.2306***	0.2157***	0.2157***
RUS(-2)	0.2754***	-0.0786***		
RUS(-3)	0.2305***			
RAS3		-0.0923***	0.2716***	0.2716***
RAS3(-1)				
RIF	0.8390***	0.9570***		
RIF(-1)	-0.3276***		-0.0160	-0.0160
Log likelihood	11993.6	14092.7	15310.1	15310.1
Akaike info criterion	-6.6787	-7.8503	-8.5227	-8.5227
Schwarz criterion	-6.6407	-7.8141	-8.4951	-8.4951
Hannan-Quinn criter.	-6.6651	-7.8374	-8.5129	-8.5129
Durbin-Watson stat.	2.0202	1.9473	1.9931	1.9931
JB Test p-value.	0.00	0.00	0.00	0.00
ARCH Test p-value	0.00	0.00	0.00	0.00
BP Test p-value	0.103	0.123	0.165	0.901

Notes : Regime 1 is the lower regime and regime 2 is the upper regime. JB, ARCH and BP refer to Normality Jarque Bera test, Engle (1982)' heteroscedasticity test and Box-Pierce test respectively. See the notes for Table 5 for more information about the other statistics.

As for Asia, the linear model points to a positive and significant dependency on the U.S. and European markets. The Islamic index has also positive effect on this market. Conerning the nonlinear investigation, we retain also a two-regime TAR model and show an asymmetric relationship with the two other markets. Furthermore, a positive shock for the Islamic index affects positively and significantly this Asian market. However, in contrast to the European market, the effect of the Islamic finance is higher when the Asian market is improving. Such result is not unexpected since the Islamic finance investments in this region are relevant because the region includes markets in Islamic countries such as Malaysia and Indonesia which can explain the development of this market in this region.

For the Islamic market, the linear model highlights significant but short-term linkages with the three conventional markets but the effect of the U.S. market on this market is more important than the other two conventional markets. The lag effect does not exceed one period, which means that even though a shock in the conventional markets is transmitted to the Islamic market, this shock does persist and a further correction is activated to maintain the decrease. As for the two-regime TAR model, we note significant interactions effects for the Islamic markets. The dependency on the U.S. market is higher in the lower regime than the second (upper) regime, while those interactions with the European and Asian markets are higher in the second regime. Such heterogeneity reflects the difference in the Islamic finance development and regulation in these regions.

In order to check the validity of these estimates, we applied a couple of misspecification tests. Accordingly, we show that for all indices, estimated residuals are not auto-correlated validating the model structure. Residuals are however characterized by an ARCH effect, which is expected for daily data. Furthermore, residuals are not normal, even the comparison of the Jacque-Bera Statistics (as well as those of Kurtosis test and the Skewness test) for stock returns (Table 1) and those of residuals (Table 6) show that these statistics are lower for residuals, suggesting that the nonlinear specification enables us to reduce leptokurtic excess, asymmetry and non-normality in the data[28].

4.3. Forecasting performance

In order to check the appropriateness of the nonlinear (TAR) model designed to capture the dependency effects, we compare the forecasting performance of the linear vs. nonlinear models. The main forecasting performance results are reported in Table 7 for k =1 (one day ahead forecasts) and for k =2. In practice, we compare both the in-sample root mean squared error (RMSE) and the mean absolute error (MAE) for each model and for each region or market. This is accomplished by computing the ratios for MAE and RMSE of the nonlinear to linear values. If the ratio is less than one, then it means that the nonlinear model outperforms the linear model and vice versa. Since the in-sample results of MAE and RMSE are quite similar in this study, we just report the results of the ratio of MAE for k=1 and k=2 only.

Table 7. Forecasting Performance MAE Ratio (Nonlinear / linear model)

horizon	Europe	United States	Asia	Islamic Market
k = 1	0.90*	0.88*	0.99	0.97*
k = 2	0.85	0.91*	0.98	0.96*
Average 1-2	0.87	0.89	0.98	0.96

Notes: a ratio of lower than one implies a better forecasting capability for the non-linear model over the linear benchmark model. (*) denotes the rejection at 5% of the null hypothesis of the Diebold and Mariano (1995) test.

Overall, the results show that the augmented TAR model significantly outperforms the linear model with the forecast horizons of one and two days. In order to check the statistical

[28] For example, JB Statistic equals 8222 for US returns, while that of the estimated residuals for US is equal to 2190.

significance of these results, we apply the Forecasting test of Diebold and Mariano (1995) test. The later checks whether punctual forecasts of linear and nonlinear models are equivalent or not. Accordingly, the null hypothesis is rejected for the US, Europe and the Islamic index, suggesting a further preference for the nonlinear model.

5. Conclusions and policy implications

This paper investigates the dynamic return linkages between the Islamic stock market (DJIM) defined based on the universe of the Dow Jones stocks and conventional stock markets for three global markets: Europe, the United States and Asia. Thus, this study has three main objectives: i) to investigate spillover effects between DJIM and each of the conventional markets in periods of tranquillity and crises; ii) to examine impulse response functions for shocks emanating from each market; and iii) to check the suitability of the linear vs. the nonlinear model to to modelling stock return dynamics.

While previous studies do not provide a unanimous conclusion on the effect of Islamic market on global conventional markets and also show that the spillover effects alternate between positive and negative, this study contributes differently by using different models. In particular, we develop appropriate econometric specifications based on the threshold model to reproduce spillover effects. These specifications are appropriate in order to test, capture and reproduce the asymmetry that is inherent in the data.

Interestingly, our findings make several contributions to the literature. i) They show significant current and lead/lag effects between the three conventional stock markets while giving a leader role to the U.S. market, and the transmission is subject to time-variations, indicating that the sign and the size of the dependency and the contagion effects vary according to the market state or regime. ii) They provide evidence that the Islamic market has a positive and stimulating effect on the three conventional markets. However, the stimulation varies per regime and also according to the market under consideration, reflecting somewhat the degree and importance of the Islamic finance development in the region where it is related. iii) Finally, they show that the combination of nonlinearity and switching-regime hypotheses in the models can help to improve the forecasting of their future return dynamics over the linear benchmark model. A natural extension of this study would be to extend the econometric methodology to take into account the ARCH effect in the data. Furthermore, a mutilvariate framework employing the threshold VAR approach would be helpful to investigate the spillover's effects in a system.

Essay 3: Interactions between Real Economic and Financial Risks in the U.S. Economy

Abstract

This objective of this study is to examine the linkages between real (economic) and financial variables in the United States in a regime-switching environment that accounts explicitly for high volatility in the stock market and high stress in financial markets. Since the linearity test shows that the linear model should be rejected, we employ the Markov-switching VEC model to examine the same objective using the Bayesian MCMC method. The regime-dependent impulse response function (RDIRF) highlights the increasing importance of the financial sector of the economy during stress periods. The responses and their fluctuations are significantly greater in the high volatility regime than in the low volatility regime.

1. Introduction

The sub-prime mortgage crisis that took place in the United States in summer 2008 has spread to other financial markets and morphed into a global financial crisis. It had contributed to the Great Recession and caused high volatility in capital markets and lowered economic growth worldwide. This crisis has renewed the interest in the migration and transmission of financial risks and volatility and their impacts on real economic activity. Since it has caused structural breaks in many economic and financial series, the relations between the financial and economic variables are likely to be nonlinear which should be accounted for in doing the analysis of this study. Thus, a single state economy is unrealistic given that the states of the economy are dynamic rather than static and the major events that are embedded in the sample period. The Markov-switching approach is a popular technique in dealing with nonlinearity and structural breaks because it allows both the coefficients and variances to change based on the prevailing regime. It also allows for the estimation of the impulse response functions and their confidence intervals based on the Markov-chain Monte Carlo method (MCMC) of Gibbs sampling.

The broad goal in this essay is to estimate a theoretically sound empirical model that examines the interactions between real economic and financial risk variables, while accounting for the effects of stress and volatility. This can be achieved through examining the following objectives. The first objective is to check nonlinearity of the considered system that contains the financial risk variables, the volatility index (VIX) and the financial stress index, and the real activity variables: the real industrial production, real capital stock and real oil prices. The presence of non-linearity is examined further by exploring the presence of regime switching. The second is to explore the interrelations between the financial risks and economic activity in the presence of financial stress and stock market volatility, using a regime-switching process. The third is to analyze whether these relationships, if they exist, are sensitive to changes in the underlying volatility regimes, given the exogenous financial risk and stress indicators. The fourth is to investigate which measure of financial risk and stress (VIX, FSI and US Economic uncertainty index)[29] has the greatest impact on these variables and therefore can be used more effectively to predict future economy. The fifth objective is to determine the ways the variables respond to a shock in both in calm and turbulent periods by performing the impulse response analysis. The final objective is to investigate the forces that affect the transmission of the underlying volatility regimes.

This paper makes contributions to the literature in two ways. First, it provides a framework that quantifies the relationship between financial and economic variables. Second, it applies the recent advances in the impulse response functions to examine the extent of the responses of shocks to the real and economic variables under the two regimes.

[29] I tried the U.S. economic uncertainty index and it doesn't lead to good results.

The empirical model that examines the interactions between the real economic and financial risk variables, while accounting for the effect of the U.S. financial stress and the stock market volatility, will have the following relationships. First, the production function for output growth as represented by changes in real industrial production is stipulated to depend on changes in capital stock, changes in labor, oil prices, financial variables, financial stress and stock market volatility. Second, the endogenous financial variable which is the real long-term interest rate depends on both the real economic and exogenous financial variables. Those exogenous financial variables include the CBOE volatility index known as VIX and Federal Reserve Bank of Saint Louis' financial stress index (FSI).

In this way, we can investigate the directional transmission of risks between real economic and financial variables. We can also explore the impacts of shocks in the capital markets' volatility and financial stress on these real and financial variables. The findings show the system follows two regimes where regime 1 (low volatility) has more than 2.5 duration time than regime 2 (high volatility). There are more interrelations between the real and financial variables in the low than the high volatility regimes. The financial variable responds faster to shocks than the oil and economic activity variables. The impacts of stock market volatility and financial stress go first through the financial variable before they reach the economic activity variables.

The remainder of the paper is organized as follows. Section 2 provides a brief review of the related literature. Section 3 presents the data description. Section 4 describes the linear and nonlinear models. Section 5 discusses the results and Section 6 concludes the paper.

2. Literature Review

Most of the recent literature that deals with financial and economic issues uses the linear vector autoregregssion (VAR) and vector error correction (VEC) models. These first generation models do not capture the nonlinear relationships among the variables which have become more common because of reoccurrences of crises, and structural breaks and differential effects of booms and busts. We plan to test and use nonlinear models with a focus on regime-switching to capture spillovers between financial and real variables in an environment that includes economic uncertainty and financial stress, in addition to normality and tranquility.

The existing literature pays more attention to the relationships between financial fundamentals and oil prices than to the relationships between financial risks and real economic activity variables which will be discussed in this paper. This review of the literature focuses on studies that use linear and nonlinear models to examine the relationship between financial fundamentals, industrial production, oil prices, *VIX*, economic uncertainty and financial stress.

2.1.Financial risks

This strand of the literature explores the transmission of financial risks among different financial markets. Fernandes, Medeiros and Scharth (2009) examine the time series properties of the daily equity *VIX* and S&P 500 stock returns. These authors suggest that *VIX* displays a long-range dependence and thus violates the weak efficiency hypothesis. They also find evidence of a strong relationship between the *VIX* and the S&P500 index return. They also show that the equity *VIX* is negatively related to the long-run oil price, suggesting that the market risk declines as demand for oil strengthens as the economy gains strength.

Figuerola-Ferretti and Paraskevopoulos (2010) consider cointegeration and the price discovery process between two types of risk credit risk, as represented by *CDS* spreads, and market risk as measured by the equity *VIX*. The authors find that the *CDS* and *VIX* are cointegrated and that *VIX* leads the *CDS* market in the price discovery process.

Bekaert, Hoerova and Duca (2012) decompose *VIX* into two components: the risk aversion and the expected stock market volatility. The authors develop the risk analysis further by investigating the dynamic links between those two risk components and the monetary policy. Their results show that only the risk aversion component responds to the lax monetary policy. However, the increasing expected stock market volatility contributes to a laxer monetary policy. Gogineni (2010) investigates the impact of changes in the daily oil price on the equity return of a wide group of industries. This author shows that stock returns of both industries that depend heavily on oil and those that use little oil but their customers use oil products are sensitive to changes in oil price.

2.2. Markov-switching modeling

As indicated, the linear VAR/VEC models which focus on one regime have been the popular approach in examining causal relationships between the variables under consideration. But most financial and economic series exhibit nonlinear behavior because of recurrence of structural breaks, and thus are subjected to some form of regime switching. Andreopoulos (2009) use the Markov-switching approach to estimate a Markov-switching model for the real oil price, the real interest rate and the unemployment in the United States. His results indicate that the real interest rate matters during expansion for equilibrium unemployment. On the author hand, the author finds evidence that the real oil price has asymmetric effects on unemployment over the business cycle, particularly during recessions only while is not being a regular feature of the US business cycle. Still, the oil price and not the real interest rate is significant for unemployment in the long-run.

Research on financial risks under regime-switching is growing. Alexander and Kaeck (2008) find that within a Markov-switching model that the iTraxx Europe display pronounced regime specific behavior. The determinants of the iTraxx are extremely sensitive to stock market volatility during periods of CDS spreads turbulence. However*, these* spreads are more sensitive to stock returns than to stock volatility during periods of ordinary market circumstances. Dionne et al. (2011) assess the ability of observed macroeconomic factors and the possibility of changes in regime to explain the proportion in yield spreads caused by credit default swaps in a reduced form model. They have sought to measure the ability of observed macroeconomic variables and switching in regimes to explain the proportion of corporate bonds' yield caused by CDS spreads. The model is calibrated out of sample with consumption, inflation, risk-free yields and default data for different investment- grade bonds. The results show that inflation is a key factor for explaining default spreads. We also find that the estimated default spreads can explain up to half of the 10 year to maturity Baa zero-coupon yield in certain regime with different sensitivities to consumption and inflation through time. The results also indicate that the proportion of default spreads in yield spreads explained by aggregate consumption growth and inflation varies across the different regimes. This proportion is the greatest during the states of low volatility of consumption growth and high and volatile inflation.

Bollerslev, Gibson and Zhou (2009) propose a method for constructing a volatility risk premium, or investor risk aversion, index. They implement the procedure with actual S&P500 option-implied volatilities (VIX) and high-frequency based realized volatilities. They estimate the stochastic volatility risk premium for the U.S. equity market and also link the variations in the risk premium to macro-finance state variables. They extract the volatility risk premium based on the difference between the implied volatility (*VIX*) and the realized volatility which is the summation of intra-day high frequency squared returns. They conclude that because the VIX index is calculated through a model-free approach, it acts as a better measure of the ex-ante risk-neutral expectations of integrated volatility than the traditional Black-Scholes implied volatilities.

Giot (2003) applies the Markov-switching model to the S&P100 VIX and the German DAX VDAX indices and finds that these indices switch from a low value state to a high value state close to the events of the 1997 Asian crisis, and have stayed almost continuously in the high-value state for the next five years. In the second part of the paper, the author highlights the structural change in the asymmetric stock index volatility vs the (positive and negative) returns relationship and finds that the leverage effect is much weaker after the summer of 1997 than before. The reaction of volatility to negative market returns rises much faster in the low-volatility state than in the high-volatility state. Ardia (2003), inspired by the stylized facts (leverage effect, clustering and mean-reverting behavior) of the S&P500 index and VIX, suggests a trading strategy that uses abnormally high volatility as a trading signal for long traders.

The more recent literature investigates whether the transition probabilities are constant and exogenous. Including the proper information variables in the transition probability function is crucial for the appropriateness of the TVTP-MS (time-varying Transition Probability) model and for the strength of the regimes identified by the model. Using a TVTP-MS model Cevik et al. (2012) investigate the factors that affect the regime-switching probabilities of the US stock market in calm and turbulent periods. They consider manufacturing and nonmanufacturing Business Activity Indices, industrial production and US Institute for Supply Management (ISM)'s. They find out that while the nonmanufacturing index only matters in the bull periods, the ISM manufacturing Business Activity Index impacts the transition probabilities in both the bull and bear regimes. Chen (2010) using four measures of oil price: the percentage change of oil price, the Oil Price Increase, the Net Oil Price Increase and the Scaled Oil Price Increase, he found out that higher oil prices lead to a higher probability of the stock markets switching from the bull market to the bear market, as well as staying in the bear regime.

Chen et al. (2013) introduce a macromodel with a finance-macro link which uses multiperiod decisions framework of economic agents. They use a Multi-Regime VAR (MRVAR) to study the impact of financial stress shocks on the macroeconomy in a large number of countries. By studying two regimes of financial stress they find out that in a regime of high financial stress, stress shocks can have large and persistent impacts on the real side of the economy, whereas in regimes of low stress, shocks can easily dissipate having no lasting effects. Aboura et al. (2013) develop a financial stress index for France by taking 17 financial variables that can be used as a real-time composite indicator for the state of financial stability in France. Using a Markov-Switching Bayesian VAR model, they show that an episode of high financial stress is associated with significantly lower economic activity, whereas movements in the index in a low-stress regime do not incur significant changes in economic activity.

Liu (2013) examines the dynamic relationships among different measures of financial risks including expected volatilities in the stock and Treasury bonds market and the gauge of financial stress on a monthly basis. Using a Markov-switching constant transition probability model, he finds a significant relationship between the financial risks and the economic activity as represented by the industrial production (*IP*). He also finds that *MOVE* and not *VIX* impacts *IP* in the conventional (linear) VEC model.

3. Data description

As indicated, this study uses monthly data to examine the interrelationships between economic activity and financial variables in an environment that accounts for economic uncertainty and financial stress. The real economic activity variables are represented by the industrial production per capita (*IPL*), the real private capital stock per capita (*KL*), and the oil price (*OIL*). The financial variables include the real 10-year Treasury note rate (*RIR*), the Federal Reserve Bank of Saint Louis's Financial Stress Index (FSI), and the S&P500 volatility index (VIX). As will be explained in the unit root tests' analysis, the capital stock is integrated of degree two, and thus we have to use capital stock per capita and industrial production per capita which are integrated of degree one. The monthly sample period ranges from 12/1993 to 9/2013.

Table 1 summarizes the notation and sources of the data series used in this study. The real private capital stock (*K*) is sourced from Haver Analytics and then it was transformed from the quarterly to the monthly frequency, using autoregressive integrated moving average (ARIMA) based on the Litterman (1983) method.[30] Employment (*L*) is the total nonfarm payroll and is obtained from the database of the Federal Reserve Bank of Saint Louis. It measures the number of U.S. workers in the economy who contribute to gross domestic product (GDP). The *OIL* represents the West Texas Intermediate price and is sourced from the Energy Information Administration. *RIR* is the difference between the 10-year Treasury constant maturity rate and inflation rate. Both series are obtained from the Saint Louis Fed's data. The financial stress index (*FSI*) measures the degree of financial stress in the markets and is constructed from 18 data financial series, where each of these series captures some aspect of financial stress. The equity

[30] This method is proven to be better than that of Chow and Lin (1971).

VIX, which is sourced from DataStream, is an index that measures expectations of volatility of the S&P500 index over the next 30-day period. It is calculated based on the options on the S&P 500 equity index and quoted in percentage points.[31] It is referred to as the "fear index" in equity market. An increase of *VIX* is usually associated with a decrease in the S&P500 index. The *VIX* usually spikes as stocks go down to capture anxiety in the stock markets.

Figure 1 shows the industrial production per capita, which is also released by the Saint Louis Fed, is an index that measures the real production output in the U.S., having 2007 as the base year. As can be seen in Figure 1, the real capital stock per capita is steady during the years 1994-2000 because both the capital stock and employment increased in those years. Then it started to move up until it peaked in 2009 as the employment dropped while the capital stock continued to rise. Its unusual behavior during last few years reflects a drop in employment more than a change in the capital stock which basically levels off in those years. The real industrial production per capita has generally an upward trend during the sample period. However it has two major bumps: the first one is in 2000-2002 which corresponds to the dot.com technology bubble recession, and the second is in the 2007-2008 which coincides with the great recession. It should be noted that this variable has these drops despite the decrease in employment, which signifies considerable decline in industrial production itself. The real WTI price doesn't change much during the years 1994-2002. Then this price increases sharply until it peaked in 2008. It plunges during the great recession and it recovers after the recession ended but still below its peak in 2008. The real long-run interest rate is highly volatile over the sample period but generally has a decreasing trend. The VIX index stays steady during the sample period except during the great recession 2007-2008 when it jumps up considerably, reflecting the heightened

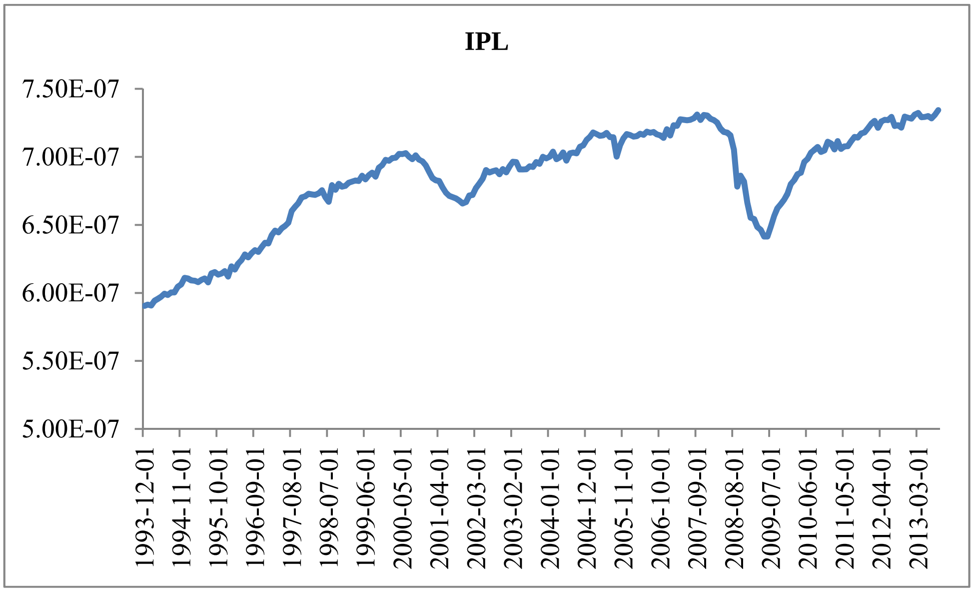
[31] For example, if VIX is 50, one can infer that the index options markets expect with a 68% probability the S&P500 index to move up or down $\frac{50\%}{\sqrt{12 \text{ months}}} \approx 14\%$ over the next 30-day period.

fear during those years. It also jumps at the end of 2010 and 2011. The financial stress index FSI shows a behavior somewhat similar to that of VIX.

Table 1. Variables' Notation

Name	Description	Source	Exog./Endog.
Real Economic Indicators			
KL	Logarithm of Real Private Capital Stock Per Capita	Haver Analytics	Endog.
IPL	Logarithm of Industrial production Per Capita (base year=2007)	Federal Reserve	Endog.
L	Total Non-Farm Employment	Federal Reserve	_____
OII	Logarithm of monthly crude oil spot price (WTI)	Federal Reserve	Endog.
Financial Indicators			
FSI	Financial Stress	Federal Reserve Bank of St. Louis	Exog.
RIR	Real Interest Rate = DSG10-Inflation Rate	Federal Reserve Bank of St. Louis	Endog.
VIX	Chicago Board Options Exchange's Market Volatility Index on near-term volatility of S&P500 stock index	DataStream	Exog.

Figure 1. Trajectories of Considered Variables



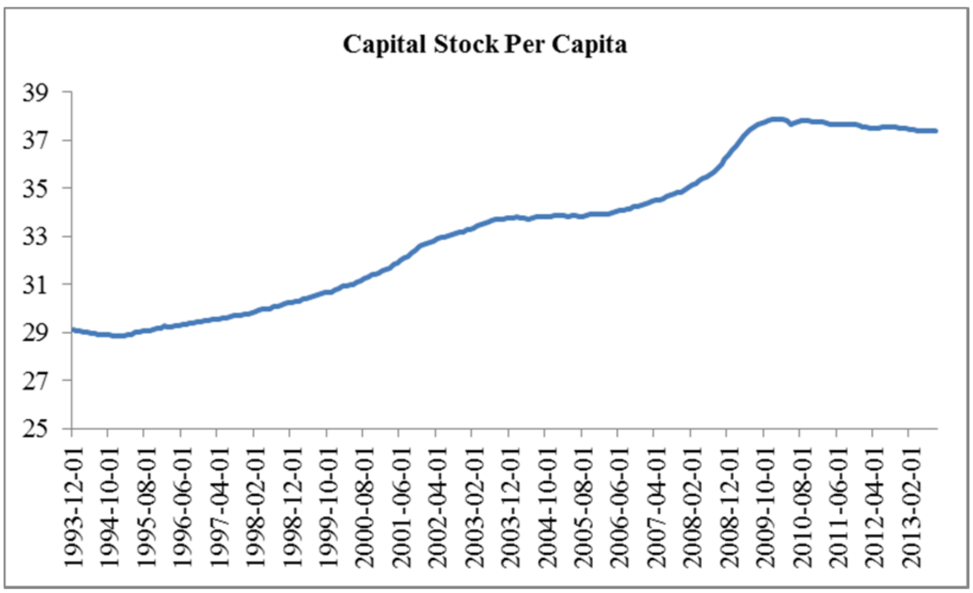
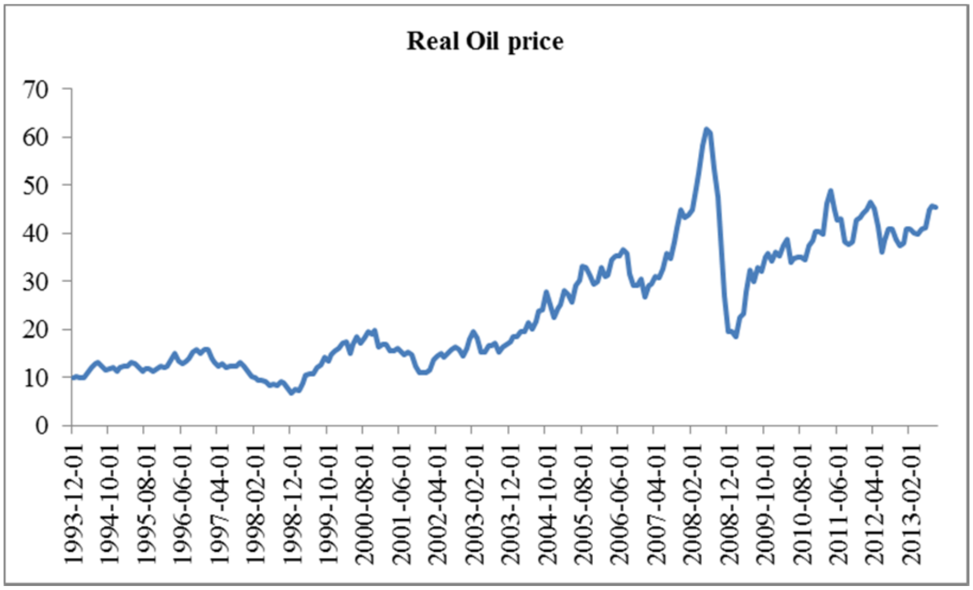


Figure 1 cont'd.



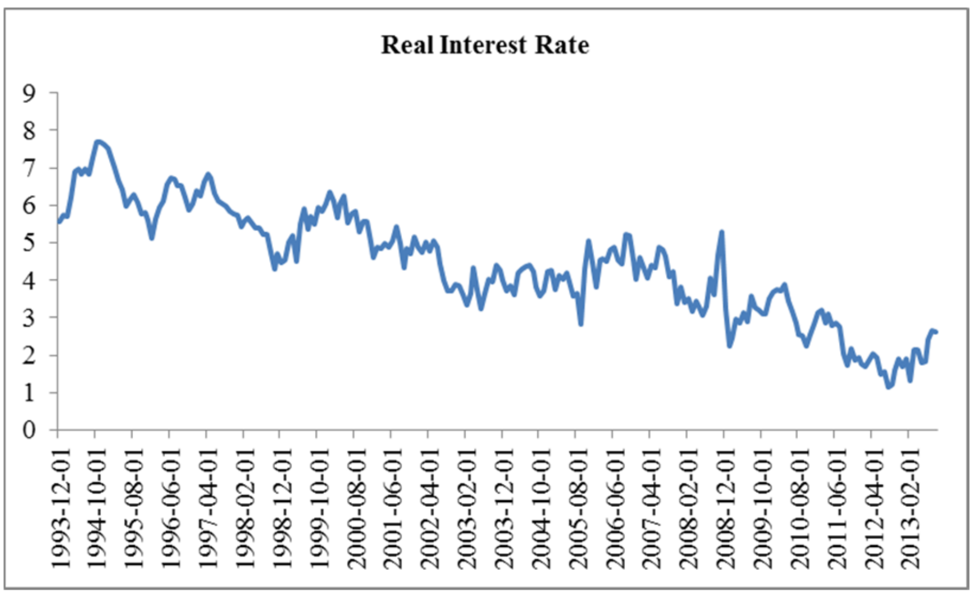
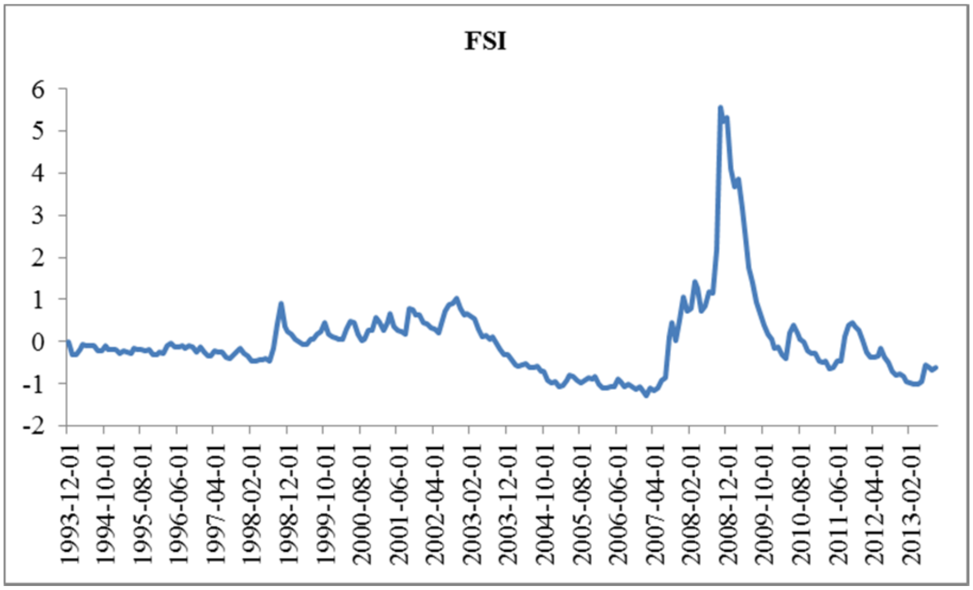
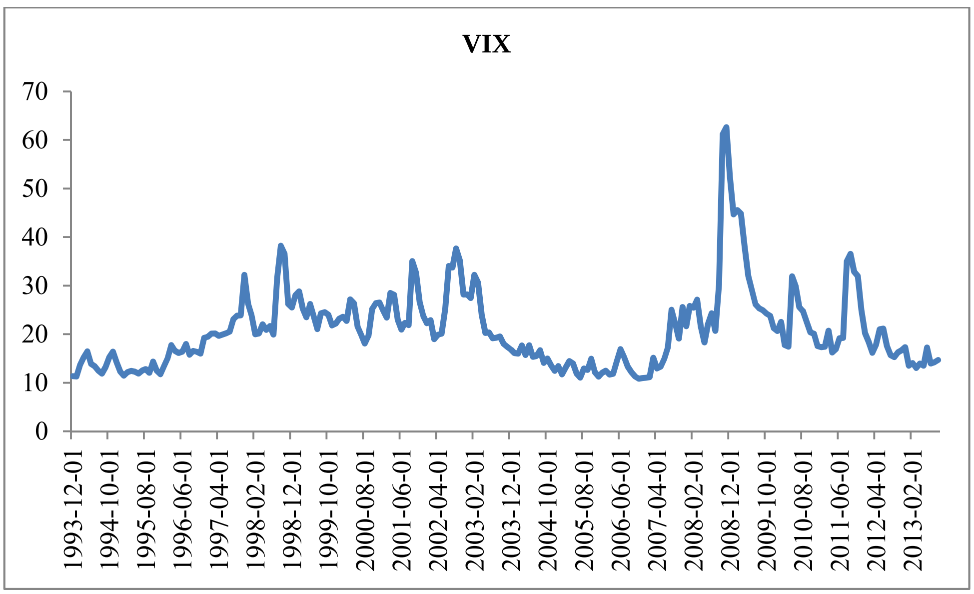


Figure 1 cont'd.





Regarding descriptive statistics (Table 2), the oil price has the highest growth in average, while industrial production per capita has the lowest among the economic variables. The growth for the capital stock per capita comes right before that of the industrial production per capita. On the other hand, the percentage change in real long-run interest rate is negative. In terms of volatility as represented by standard deviation, the real long-run interest rate has more volatility than the oil price while both are much more volatile than the industrial production per capita and the capital stock per capita.

Table 2. Descriptive Statistics

	Real Economic indicators			Financial indicators		
Variable	*DIPL*	*DKL*	*DOIL*	*DRIR*	VIX	FSI
Mean	0.000920	0.001052	0.006419	-0.003163	20.84702	0.014932
Median	0.001100	0.000935	0.014685	-0.007834	19.68750	-0.170000
Maximum	0.018212	0.006269	0.205494	0.500601	62.63947	5.565000
Minimum	-0.039669	-0.003428	-0.323713	-0.491203	10.81762	-1.289000
Std. Dev.	0.006060	0.001470	0.079778	0.113142	8.184033	0.997722
Skewness	-1.620666	0.636963	-0.737485	0.028350	1.803219	2.853865
Kurtosis	12.05056	4.091191	4.736866	6.790446	8.320367	14.51918
Jarque-Bera	912.6366	27.78416	51.27334	141.9106	407.9628	1632.039
Probability	0.000000	0.000001	0.000000	0.000000	0.000000	0.000000
Observations	236	236	236	236	237	237

Notes: All variables except *RIR* and FSI are in first difference of natural logarithm. The sample period is from 1993/12 – 2013/9. The Variables are as follows: *KL* is real private capital stock per capita, *IPL* is real industrial production per capita, *OIL* is oil price, *RIR* is real 10 year treasury note rate, VIX is S&P500 volatility and FSI is financial stress,.

All the variables of interest except *RIR* have asymmetric distributions as revealed by the skewness statistics. The kurtosis statistics for FSI, VIX*, DKL, DIPL and DRIR* are higher than 3, thereby implying that the extreme values for these variables may occur more frequently than would be predicted by the normal distribution. The Jarque-Bera statistics for all variables reject the null hypothesis of normal distribution at the 1% significance level.

We use the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) statistics to test for unit roots among the variables. The results of these tests for both level and first difference are shown in Table 3. The existence of unit roots for *IP* and *L* in level cannot be rejected, while it is rejected for their first differences. This means that they are I(1). On the other hand, the presence of unit roots for the private capital stock (*K*) cannot be rejected in the first difference either which means that K is I(2). This should justify why we are using per capita for capital stock and consistently for industrial production.

Table 3. Linear Unit Root Results

	ADF	PP	ADF	PP
Real Economic Indicators	Level		First Difference	
K	-2.4837	3.5697	-1.1631	-1.8970
IP	-2.4727	-2.0076	-3.5510**	-13.658***
L	-2.0349	-1.7050	-3.2250*	-5.5689***
KL	-2.3877	-2.4583	-3.1395***	-5.3834***
IPL	-2.6931	-2.2280	-4.3016***	-14.905***
OIL	-3.1160	-3.0880	-11.574***	-11.574***
Financial indicators				
FSI	-3.1327**	-2.9327**	-11.483***	-11.459***
RIR	-2.1468	-2.4119	-13.563***	-13.698***
VIX	-3.5613**	-3.8650**	-12.193***	-13.611***

Notes: *, ** and *** denote significance at the 10, 5 and 1 percent levels respectively, at which the null hypothesis of unit root is rejected for ADF and PP tests.

Johansen cointegration test requires that all endogenous variables be I(1). For this purpose, we divide *K* by *L*, and capital stock per capita is I(1). For consistency, we divide *IP* by *L* and get *IPL* which is also I(1). All tests except DF-GLS and ERS support the presence of unit roots in *OIL* which we consider to be I(1). Finally, all tests reject the presence of unit roots in VIX which means it is I(0). However, the ADF and PP tests imply the presence of unit roots for FSI.

4. Empirical Models

To investigate the linkages between the economic and financial variables in an environment of economic and financial uncertainty, we employ linear and nonlinear models. We test for linearity of the vector error-correction model and if this specification is rejected then we opt for using the nonlinear Markov regime-switching model because it can examine the interactions among the variables in both tranquility and turmoil environments.

In order to estimate the models, we start with Johansen's cointegration method for the system that includes IPL, KL, RIR, OIL as the endogenous variable and VIX and FSI as exogenous. The system is based on an aggregate production function which depends on labor, capital stock and energy represented by oil (Hamilton, 2003). This function is modified to include the effect of uncertainty in the financial sector which is represented by the measure of fear and volatility in the stock markets VIX and the financial stress variable FSI as explained earlier. The capital stock is based on cumulative investment which is a function of interest rate and the other variables in the system. Therefore, production decisions are based on a confluence of factors that reflect the interactions of the real and financial sectors in the economy. Then production which is captured by industrial production can be specified by

$$\mathrm{IP_t = f(K_t, L_t, RIR_t, OIL_t, Z_t)}$$

where these variables in this function are defined as before except Z_t which is assumed to be exogenous and represents financial stress and uncertainty. Because of certain stylized facts about the capital stock as explained earlier, we have to express this function in per capita terms for industrial production and capital stock as given by

$$\mathrm{IPL_t = f(KL_t, RIR_t, OIL_t, Z_t)}$$

After estimating the linear model, the linearity of this model will be statistically tested and the nonlinear Markov regime-switching (MS) method will be employed. Using the Johansen (1988, 1991) maximum likelihood procedure to test for cointegration, Table 4 shows that this test suggests two vector error corrections (ECTs). If the results warrant using the MS model, we follow Krolzig et al. (2002) by incorporating the cointegrating properties into the MS model.

Table 4. Estimation of The Linear VEC Model

Data Trend:	None	None	Linear	Linear	Quadratic

Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	1	2*	2	2	2
Max-Eig	1	2*	2	2	2

Coint. Eq.	CointEq1	CointEq2
IPL(-1)	1.000000	0.000000
KL(-1)	0.000000	1.000000
RIR(-1)	-0.311030**	-0.011773
OIL(-1)	-1.512105***	-0.258543***
C	7.275194***	3.019390***

Error Correction:	D(*IPL*)	D(*KL*)	D(*RIR*)	D(*OIL*)
ECT-1	-0.032416***	0.002288***	0.161342	-0.119552
ECT-2	0.075701***	-0.005168***	-0.454348	0.254933
D(*IPL* (-1))	-0.180679***	-0.015684	-4.433990	1.488268
D(IPL (-2))	-0.055570	-0.003628	-15.78229***	0.798216
D(KL(-1))	-0.393629	0.307834***	-19.53683	-2.635001
D(KL(-2))	0.049367	0.313821***	-3.777119	5.818459
D(RIR(-1))	-0.000673	2.58E-05	-0.064434	0.011496
D(RIR(-2))	-0.000310	-3.17E-05	-0.136075***	0.004732

D(OIL(-1))	0.011483***	-0.000711	0.008350	0.182233***
D(OIL(-2))	0.008510*	-0.000234	1.363156***	0.035550
VIX(-1)	0.000187***	3.05E-05***	-0.008137**	-0.002287***
FSI(-1)	-0.003957***	0.000195	0.021404	0.003183
Log likelihood	2420.214			
Akaike information criterion	-20.12097			

4.1. Linear vector error-correction model:

Let X_t denote a *p*-dimensional column of the *I*(1) variables, which follows the following VAR(*k*) process:

$$X_t = A_1 X_{t-1} + A_2 X_{t-2} \dots + A_k X_{t-k} + B_1 Z_{t-1} + \cdots + B_j Z_{t-s} + \mu + \epsilon_t \qquad (1)$$

where μ is a deterministic term. k is the order of lag length and ϵ_t is a Gaussian error term.[32] Vector X includes the endogenous variables *IPL*, *KL*, and *OIL* which are expressed in logarithmic terms. Vector Z includes the exogenous variables VIX and FSI. The VAR(*k*) process can be written in the following VECM representation:

[32] The deterministic time trend can be included as well.

$$\Delta X_{t} = u + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \sum_{j=1}^{s} \varphi_j Z_{t-j} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, \Sigma) \tag{2}$$

where Π and Γ_i are *pxp* matrices of coefficients representing the long-run impacts and the short-run adjustments, respectively. The matrix Γ_i represents the interim multipliers. The hypothesis of cointegration states that the long-run impact matrix, Π, can be rewritten as:

$$\Pi = \alpha \beta ' \tag{3}$$

where α and β are *pxr* matrices. The rows of matrix β form the cointegrating vectors, while matrix α contains the loading factors which are the weights of the cointegrating vectors in the various equations. We will apply the linear VEC model to the monthly data to account for interrelations of the financial variables with the economic activity variables.

We will also use both the Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SC) to determine the VAR and cointegration specifications and the lag lengths. However, if there is a conflict, we use the SC following the literature.

4.2. Tests for nonlinearity

To investigate the linearity assumptions in the VEC models, we will first carry out the multivariate Jarque-Bera residual normality test because if the distribution is not normal, it implies the presence of frequent outliers and frequent structural breaks which are the same properties that a nonlinear model has. This test compares the third and fourth moments of the residuals to those for the normal distribution. If the results reject the null hypothesis that the residuals follow the multivariate normal distribution, then they imply the likely presence of nonlinearity in the VEC model possibly due to frequent structural breaks. This leads one to investigate the presence of regime dependence of the relationships between variables in an MS-VEC model.

Additionally, when a Markov-switching model is estimated, we apply the conventional likelihood ratio LR test and the Davies test developed in Davies (1987) to test the linear specifications of the VEC model versus the non-linear regime-switching specification of the VEC model. The conventional LR test may involve the nuisance parameter problem, which means that when there are unidentified parameters under the null hypothesis, the likelihood ratio statistic does not have the standard asymptotic χ^2 distribution. Therefore, we include the adjusted LR test, known as the Davies (1987) statistics as a cure. The test is used to calculate the approximate upper bound for the significance level of the adjusted LR statistic[33].

4.3. Markov regime-switching VEC model

The linear VEC model discussed above presumes that the long-term cointegration, the short- term adjustments and the impacts of exogenous variables are constant over time. However, this assumption may be questionable since the comovements of relevant variables might be

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[33] Let T denote the LR statistic, m the number of coefficients in the mean that vanish under the null hypothesis, and q the number of transition probabilities that vanish under the null hypothesis, then the conventional LR test is: $P[\chi^2(m+q) > T]$.

The approximate upper bound under the adjusted LR test is given by:

$$P[\chi^2(q) > \mathrm{T}] + 2\mathrm{T}^{1/2} exp\{\left(\frac{q}{2} - 0.5\right)\log(T) - \frac{\mathrm{T}}{2} - \frac{q}{2}\log(2) - \log\left(\frac{q}{2}\right)\}$$

If the adjusted LR test statistic exceeds the approximate upper bound, then the null hypothesis of linear specification is rejected.

subjected to structural breaks or regime changes, particularly when the transmission of risks is under consideration.

In order to account for the regime-dependent effects in our VEC model, we incorporate the Markov-switching methodology by allowing for the presence of regime-dependent error-correction terms, the dynamics of the stationary part, and the impacts of exogenous variables. The model is piecewise linear in each state but nonlinear across regimes. To carry the cointegrating properties derived in the linear VECM to the regime-switching model, we follow the methodology in Krolzig (1997). Krolzig et al. (2002) use a two-step approach for MS-VECM modeling. In the first step, cointegration is established and vector error correction terms (ECTs) are estimated using the Johansen (1988, 1991) maximum likelihood procedure. In the second step, ECTs enter nonlinearly to the MS-VECM. In this approach, the endogenous variables adjust nonlinearly (asymmetrically) to the equilibrium.

We aim to estimate the model with the unobservable discrete state variable s_t, which has two possible states ($s_t = 1 \text{ } or \text{ } s_t = 2$)[34], given as:

$$\Delta X_t = u + \sum_{i=1}^{k-1} \Gamma_i(s_t)\Delta X_{t-i} + \Pi(s_t)X_{t-1} + \sum_{j=1}^{s} \varphi_j(s_t)Z_{t-j} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, \Sigma(s_t)) \tag{4}$$

The endogenous and exogenous variables in this model are defined as in the linear VEC model provided in Eq. (2). The coefficients of the short-run impacts Γ_i, the coefficients of the dynamics of the stationary part Π, the coefficients for exogenous variables, φ, and the variance-covariance

[34] We conduct the LR ratio test and use the Akaike and Schwartz information criteria on the number of regimes. The evidence supports that the number of regimes is two and not three. This result is available upon request.

matrix of the innovations, Σ, are all conditioned on the realization of the state variable s_t (i.e. $\Gamma_i(s_t = 1) \neq \Gamma_i(s_t = 2)$. We place a restriction on the coefficients of the dynamics of the stationary part Π, assuming that only the α component is state dependent, while the β component is state-independent.

To determine the state transition probabilities, we follow Hamilton (1994) to define the transition probability matrix. The matrix is specified as:

$$P = \begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix}, \text{ with } \sum_{j=1}^{2} P_{i,j} = 1 \text{ , and } P_{i,j} \geq 0 \text{ for i = 1, 2,}$$

where the P_{ij} element of the i-th row and j-th column of the above matrix describes the transition probability from state i to state j. The expected duration of regime i is defined as $E(s = i) = 1/(1 - P_{ii})$. A shorter expected duration is usually expected for the high volatility state.

The log-likelihood function is given by the sum of the regime log-densities of the observations conditional on the history of the process:

$$L(\theta|I_t) = \sum_{t=1}^{T} \ln f(x_t\, |I_{t-1}; \theta) \tag{5}$$

with

$$f(x_t|I_{t-1}; \theta) = f(x_t, s_t = 1|I_{t-1}; \theta) + f(x_t, s_t = 2|I_{t-1}; \theta)$$

$$= \sum_{\delta=1}^{2} f(\, x_t|s_t = \delta, I_{t-1}; \theta) prob(s_t = \delta|I_{t-1}; \theta)$$

where I_t is the information set matrix at time t and θ is the set of estimated parameters. The likelihood function is maximized to obtain the estimates of the parameters of the model. There are three commonly used methods used for estimating the parameters of the MS models which are the maximum likelihood (ML), the expectation maximization (EM) and Bayesian Monte

Carlo Markov Chain (MCMC) methods. First, the simplest method is ML but this method is computationally demanding and may have slow convergence. Second, the EM algorithm method is more commonly used for estimation of the MS models. The drawbacks of this method include slow convergence and disability of its algorithm to yield the standard errors directly. Third, the Bayesian MCMC parameter estimation is based on the Gibbs sampling. It may not be possible to compute the full vector of likelihoods for each regime in each period with the ML and EM methods in certain cases. To avoid this problem, the MCMC works only with one sample path for the regimes rather than a weighted average of sample paths over all regimes (for more information see Balcilar et al., 2014). We perform the MCMC integration with 50,000 posterior draws with a 20,000 burn-in draws.

4.4. Impulse response analysis for the MS model

We analyze the dynamic interactions between the real and financial variables using the impulse response function (IRF). Computing the multi-step IRFs from nonlinear time series models is complicated because no ordinary method of computing the future path of the regime process exists. The IRFs of the MS-VEC model should ideally integrate the regime history into the propagation period, which is not easily resolved. Two approaches arose in the literature as a solution to the history dependence problem of the IRFs in the MS-VEC models. For this paper we use the approach of Ehrmann et al. (2003) for regime-dependent IRFs (RDIRF) and we combine it with the Bayesian MCMC integration (Balcilar et al., 2014).

Analogous to the Bayesian impulse responses for the linear VAR models, using the approach of Ni et al. (2007), we derive the posterior density of the RDIRFs from the Gibbs sampling. The simulations of the posteriors of the parameters jointly with the identification of the structural shocks via the Gibbs sampler directly yield the posterior densities of the RDIRFs. The confidence bands are obtained by the MCMC integration with a Gibbs sampling of 50,000 posterior draws with a burn-in of 20,000.

5. Results

We will present the empirical results for the two models specified in the methodology, which are the linear VEC model and the Markov regime-switching model. We will also apply the linearity test to the estimated linear model and determine which model will be statistically rejected.

5.1. Linear vector error-correction model:

The linear VEC model has two cointegrating vectors among the four economic, financial and oil variables under consideration, which suggest that there are two common stochastic trends (Table 4). In both long-run cointegrating (equilibrium) relationships, the oil price (*OIL*) is a loading factor that drives the long-run adjustment of the real industrial production per capita (*IPL)* and the real capital per capita (*KL*) to the equilibrium. Moreover the real long-run interest rate is also a loading factor in the first cointegrating vector. This is not surprising because the interest rate is influenced by the Fed and is a linking variable between the real and financial sectors, while the oil price which is influenced by OPEC affects physical investment as a substitute for capital or as a fuel and the financial variables because of the financialization of the oil market.

In this linear VEC model, both *IPL* and *KL* participate in the correction towards the long run equilibrium, while *RIR* and *OIL* do not. In the short run, *IPL* is influenced by itself, the oil price and the two exogenous financial variables, FSI and VIX. This finding underlines the importance of financial shocks on real economic activity in the short-run and also emphasizes the importance of the financial sector in the real economy. As in the case for *IPL*, *KL* also participates in the error-correction and convergence to the long-run equilibrium but at a much lower speed than *IPL* does. In the short-run, *KL* is affected by itself and VIX only, which also implies less short-run adjustment than for *IPL*. Interestingly, *KL* is not significantly impacted by the oil price, which implies there is not much substitution between this factor and others as a result of changes in the oil price. This may be explained by not having too high oil prices on average to force factor substitution. In contrast to the two real economic variables, *RIR* is not correcting to the equilibrium in the long-run in this linear model. However, in the short-run it is responding to changes in itself, *IPL*, *OIL* and VIX. This also shows that real economic variables can affect financial variables in the short-run due to changes in production and oil prices.

We also apply the adjusted LR test to test the linearity versus non-linear regime switching specifications. The adjusted LR statistics are considerably above the upper bound derived from the procedure in Davies (1987). Therefore, the linear specification of the VEC model should be rejected.

5.2. Markov Regime-Switching vector error-correction model

The results of the linear VEC model without any regime structure may simply capture the average effect or the normal state of the economy, thereby this model is rejected by the linearity test. Within the MS-VEC model, we may likely find the parameter of a particular variable to be significant in one regime while not in another, or it may even reverse its sign across regimes. If this occurs, then the MS-VEC model provides additional insight into the financial and economic dynamics which the linear model cannot provide with its single regime. Moreover, when a structural change occurs, a time-varying process poses a problem for estimation and forecasting in the single regime because there would be a shift in the parameters. This process leads to treating regime-shifts not as a singular event but rather as a system governed by an exogenous stochastic process.

Upon examining the estimation results for the short-run adjustments in Table 5 for the MS-VEC model, the evidence shows the presence of two regimes and two lags. One can realize two findings from the estimation of this model: All the variables under both regimes have many significant relationships; and the relationships are more significant under the first than the second regime. The results show full significant feedback relationships between industrial production per capita, capital stock per capita and real long-run interest rate under the first regime. It is worth noting that VIX which captures fear and volatility in the stock market has a significant influence on the real economic activity and the financial variables except the capital stock per capita under the first regime but it affects all variables under the second regime which is the high volatility regime, underscoring the impact of fear in the stock market on the system. On the other hand, FSI has a significant impact on all real and financial variables under both regimes, but this impact is smaller than that of VIX in the first period under both regimes. Finally, the oil price affects all the variables under both regimes since oil can wear several hats as a factor substitute, a feedstock and a financial variable. The oil price effect on all variables is negative in the first regime particularly on *IPL*, except for the capital stock, which may indicate the presence of small substitution between oil and capital and the expectation of higher inflation.   This effect increases the real-long run interest rate, which implies the oil shock increases inflation expectations. However, the oil impact is mixed in the second regime.

Table 5. Estimation of the MS-VEC Model

Error Correction:	D(IPL)	D(KL)	D(RIR)	D(OIL)
Low volatility regime (regime 1)				
D(IPL(-1))	-0.00271***	0.00143***	-0.52523***	0.031625***
D(IPL(-2))	-0.56391***	-0.02045***	-18.9612***	0.21726
D(KL(-1))	-0.12581***	0.017355***	-5.28191***	-1.88392***
D(KL(-2))	-0.54641***	0.374269***	29.51389***	-15.1474***
D(RIR(-1))	-0.27715***	0.379369***	124.6838***	6.614142***
D(RIR(-2))	0.002566***	0.000332***	-0.20895***	-0.04134***
D(OIL(-1))	-0.00071***	9.98E-05***	-0.16264***	-0.02921***
D(OIL(-2))	-0.00198	0.00313***	-0.85876***	-0.01082
D(VIX(-1))	0.000136	-0.00027	2.613759***	0.005179
D(VIX(-2))	0.000151***	-1.5E-05	-0.0192***	-0.00156***
D(FSI(-1))	-0.00018***	3.11E-05***	-0.01748***	-0.00587***
D(FSI(-2))	0.001394***	0.001265***	0.511776***	-0.02783***
Ect1	-0.00690***	-0.00103***	-0.46838***	0.071659***
Ect2	-0.07666***	0.001032***	1.090648***	-0.56573***
cons	0.175026***	-0.00192***	-2.90024***	1.261271***
Variance	0.0000458***	0.00000103***	0.13932926 ***	0.00567957 ***
High volatility regime (regime 2)				

D(IPL(-1))	-0.0009	0.000461***	-0.03228	0.042395***
D(IPL(-2))	-0.28006***	-0.01182**	5.10928**	-0.5528
D(KL(-1))	0.086827***	0.001335	-4.63656**	-0.39525
D(KL(-2))	-0.42528**	0.337199***	-20.748	-2.83755
D(RIR(-1))	0.113652	0.359182***	22.4996	8.55703***
D(RIR(-2))	0.001796***	-1.4E-05	-0.25595***	0.021109***
D(OIL(-1))	0.001312**	0.000132	-0.15677***	0.017423***
D(OIL(-2))	-0.00295	-0.0015***	-0.26477***	-0.0574***
D(VIX(-1))	0.010466***	-0.00087*	1.141458***	-0.05467***
D(VIX(-2))	0.00017***	7.2E-05***	0.014921***	-0.00508***
D(FSI(-1))	4.78E-05	-4.9E-05***	-0.03903***	0.000274
D(FSI(-2))	-0.00469***	0.000355**	-0.02943	0.129101***
Ect1	0.001426	0.000145	0.158255***	-0.08787***
Ect2	-0.03758***	0.003797***	0.549614***	-0.16493***
cons	0.087459***	-0.00861***	-1.47489***	0.345811***
Variance	0.0000338***	0.0000012***	0.14420381 ***	0.00609372 ***
Transition Probabilities				
P(1,1)	0.069865***			
P(1,2)	0.930134***			
P(2,1)	0.835600***			
P(2,2)	0.164399***			
MS-VEC Model	*Linear VEC*			
Log likelihood	Log likelihood			
2544.3361	2420.214			
Akaike AIC	Akaike AIC			
-20.44541	-20.15815			
LR linearity test:				
LR	Chi-Square p-value	Davies p-value		
333.50664	3.26992e-019	5.96773e-035		

Finally, the real long-run interest rate has also a significant effect on all variables, having a positive effect on the capital stock per capita, oil price and real long run interest rate but a negative effect on industrial production per capita in the first period under the first regime. The positive impact maybe related to having an increase in interest rate when the economy is strengthening. In other words, the positive shock in the interest rate may be due to a strong demand shock in a booming economy. The impact in the next regime is mixed and is not as significant as the first regime. The corrections to the long-run equilibrium are more significant for both cointegrating vectors under the first than the second regime. The speed of adjustment is much higher for the real long-run interest rate than for the real economic and oil price variables under both regimes. This is not surprising as financial assets move faster than economic and oil variables. Moreover, the oil price which represents commodities that have been financialized adjusts faster than the economic variables under consideration. In the second regime, the error correction terms of the second cointegratinig vector are all significant but for the first cointegrating vector they are only significant for the real long run interest rate and the oil price.

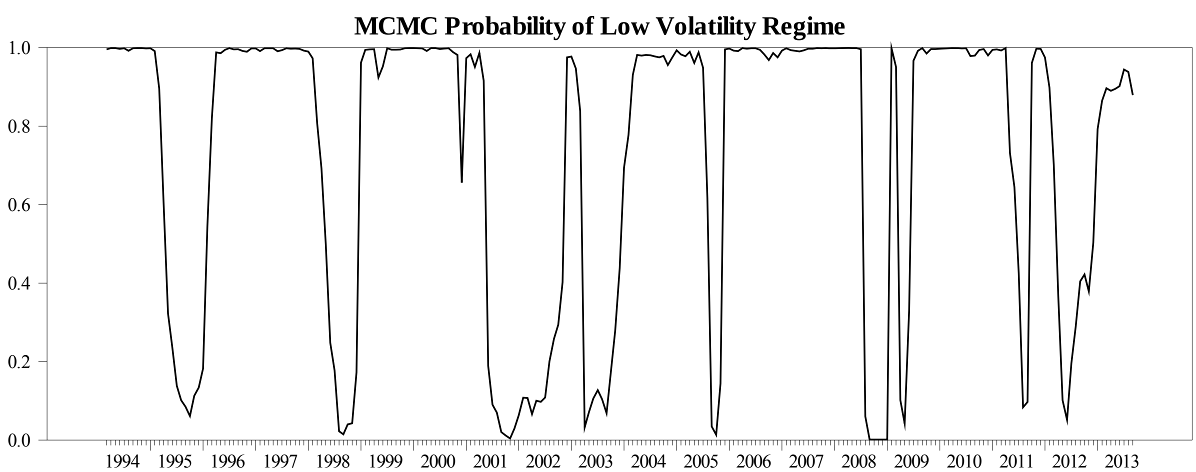
The evidence shows the two regimes have different expected durations.[35] The expected duration of the high variance state (regime 2) is only 65 months, while for the low variance state (regime 1) it is 171 months. Thus, on average the system stays more than 2.5 times as much in the low state as in the high state, as shown in Figure 2 for smooth probability. As expected, during the Septmeber 11, 2001 New York attack, the 2001-2002 dot.com bubble and the 2008-2009 financial crisis, the system stays most of the time in regime 2. However, in the post-Great Recession recovery period and post other crisis periods, the system corrects course and stays in regime 1 (low volatility regime) most of the time (see Figure 2). This finding suggests that the system has started to return back to normality for most of the post crisis periods. It is worth mentioning that the economy has some growth trouble in 2011/2012 where it stays in high volatility regime as uncertainty rises due to lower economic growth. This period coincides with the uero-zone debt crisis.

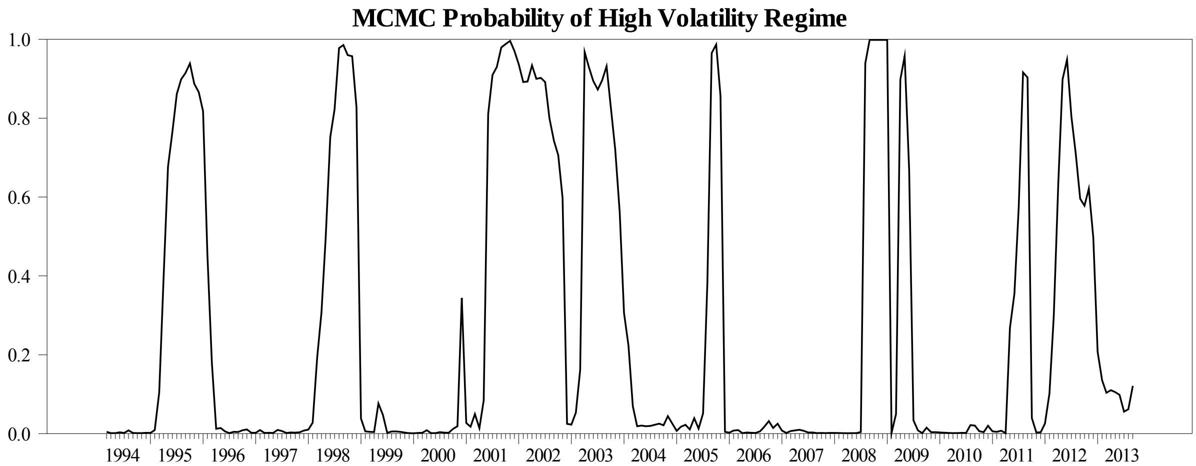
5.3. Impulse response analysis under regime switching

[35] We tested the number of regimes up to 3. The two-regime model is the preferred one by statistical tests. The results are available upon requests.

We perform the regime-dependent impulse response (RDIR) analysis with the 90% confidence bands for the model under two regimes based on 5,000 posterior draws with a burn-in of 2,000. Figure 3 shows the results for the impulse response analysis for the MS-VEC model.

Figure 2. Monte Carlo Markov Chain Transition Probabilities of Low (Regime 1) and High (Regime 2) Volatility Regimes

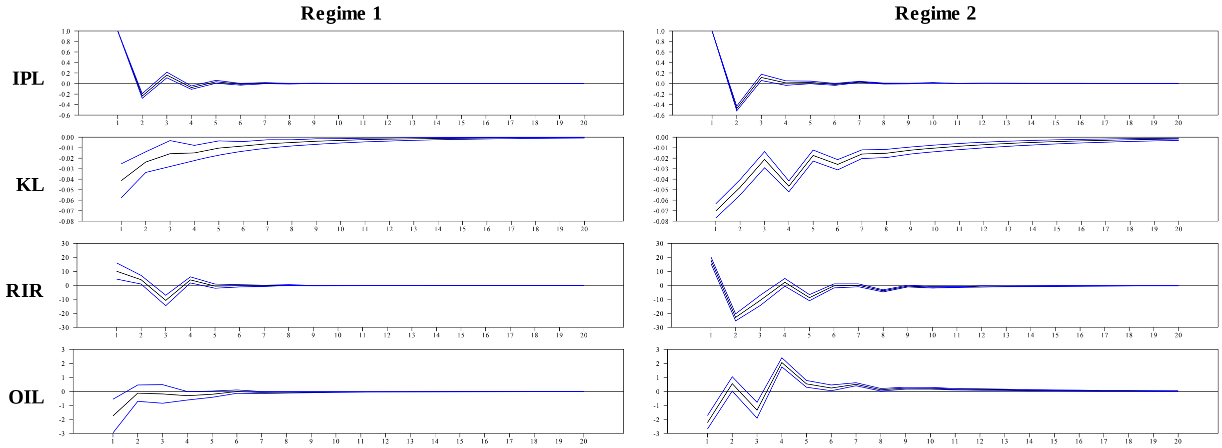




Notes: the monthly time period ranges from December, 1993 to September 2013.

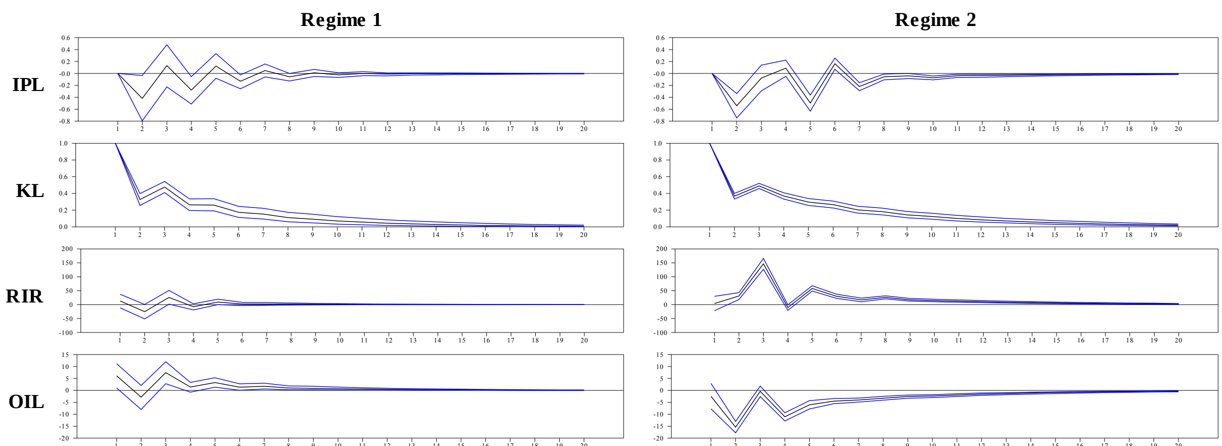
Figure 3. Monthly Impulse Response Analysis

Responses to one unit shock in *IPL* based on the Bayesian MCMC:



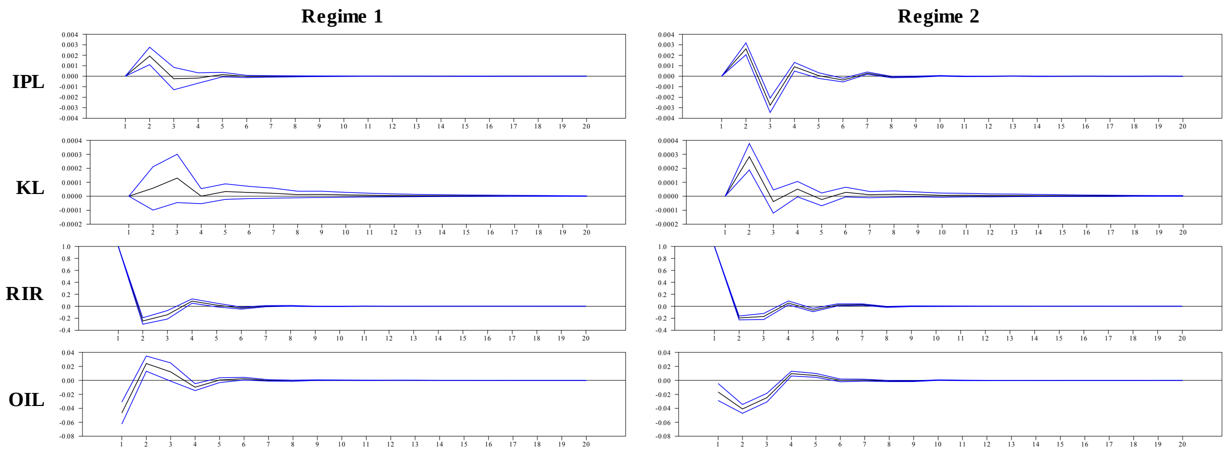
Impulse Responses to IPL

Responses to one unit shock in *KL* based on the Bayesian MCMC:



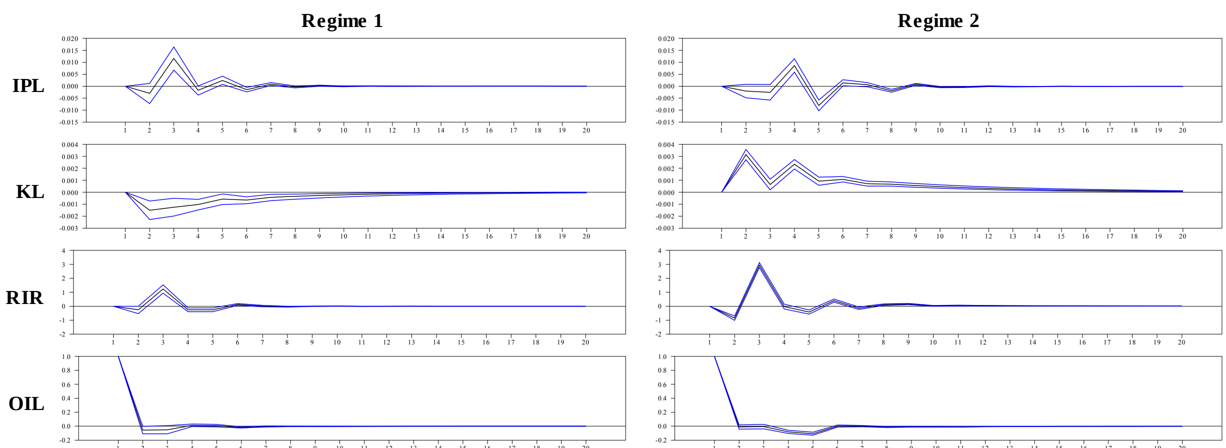
Impulse Responses to KL

Responses to one unit shock in *RIR* based on the Bayesian MCMC:



Impulse Responses to RIR

Responses to one unit shock of *OIL* based on the Bayesian MCMC:



Impulse Responses to OIL

Let us first examine the responses of all variables to a shock from *IPL*. The positive shock to *IPL* may be caused by changes is one or both variables that make up this per capita variable. It may be the result of increases in industrial production or decreases in labor. The responses of *IPL* to a positive shock of its own are significant as they instantly drop and then fluctuate before they stay steady and become persistent after four months under both regimes–However, the instant drop is greater in the second (high volatility) regime but the fluctuations are similar in both regimes. The reactions of *KL* to the positive shock in *IPL* drop initially under both regimes but the KL fluctuations are almost twice as large in the second regime as in the first regime. The drop in the per capita capital under both regimes suggests that as investment decreases industrial production per capita drops. It also implies that the variable that has dropped is more likely the industrial production and not labor. The real long run interest rate initially goes up before stabilizing under both regimes with more fluctuations in the high volatility regime, which collaborates with the declines in industrial production and the capital stock. The three variables join forces and point out that the economy was initially going through a contraction. The oil price, which is also a global factor, drops initially which may suggest that the U.S. initial economic contraction may have global causes.

A shock to the per capita capital stock means a shock to the capital stock, labor or both. When it is positive, it means capital stock goes up or labor goes down. The responses of *KL* to its own shocks are also significant and they instantly drop and then stay steady and persistent as the economy recovers under both regimes. It lasts for 16 months under the low volatility regime and 20 months under the high volatility regime. It is also likely that the drop in the capital per capita is also caused by decreases in investment and not increases in labor. The impact on *RIR* is not significant in the first regime as the response straddles along the horizontal axis but is highly significant and volatile in the second regime. Oil also exhibits a similar response under both regimes.

When it comes to the responses to the *RIR* shocks, it drops considerably after a positive initial own shock. This leads to positive initial responses from both *IPL* and *KL* under both regimes. The oil price initially goes down before it rises and later stabilizes under the normal regime. However this response is different under the second (high) volatility regime as it plunges for two month before it eventually moves up and stabilizes.

The responses of the oil price to its own shocks are initially negative but they recover within few months as *IPL* and *KL* move up. After the initial plunge the oil price moves very close to the horizontal axis and then persists. The responses to the oil shocks are more volatile in the second regime than the first one.

6. Conclusion

The major goal of this paper is to examine and quantify the linkages between real and financial variables in the United States in an environment that accounts for high volatility in the stock market and high stress in financial markets. This objective has been first examined by employing a linear VEC model for the real and financial sides of the economy. This model shows there are some interactions between the variables. However, the linearity test shows that the linear model should be rejected. Therefore, we employ the Markov-switching VEC model to examine the same objective using the Bayesian MCMC method. Many more interactions between the real and economic variables have been found in the low than the high volatility regimes of this model than in the single regime, linear model.

The corrections to the long-run equilibrium are significant for both cointegrating vectors under the first regime. The speed of adjustment is much higher for the real long-run interest rate than for the real economic activity and oil price variables. Moreover, the oil price shows higher speed of adjustment to the long-run equilibrium than the real economic variables due to financialization of its market. These two results together demonstrate that the assets that are traded on the financial markets adjust faster than the real economic variables.

We also employ the (RDIR) function to examine the extent of the responses of shocks to the real and economic variables under the two regimes. We find that the responses and their fluctuations are significantly greater in the high volatility regime than in the low volatility regime. FSI which captures stress in financial markets has a significant impact on all real and financial variables under both regimes, particularly on the real long run interest rate. It seems that increases in financial stress go through the long term interest rate channel first, which in turn affects investment and industrial production per capita. This implication highlights the importance of the financial sector of the economy during stress periods. Financial stress seems to affect the oil market because of increased financialization of this market. The VIX effect is larger than that of FSI in the first lagged period and the opposite is true for the second lagged period under both regimes. High volatility in the stock market as reflected by VIX also affects industrial production per capita, real long run interest rate and oil price under both regimes. VIX does not affect the capital stock per capita under the first regime. This implies that VIX, which measures volatility in the expected 30 days, does not directly affect investment which usually depends on long term decisions. However, VIX affects investment and capital stock in the shorter high volatility regime. Investers fear high volatility.

When it comes to the WTI price, it is interesting to note that this price has a negative effect on all variables under both regimes except the capital stock, which implies that there is a small substitution between oil and capital in the U.S. economy.

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