A triangle of hedging, multi-asset diversification and downside risk strategies for Eurozone stock markets

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Abstract

This paper examines the dynamic dependence, hedge and risk management strategies of bonds, crude oil, gold and VIX futures for the Eurozone stock markets. The multivariate asymmetric dynamic conditional models are used to estimate the time-varying correlations and optimal hedge ratios. Different portfolio strategies under crisis and non-crisis situations are compared to find the best portfolio mix for European stock markets. The results show that hedge effectiveness and portfolio risk management performance of alternate investment avenues are not the same for all markets and when executing different portfolio strategies. The risk management performance of assets also changes under crisis and non-crisis situations, and there is no single hedge asset for all times. These findings provide useful insights for investors for risk management practices.

JEL Classifications: G15; Q43

EFM Classification Codes: 370

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1. Introduction

Stock markets are contagious and heavily interlinked, thus resulting in losses for investors and panic behavior (Kokholm, 2016). A negative shock to one market increases the probability of negative shocks to other markets (Aït-Sahalia et al., 2015). As a result of these extreme loss events, correlation among the various asset classes has increased, and the diversification benefits for global investors have thus been reduced.

The financial innovations in volatility trading markets, e.g., volatility derivatives such as VIX futures, exchange traded products and options make volatility trading more accessible to a broad range of investors (Whaley, 2009). Investors can reduce their losses on equity portfolios by taking a long position in VIX options or futures during economic downturns (Park, 2016).These equity volatility derivatives are considered natural diversifiers due to their remarkable negative correlation with stock markets during crises (Alexander et al., 2016). The explosive growth of volatility products in terms of volume and market capitalization shows the growing demand for tradable volatility derivatives to hedge downside risk (Lin and Lin, 2016).

Volatility trading received immense attention with the introduction of the volatility index (VIX) by the Chicago Board Option Exchange (Whaley, 2013). The VIX index measures the implied volatility of the S&P 500 index options over the subsequent 30 days. Few studies have highlighted the diversification benefits of investing in VIX (McFarren, 2013; Hood and Malik, 2013; Moran, 2014), whereas Deng et al., (2012) found that the diversification benefits of VIX futures for equity portfolios are short lived. Similarly, Alexander and Korovilas (2013) documented that the diversification benefits of VIX futures are limited to periods of high volatility. Husson and McCann (2011) show that volatility related assets do not deliver the required performance because the lack of cash-and-carry-arbitrage cast doubt on volatility exposure. However, Fernandes et al. (2014) find that the VIX has better investment opportunities compared to other derivatives such as CDS and commodity futures.

The present paper, for the first time, to the best of our knowledge, provides a rigorous comparison of the hedging, diversification and risk reduction potential of commodities (gold and crude oil), benchmark bonds and VIX futures for Eurozone stock markets because the recent European sovereign debt crisis has led to the reassessment of the risks of the European financial markets. The crisis also caused fear among investors and asset managers that the governments may default due to rising government deficits and debt levels in several European countries (Bessler and Wolff, 2014). Therefore, investors and fund managers investing in European financial markets have to devise new investment strategies to address the various types of risk.

In this context, the present study adds value to the existing literature in a number of ways: first, we model the asymmetric dynamic conditional correlations between stock markets and different alternative asset classes, i.e., bonds (debt instrument), crude oil (commodity), gold (precious metal) and VIX (volatility derivative); second, we comparatively examine the hedging effectiveness of these alternative assets for five sub-samples to reflect the crisis and non-crisis situations in the stock markets; third, we employ several risk and down side risk measures to determine the significant importance of constructing mixed asset portfolios under different market conditions.

The results highlight that VIX futures offer the best effective hedge and diversification to stock market returns using a specific weightage strategy. In an equally weighted portfolio, bonds outperform crude oil, gold and VIX. However, gold shows better performance for the Greek stock market. Oil futures provided comparatively better performance during the Euro area crisis of 2011-12, when a risk minimizing portfolio strategy was executed. In sum, we show that a full sample based hedge or diversification strategies is prone to losses, and in fact, there is no single solution for all market conditions.

The rest of the paper is organized as follows: Section 2 provides the related literature, and Section 3 discusses the methodology used in this paper. Section 4 describes the data and discusses the estimation results. Finally, we conclude in Section 5.

2. A brief literature review

Liu et al. (2014) explored the European stock markets to construct an optimal portfolio, and they found limited diversification benefits within the Eurozone. However, Cheung and Miu (2010) documented that diversification through commodity futures is only beneficial when they are bullish. Rudolf et al. (1993) found a positive correlation between commodities and stocks in periods of extreme stock market declines. In addition to that, Daskalaki and Skiadopoulos (2011) designed portfolios considering stock, bonds and commodities for in- and out-of-sample analysis to account for the higher moments of the asset returns distribution. They argued that the diversification benefits of commodities are limited to commodity boom periods only. Mull and Soenen (1997), Gueyie and Amvella (2006) and Kroencke and Schindler (2012) show that diversification through alternative asset classes is limited. The main findings of the reported literature are that the global equities and alternative asset classes such as commodities and hedge funds offer limited diversification during episodes of financial downturns.

There was an extensive debate in the early literature on the volatility index, which mainly focused on testing and building pricing models (Zhang and Zhu, 2006; Lu and Zhu, 2010), models to forecast the VIX (Nossman and Wilhelmsson, 2009; Konstantinidi and Skiadopoulos, 2011), examining the term structure (Zhang et al., 2010) and inspecting the causal relation between VIX cash and futures (Shu and Zhang, 2012). The empirical evidence of equity diversification through VIX futures is not only scant but also limited to U.S. investors and equity markets (see, e.g., Chen et al., 2011; Hill, 2013; Jung, 2016). Volatility derivatives such as VIX futures make volatility trading more accessible to a broad range of investors (Whaley, 2000; Szado, 2009; Stanescu and Tunaru, 2012 and Whaley, 2013). The diversification benefits of short and mid-term VIX futures also vary; for instance, Guobuzaite and Martellini (2012) depict that mid-term futures perform better than short-term ones for the European stock markets. Contrary to this, Warren (2012) found that a short-term position in VIX futures significantly increases the sharp ratio of a portfolio composed of U.S. equities and alternative assets. Signori et al. (2010) documented that VIX futures significantly diversify the optimal portfolios compared to the portfolio composed of stocks. More recently, Hancock (2013) used different hedging approaches to evaluate the hedging effectiveness of short-term VIX futures for U.S. equity markets and depicted that the portfolio insurance strategy requires careful choice in the selection of an appropriate tool for optimization.

The most recent study in this vein is by Basher and Sadorsky (2016), in which they compare the hedge effectiveness of different alternate assets (bond, oil, gold and VIX index) for the index representing emerging market stocks. They find that oil provides the best hedge for emerging stock markets. Notably, the authors use the VIX index, which is a non-tradable instrument. We consider the use of the VIX index, instead of the VIX futures, a reason for the findings of oil being the best hedge; the VIX index is an implied volatility index, and it’s very high volatility (in terms of standard deviation) results in lower hedge performance. In fact, hedging through volatility derivatives is only possible by using VIX futures or VIX exchange traded products. We also posit that the calculation of hedge effectiveness for the full sample without disaggregating the crisis and non-crisis situations may also result in misleading conclusions.

3. Methodology

3.1. Asymmetric dynamic conditional correlation estimation

The correlations estimates between stock market returns and different asset returns are obtained using multivariate asymmetric dynamic conditional correlation – the generalized auto-regressive conditional heteroskedasticity (ADCC-GARCH) model proposed by Cappiello et al. (2006).[1] The GARCH-type models enable detecting the changes in correlations if the volatility shocks and returns are substitutes and/or complements. A vector (n × 1) of asset returns (r_t) and an auto-regressive - AR(1) term of the r_t conditioned on the information set I_{t-1} can be written as follows:

$$r_t = \mu + \alpha r_{t-1} + \varepsilon_{t,} \tag{1}$$

The residuals in equation-1 are modeled as $\varepsilon_t = H_t^{1/2} z_t,$ where H_t denotes the conditional covariance matrix of r_t, and z_t is a vector (n × 1) of random errors, i.e., (*i.i.d*). First, the GARCH parameters are estimated, and in the second step, the conditional correlations are estimated. Let

$$H_t = D_t R_t D_t \tag{2}$$

[1] Notably, we also considered the DCC-MGARCH model of Engel (2002) and GO-GARCH of Weide (2002). The dynamic correlation estimates are the same under DCC and ADCC specifications; however, GO-GARCH provides different variations in the dynamic correlations. We finally chose the ADCC-MGARCH model based on different information criteria and only provide the technical details of the final model, i.e., ADCC specifications, for the brevity of space and because it was the best model for all considered countries. The results of the DCC and Go-GARCH models are available from the authors upon request.

where H_t and D_t denote the (n × n) conditional covariance and diagonal matrix, respectively, with a time-varying standard deviation (σ) on the diagonal matrix as follows:

$$D_t = diag\left(h_{1,t}^{1/2}, \dots h_{n,t}^{1/2}\right) \tag{3}$$

and the conditional correlation matrix of an asset returns is shown by R_t and can be written as:

$$R_t = diag\left(q_{1,t}^{-1/2}, \dots q_{n,t}^{-1/2}\right) Q_t diag\left(q_{1,t}^{-1/2}, \dots q_{n,t}^{-1/2}\right) \tag{4}$$

The expressions of h in equation (3) show the conditional variance estimated from the univariate GARCH, and the elements of a diagonal matrix (H_t) with a (1,1) specification can be written as follows:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \tag{5}$$

where the Q_t is a symmetric and positive definite matrix.

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 z_{t-1} z_{t-1}^{'} + \theta_2 Q_{t-1} \tag{6}$$

and the $\bar{Q}$ is the (n × n) unconditional correlation matrix of the standardized residuals $z_{i,t}\left(z_{i,t} = \varepsilon_{i,t}/\sqrt{h_{i,t}}\right)$. However, the non-negative parameters (θ_1 and θ_2) with the exponential smoothing process are constructed to show the mean reverting process of estimated DCCs, if $\theta_1 + \theta_2 < 1$. Then, the correlation estimator is,

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,j,t}}} \tag{7}$$

Furthermore, the asymmetric DCC-MGARCH model of Glosten et al. (1993) as extended by Cappiello et al. (2006) can be written as:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + d_i \varepsilon_{i,t-1}^2 I(\varepsilon_{i,t-1}) \quad (8)$$

The indicator function, i.e., equal to one if $\varepsilon_{i,t-1} < 0$, and 0 otherwise in equation (8), indicated by the $I(\varepsilon_{i,t-1})$ and in A-DCC settings, i.e., if the value for d_i is positive, then the variance will increase more by the negative residuals than by the positive residual. The ADCC models cater to the sudden drops in an asset price and determine whether the bad news increases the volatility more than the good news does.

The dynamics of Q for the ADCC model are given as:

$$Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\overline{Q^-}G) + A'z_{t-1}z_{t-1}' + B'Q_{t-1}B + G'z_t^- z_t^{'-} \quad (9)$$

A, B and G are the (n x n) parameter matrices in equation (10), where the zero-threshold standardized errors z_t^- = $z_t$if <0, and 0 otherwise. The unconditional matrices of z_t and z_t^- are presented by the Q and Q−, respectively.

We investigated the AR(1) in the mean equation in each GARCH model because the financial time series exhibit volatility clustering, autocorrelation and fat tails.

3.2. Hedging effectiveness

Next, we compare the hedge effectiveness of different asset classes using the asymmetric dynamic conditional correlation estimates from the ADCC-MGARCH models. The returns on the portfolios composed of spot and future positions are represented as follows:

$$R_{H,t} = R_{S,t} - \gamma_t R_{F,t} \quad (10)$$

Where $R_{H,t}$ shows the return on hedged portfolio, $R_{S,t}$ and $R_{F,t}$ are the returns on spot and futures positions, respectively, and $\gamma_t$represents the hedge ratio, the number of future contracts that must be sold if the investor is long in the spot position. The variance of the hedged portfolio conditional on the information set at time t−1 is:

$$var(R_{H,t}I_{t-1}) = var(R_{S,t}\mathrm{I}_{t-1}) - 2\gamma_t cov(R_{F,t,}R_{S,t,}\mathrm{I}_{t-1}) + \gamma^2{}_t var(R_{F,t}\mathrm{I}_{t-1}) \qquad (11)$$

The optimal hedge ratios (OHRs) are the γ_t that minimize the conditional variance of the hedged portfolio. The optimal hedge ratio conditional on the information set I_{t-1} can be obtained by taking the partial derivative of the variance with respect to γ_t and setting the expression equal to zero (Baillie and Myers, 1991).

$$\gamma^*{}_t I_{t-1} = \frac{cov(R_{S,t,}R_{F,t,}|I_{t-1})}{var(R_{F,t,}|I_{t-1})} \qquad (12)$$

The conditional volatility estimates from GARCH models can be used to construct hedge ratios (Kroner and Sultan, 1993). A long position in one asset (say asset i) can be hedged with a short position in a second asset (say asset j). The hedge ratio between spot and futures prices is

$$\gamma^*{}_t|I_{t-1} = h_{SF,t}/h_{F,t} \qquad (13)$$

where $h_{SF,t}$ is the conditional covariance between spot and futures returns, and $h_{F,t}$ is the conditional variance of futures returns. The performance of different OHRs obtained from different GARCH models is measured using the hedging effectiveness (HE) index (e.g., Chang et al., 2011; Ku et al., 2007).

$$HE = \frac{var_{unhedged} - var_{hedged}}{var_{unhedged}} \qquad (14)$$

The hedge performance of an asset is determined from its hedge effectiveness (HE), e.g., the higher the(HE) index is, the higher the effectiveness of the model is (Ku et al, 2007; Chang et al., 2011 and Basher and Sadorsky, 2016).

3.3. Risk management strategies

Furthermore, we examine different risk management strategies by constructing different portfolios based on optimal portfolio weights following Reboredo (2013), Hammoudeh et al. (2014), Chkili (2016) and Harrathi et al. (2016). The optimal weights of the portfolio II, subject to a no-shorting constraint, are calculated following Kroner and Ng (1998) and are given as follows:

$$w_t^F = \frac{h_t^S - h_t^{FS}}{h_t^F - 2h_t^{FS} + h_t^S}, \quad with w_t^F = \begin{cases} 0 & w_t^F < 0 \\ w_t^F & 0 \leq w_t^F \leq 1 \\ 1 & w_t^F > 1 \end{cases} \tag{15}$$

The weights of the portfolio III are calculated to follow a variance minimizing strategy, i.e., an investor can take a long position in stocks and short in future assets, i.e., the optimal hedge ratio as in equation-13 and the portfolio constructed using equation-10. The portfolio IV is an equally weighted portfolio designed following DeMiguel et al. (2009) such that equal weights are assigned to stock and other assets in the portfolio. In equation-15, w_t^F shows the optimal weight of the future asset obtained using the estimates of ADCC-GARCH models, and the stock index weights are computed as (1 - w_t^F). The conditional volatility and covariance are represented by (h_t^F, h_t^S) and h_t^{FS}, respectively, in both equation-15, F denotes the future asset, and S represents the stocks.

The risk reduction effectiveness of portfolios (II, III, and IV composed of stock and bond/oil/gold or VIX futures) is assessed by comparing the percentage reduction in the variance with the benchmark portfolio I comprising only stock markets.

$$RE_{Var} = 1 - \frac{Var(P_j)}{Var(P_{\mathrm{I}})} \tag{16}$$

Where $Var(P_j)$ and $Var(P_{\mathrm{I}})$ show the variance of the asset portfolio based on different weights according to the above specifications and the benchmark stock portfolio, respectively. The risk reduction effectiveness takes values between 0 and 1, and a higher value indicates higher risk reduction effectiveness. Moreover, we applied different measures, e.g., value-at-risk (VaR) reduction, expected shortfall reduction, semi-variance and regret reduction to ascertain the diversification effects of bonds, crude oil, gold and VIX futures. The VaR measure provides the information about maximum loss and expected returns of a portfolio at a given time t at a certain level of confidence, i.e., (1-p).

$$\Pr(R_t \leq VaR_t | \psi_{t-1}) = p \tag{17}$$

Hence, the VaR of a portfolio is shown as follows:

$$VaR_t(p) = \mu_t - t_v^{-1}(p)\sqrt{h_t} \tag{18}$$

Where μ_t and $\sqrt{h_t}$ denote the conditional mean and standard deviation, respectively, and $t_v^{-1}(p)$ shows the pth quartile of the t distribution and *v* degrees of freedom. The maximum loss because of exceeding VaR is reported as expected shortfall (ES) and is given as:

$$ES = E\big(R_t \big| R_t < VaR_t(p)\big) \tag{19}$$

Disparate to the variance measures, e.g., assigning equal weights to negative and positive shocks, the semi-variance (SV) approach measures the returns variability that is below a specific threshold, and it is given as:

$$SV = E[min\{0, R_t - E(R_t)\}]^2 \tag{20}$$

Furthermore, the regret reduction (Re) displays the expected return, i.e., below zero are given as follows:

$$Re = -E[min\{0, R_t\}] \tag{21}$$

4. Data and Findings

4.1. Data overview

The data set comprises a large sample of selected stock markets of Europe, namely, Austria, Denmark, Finland, Greece, Ireland, Norway, Portugal, Spain, the Czech Republic and Poland, along with the daily benchmark bond indices denominated in local currencies. The data of gold and oil futures traded at NYMEX and the volatility index (VIX) futures are in U.S. dollars. The continuous future contract type 0 is considered the nearby contract as it switches over on the 1st day of each trading month. The sample spans the period of April1, 2004 to December 31, 2015, a total of 3,066 daily observations, and all the data have been obtained from Thomson Reuters DataStream (Thomson Financials). Table-1 reports the summary statistics of the return series computed as $r_t=\ln(P_t/P_{t-1})$, where P_t and P_{t-1} denote the current and previous day prices, respectively. The average stock market returns are highest for Denmark, Norway and Poland, and as expected, the average stock market returns are lowest (negative) for the Greek stock market. Average benchmark bond returns are the highest for the Czech Republic and, again,the lowest in the case of Greece. Except for the Greece and Ireland bond indices, all stock and bond returns are negative skewed. The obtained returns on gold futures are higher than the crude oil and VIX futures. However, in terms of volatility, the returns series of VIX futures, crude oil futures and Greek stock and bond returns are highest, and the standard deviation of VIX futures is highest among others. The kurtosis values for all returns series are higher than normal, i.e., [3], and highest for the Greek bond returns. The null hypothesis of normality using the Jarque-Berra test is rejected for all cases, and the distributions are non-normal. The ARCH effect is present in all series up to lag 12; thus, our choice of GARCH-type models is appropriate to examine the dynamic dependence among stocks, benchmark bonds, crude oil, gold and VIX.

Table-1
Statistical properties of stock markets, benchmark bonds, oil, gold and VIX returns

	Mean	St. Dev.	Skewness	Kurtosis	J-B	ARCH (12)
Panel A:Stock market returns						
Austria	0.0081	1.5767	-0.2870	9.3442	5,183.8***	1,489.0***
Denmark	0.0441	1.2773	-0.2855	10.1415	6,557.0***	1,320.0***
Finland	0.0076	1.3832	-0.1680	7.6217	2,743.2***	404.7***
Greece	-0.0419	1.9802	-0.2681	9.2696	5,058.3***	274.1***
Ireland	0.0086	1.4664	-0.5995	11.0817	8,527.5***	1,359.0***
Norway	0.0377	1.4689	-0.6228	9.6349	5,822.0***	1,561.0***
Portugal	-0.0115	1.2407	-0.1918	9.9947	6,269.2***	674.3***
Spain	0.0045	1.4484	0.1094	10.0576	6,369.2***	772.8***
Czech Republic	0.0046	1.4412	-0.5531	18.6658	31,508.3***	1,114.0***
Poland	0.0218	1.2296	-0.5146	7.2238	2,414.4***	488.0***
Panel B:Bond market returns						
Austria	0.0116	0.3397	-0.2423	5.7316	983.2***	357.7***
Denmark	0.0102	0.3634	-0.0120	7.4387	2,517.0***	377.3***
Finland	0.0099	0.3306	-0.1192	4.7055	378.8***	628.0***
Greece	-0.0187	1.9477	0.9245	89.7710	962,292.2***	535.1***
Ireland	0.0085	0.5736	0.4957	32.5933	112,004.6***	552.8***
Norway	0.0080	0.3498	-0.2418	7.4435	2,552.3***	702.7***
Portugal	0.0097	0.8207	-0.5886	45.0739	226,321.8***	321.4***
Spain	0.0097	0.4941	0.9808	18.3154	30,456.8***	285.0***
Czech Republic	0.0125	0.3206	-0.0456	21.5748	44,077.6***	162.4***
Poland	0.0103	0.4443	-0.1780	14.4663	16,812.3***	600.3***
Panel C: Commodities and VIX						
Crude Oil	0.0009	2.3153	0.0742	7.8271	2,979.5***	619.0***

Gold	0.0299	1.2112	-0.3885	8.2712	3,626.8***	319.1***
Volatility Index	-0.0032	3.8878	0.6940	6.9673	2,256.8***	440.2***

Note: St. dev. and J-B stands for standard deviations and Jarque-Bera test of normality, respectively. ARCH(12) is the Lagrange multiplier test for autoregressive conditional heteroscedasticity of lag order 12. *** indicate rejection of null hypothesis of normality and ARCH effect at the1% level of significance.

The estimated unconditional correlations of the stock market returns and benchmark bonds, crude oil, gold and VIX are reported in Table-2. The correlations vary substantially across pairs. However, the stocks and VIX pair seems different from the other pairs; the correlation values for this pair are negative and significant for all stock markets. In the case of benchmark bonds and stock pairs, correlation values are negative but smaller than the VIX pair. However, the bonds of Greece, Poland, Spain and Poland have significant positive correlations with their respective stock indices. Crude oil shows a significant positive correlation with all selected European stock markets. In comparison to crude oil, gold shows a weak and even negative correlation in some cases.

Table-2

Correlation of country-wise stock markets with bond, oil, gold and VIX

	Bond	Crude Oil	Gold	VIX
Austria	-0.2432***	0.2889***	0.0961***	-0.3602***
	(-13.876)	(16.705)	(5.3420)	(-21.375)
Denmark	-0.2207***	0.2528***	0.0680***	-0.3221***
	(-12.524)	(14.464)	(3.7701)	(-18.836)
Finland	-0.3636***	0.2687***	0.0710***	-0.3855***
	(-21.607)	(15.444)	(3.9384)	(-23.125)
Greece	0.2746***	0.0506***	0.0248	-0.1365***
	(15.805)	(2.8044)	(1.3709)	(-7.6252)
Ireland	0.0049	0.2084***	-0.0059	-0.3451***
	(0.2706)	(11.793)	(-0.3269)	(-20.353)
Norway	-0.2299***	0.3892***	0.1737***	-0.3391***
	(-13.076)	(23.386)	(9.7633)	(-19.950)
Portugal	0.2047***	0.2602***	0.0418**	-0.3426***
	(11.575)	(14.916)	(2.3135)	(-20.188)
Spain	0.1808***	0.2751***	0.0558***	-0.4031***
	(10.173)	(15.841)	(3.0925)	(-24.379)
C. Republic	-0.0212	0.0875***	0.0314*	-0.2168***
	(-1.1718)	(4.8618)	(1.7413)	(-12.293)

Poland	0.1591***	0.0745***	0.0446**	-0.1543***
	(8.9190)	(4.1341)	(2.4707)	(-8.6463)

Note: Numbers in the parenthesis are t statistics. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

4.2. Empirical findings

The study aims to examine the dynamic hedging properties of bond, crude oil, Gold and VIX for European stock markets. In doing so, we first estimate asymmetric conditional correlations using GARCH models with each including a constant and an AR (1) term in the mean equation. The models were also examined using different distribution assumptions; however, the results are not reported here for brevity. The ADCC models are estimated using a multivariate t (MVT) distribution.

4.2.1. The GARCH Models estimation results

The estimation results of ADCC models are reported in Table-3, where Panels A and B report the coefficients of country-wise stock market and bonds returns, respectively. Panel C shows the coefficients of crude oil, gold and VIX futures. Panel D reports the overall model parameters with different information criterion. The estimates of conditional mean (μ) are positive and statistically significant for stocks, bonds, crude oil and gold and significantly negative for VIX. The Norwegian stock market (VIX) has the highest (lowest) conditional mean. The magnitude of long-term volatility persistence (β) is very high and varies between 0.86 and 0.96, an indication of high long-run volatility persistence over the sample period. The sum of short and long-term volatility parameters ($\alpha + \beta$) is less than 1, which shows the stability of our ADCC specifications.

The estimated asymmetric terms (γ) are positive for all stock and bond markets, except Norway, where they are significant, and thus indicate the asymmetric volatility behavior, i.e., negative shocks have a greater impact than positive shocks of the same magnitude. Chkili et al. (2011) have reported similar behavior for emerging markets including large BRICS. The asymmetric terms (γ) are negative and significant for gold and VIX implying that negative shocks decrease the conditional volatility, which is also consistent with Basher and Sadorsky (2016). These findings indicate that leverage effects are present due to asymmetric information, heterogeneity and/ordue to arbitrage activities. Overall findings of ADCC specifications (Panel D) shown by parameter estimates (θ_1 and θ_2) are positive and statistically significant. Notably, the volatility shocks are asymmetric and vary in magnitude; therefore, the portfolio managers/investors should take portfolio decisions with a particular emphasis on volatility dynamics (Chikili, 2016: Rahim and Masih, 2016).

Table-3
Parameter estimates of asymmetric DCC-GARCH models
Panel A: stock market returns

Country	μ	a	Ω	*a*	*β*	*γ*	*λ*
Austria	0.063***	0.064***	0.035***	0.013	0.906***	0.118***	8.525***
	(0.021)	(0.018)	(0.011)	(0.010)	(0.019)	(0.025)	(1.235)
Denmark	0.076***	0.020	0.050***	0.050***	0.846***	0.142***	7.161***
	(0.017)	(0.019)	(0.016)	(0.015)	(0.032)	(0.034)	(1.042)
Finland	0.057***	0.043**	0.023***	0.003	0.921***	0.118***	7.084***
	(0.019)	(0.019)	(0.008)	(0.008)	(0.017)	(0.025)	(0.893)
Greece	0.053**	0.072***	0.036***	0.072***	0.886***	0.077***	5.794***
	(0.025)	(0.018)	(0.013)	(0.017)	(0.022)	(0.027)	(0.746)
Ireland	0.073***	0.027*	0.021***	0.048***	0.895***	0.089***	7.560***
	(0.017)	(0.019)	(0.007)	(0.013)	(0.018)	(0.024)	(1.086)
Norway	0.075***	-0.001	0.029***	0.030***	0.887***	0.127***	9.601***
	(0.018)	(0.019)	(0.008)	(0.011)	(0.019)	(0.027)	(1.561)
Portuguese	0.045***	0.072***	0.010***	0.044***	0.900***	0.104***	7.281***
	(0.015)	(0.020)	(0.004)	(0.013)	(0.018)	(0.024)	(0.928)
Spain	0.050***	0.022	0.016***	0.000	0.916***	0.151***	7.049***
	(0.017)	(0.018)	(0.005)	(0.009)	(0.017)	(0.027)	(0.842)
C. Republic	0.047***	0.025	0.051***	0.073***	0.848***	0.092***	6.435***

	(0.018)	(0.019)	(0.012)	(0.014)	(0.021)	(0.026)	(0.673)
Poland	0.046***	0.048***	0.018***	0.036***	0.925***	0.050***	6.162***
	(0.017)	(0.018)	(0.007)	(0.010)	(0.017)	(0.018)	(0.676)

Panel B: Bond market returns

Country	μ	a	Ω	*a*	*β*	*γ*	*λ*
Austria	0.014**	0.083***	0.002**	0.046***	0.930***	0.016**	7.805***
	(0.006)	(0.019)	(0.001)	(0.012)	(0.017)	(0.014)	(1.035)
Denmark	0.010*	0.072***	0.002	0.049**	0.939***	-0.003	5.079***
	(0.006)	(0.019)	(0.002)	(0.020)	(0.035)	(0.015)	(0.489)
Finland	0.011**	0.058***	0.001***	0.042***	0.948***	0.002*	9.886***
	(0.006)	(0.019)	(0.000)	(0.007)	(0.008)	(0.011)	(1.598)
Greece	-0.003	0.162***	0.010***	0.145***	0.810***	0.090***	3.907***
	(0.009)	(0.019)	(0.003)	(0.037)	(0.040)	(0.032)	(0.218)
Ireland	0.016***	0.109***	0.003***	0.004	0.932***	0.103***	4.117***
	(0.006)	(0.018)	(0.001)	(0.017)	(0.027)	(0.023)	(0.324)
Norway	0.015***	0.105***	0.002	0.076***	0.922***	-0.035**	3.962***
	(0.005)	(0.019)	(0.002)	(0.032)	(0.036)	(0.017)	(0.302)
Portuguese	0.007	0.159***	0.006**	0.098**	0.864***	0.072***	4.113***
	(0.008)	(0.019)	(0.003)	(0.041)	(0.040)	(0.027)	(0.346)
Spain	0.004	0.112***	0.001**	0.018*	0.944***	0.064***	6.988***
	(0.007)	(0.019)	(0.001)	(0.011)	(0.014)	(0.016)	(0.918)
C. Republic	0.012***	0.088***	0.009***	0.145***	0.789***	0.079*	2.849***
	(0.004)	(0.017)	(0.003)	(0.041)	(0.049)	(0.047)	(0.155)
Poland	0.009**	0.028*	0.013	0.114***	0.820***	0.131**	2.637***
	(0.004)	(0.016)	(0.008)	(0.031)	(0.068)	(0.063)	(0.086)

Panel C: Commodities and VIX returns

	μ	a	Ω	*a*	*β*	*γ*	*λ*
Oil	0.019	-0.040**	0.015**	0.020***	0.952***	0.051***	9.467***
	(0.030)	(0.019)	(0.007)	(0.006)	(0.003)	(0.011)	(1.664)
Gold	0.060***	-0.032**	0.008***	0.039***	0.962***	-0.027***	4.576***
	(0.016)	(0.016)	(0.003)	(0.007)	(0.001)	(0.009)	(0.393)
VIX	-0.307***	-0.012	0.009	0.033***	0.965***	-0.038***	3.369***
	(0.046)	(0.016)	(0.028)	(0.006)	(0.001)	(0.014)	(0.166)

Panel D: Overall model estimates

	θ_1	θ_2	θ_3	*λ*	AIC	BIC	LL
Austria	0.015***	0.971***	0.001*	6.485***	15.85	15.94	-24,246
	(0.002)	(0.005)	(0.001)	(0.275)			
Denmark	0.012***	0.975***	0.000	6.045***	15.66	15.75	-23,950
	(0.002)	(0.006)	(0.001)	(0.245)			
Finland	0.014***	0.974***	0.003**	6.241***	15.57	15.67	-23,821
	(0.002)	(0.006)	(0.001)	(0.252)			
Greece	0.010***	0.984***	0.007**	6.411***	18.37	18.47	-28,116

	(0.002)	(0.004)	(0.001)	(0.277)			
Ireland	0.013^{***}	0.977^{***}	0.005^{**}	6.090^{***}	16.14	16.23	-24,688
	(0.002)	(0.005)	(0.001)	(0.247)			
Norway	0.011^{***}	0.976^{***}	0.002^{*}	6.078^{***}	15.68	15.78	-23,993
	(0.003)	(0.010)	(0.002)	(0.246)			
Portuguese	0.013^{***}	0.978^{***}	0.000	5.881^{***}	16.40	16.49	-25,084
	(0.002)	(0.005)	(0.001)	(0.233)			
Spain	0.013^{***}	0.981^{***}	0.002^{*}	6.468^{***}	16.11	16.20	-24,643
	(0.002)	(0.003)	(0.001)	(0.274)			
C. Republic	0.012^{***}	0.965^{***}	0.003^{**}	5.619^{***}	15.60	15.69	-23,860
	(0.002)	(0.010)	(0.002)	(0.208)			
Poland	0.012^{***}	0.967^{***}	0.004^{**}	5.631^{***}	16.15	16.24	-24,703
	(0.002)	(0.009)	(0.002)	(0.210)			

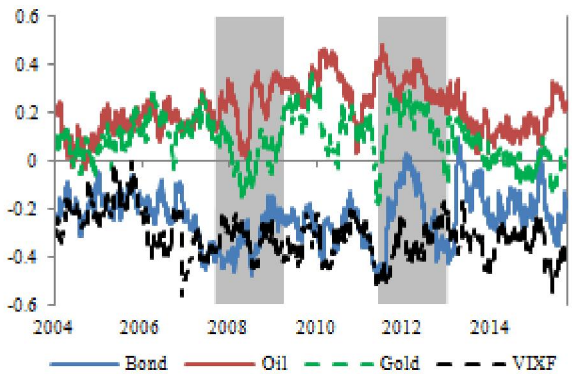
Notes: ADCC estimated using a multivariate t (MVT) distribution. All specifications include a constant and an AR(1) term in the mean equation. ***, **,* indicate significance at the 1%, 5% and 10% levels, respectively. Values in () represent the standard errors.

4.2.2. Dynamic conditional correlations

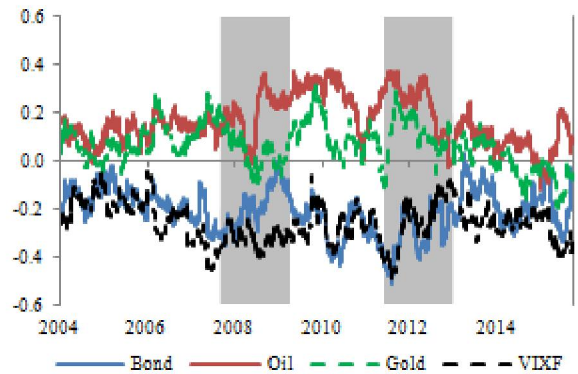
Figure-1 shows the dynamic conditional correlations of country-wise stock market returns with bond, oil, gold and VIX using the ADCC specification. The shaded grey areas indicate the U.S. and Eurozone recession periods dated by the National Bureau of Economic Research (NBER) and the Centre for Economic Policy Research (CEPR), respectively. Four distinct conclusions can be drawn from these plots. First, the correlation of stock markets with oil and gold is positive in most of the cases. Second, the correlation of stock markets with bonds and VIX is negative. Third, significant variations are observed for all correlation pairs. Finally, the correlations suddenly drop/rise before, during and after crisis episodes. These findings are important and suggest that any decision regarding hedge effectiveness of alternate asset classes must not be based on the full sample.

Figure-1: Dynamic condition correlations of stock markets with bond, oil, gold and VIX futures

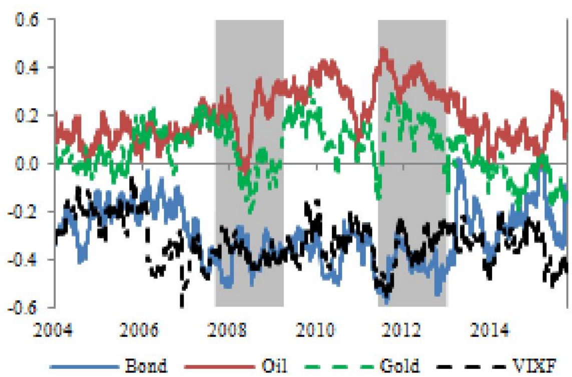
Austria



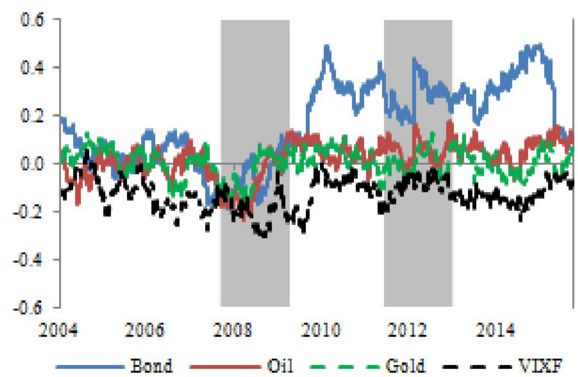
Denmark



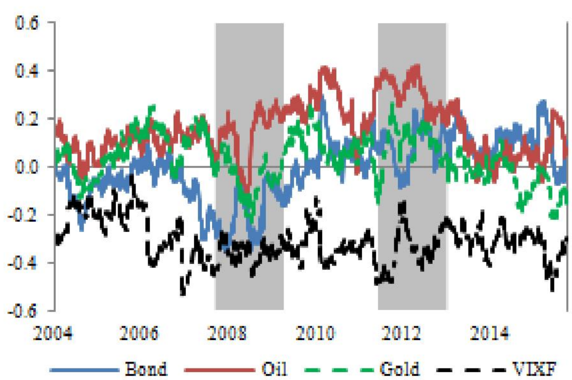
Finland



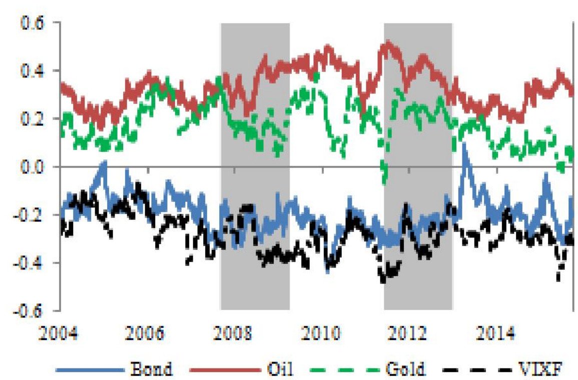
Greece



Ireland

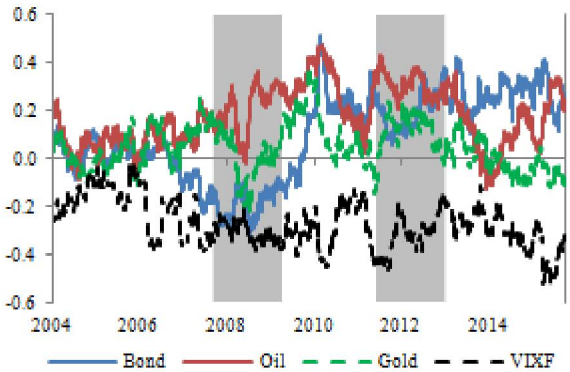


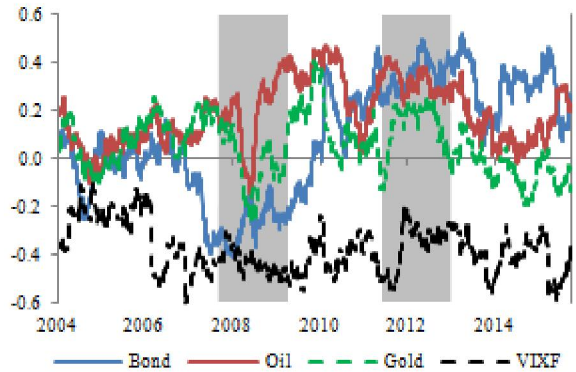
Norway



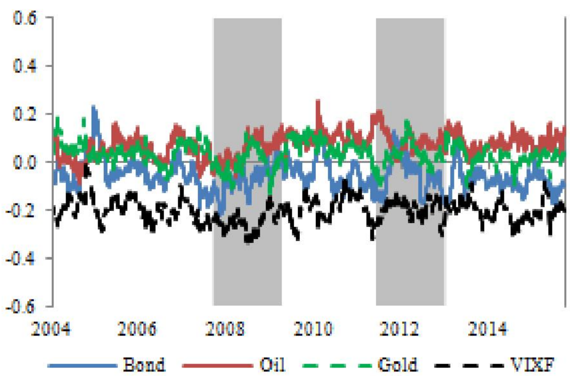
Portugal

Spain

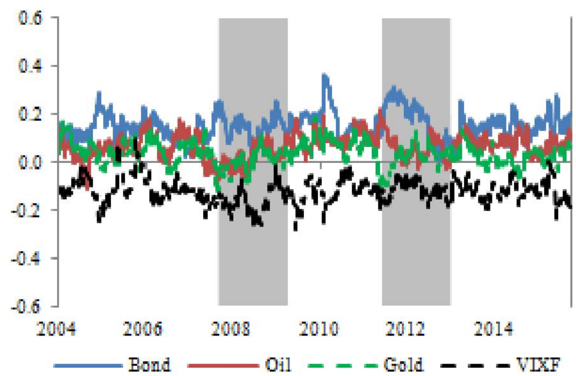




C. Republic



Poland



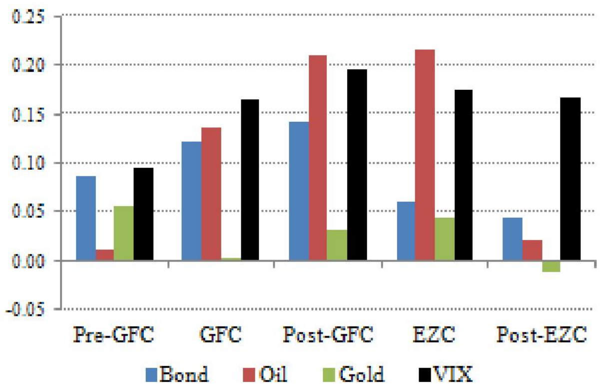
Note: The gray area indicates the 2007/09 US recessions dated by the National Bureau of Economic Research (NBER) and the 2011/12 Euro Area recessions dated by the Centre for Economic Policy Research (CEPR).

4.2.3. Hedge effectiveness

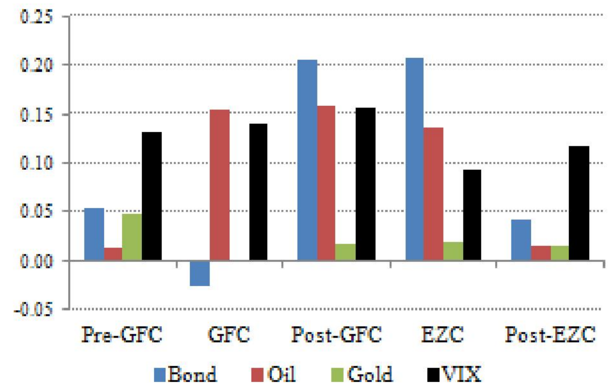
As the findings of asymmetric dynamic correlation analysis reveal, the correlation dynamics change over the five sub-samples (there are five distinct periods in Figure-1, two for crisis and three for non-crisis situation). Hence, the hedge effectiveness of different assets is calculated (using equation-14), and the results are presented in Figure-2, for a better comparison, for five different sub-samples and across selected four asset classes. It is interesting to note that there is no single best hedging asset for all stock markets and for all periods, i.e., crisis and non-crisis situations. This is an important finding and could not have been possible without such extensive analysis.

Figure-2: Hedge effectives of different asset classes for different sub-samples

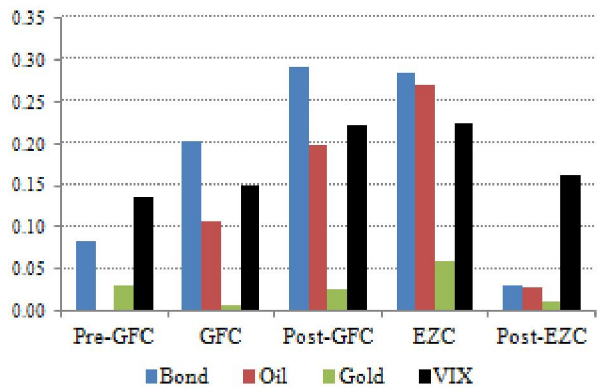
Austria



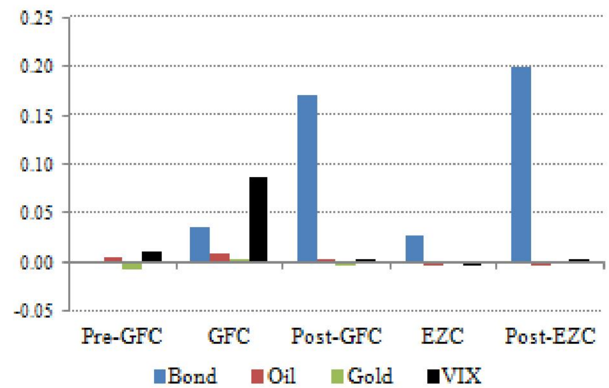
Denmark



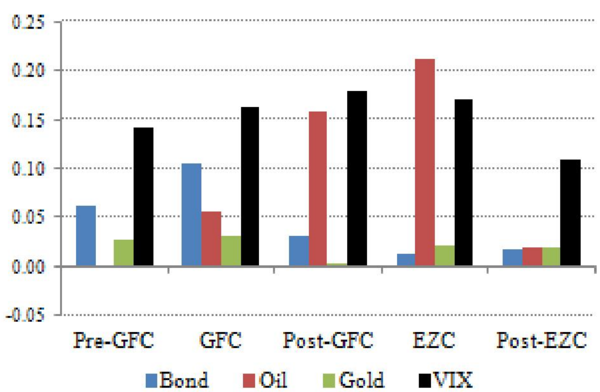
Finland



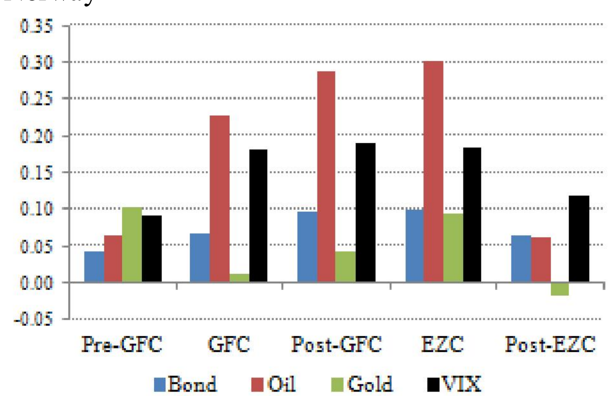
Greece



Ireland

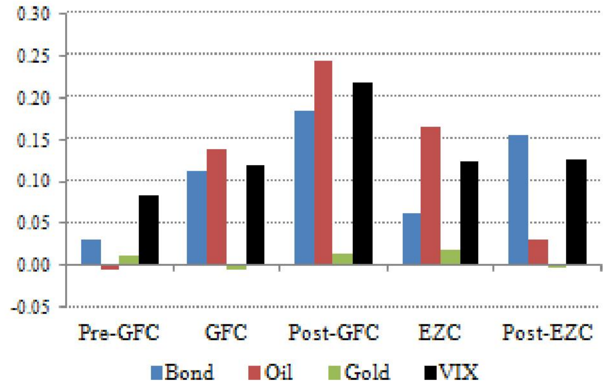


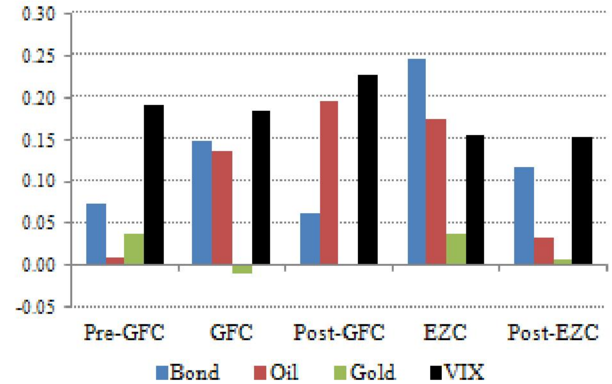
Norway



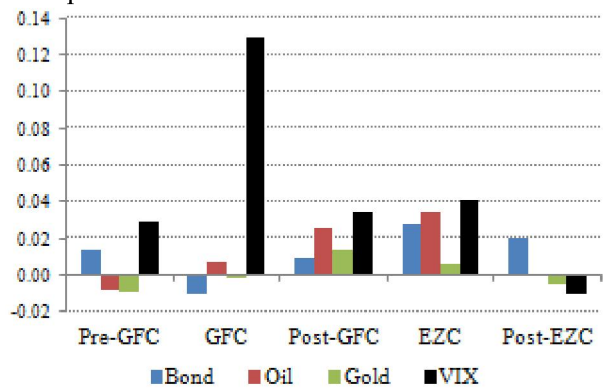
Portugal

Spain

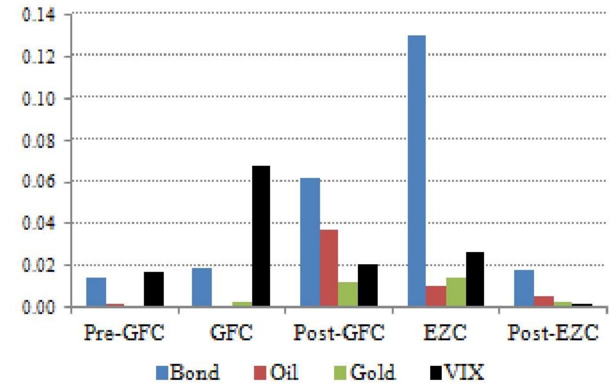




C. Republic



Poland



Note: The GFC indicates global financial crises of 2007-08 dated by the National Bureau of Economic Research (NBER), and EZC indicates Eurozone crisis of 2011-12 dated by the Centre for Economic Policy Research (CEPR).

4.2.4. Risk management implications

Finally, we evaluate the usefulness of benchmark bonds, crude oil, gold and VIX futures in two portfolios whose weights are determined according to equations 10) and 15 and an equally weighted portfolio relative to benchmark portfolios comprising only stock markets. In sum, we consider three different portfolio mixes, four risk and downside risk reduction measures and five sub-samples, to examine the risk reduction and hedge performance of bonds, oil, gold and VIX. Overall, our results show that the benchmark bonds provide a better portfolio to protect all stock markets in an equally weighted portfolio (portfolio IV), except for Greece and Portugal, for which gold performs better. In the case of portfolio II (Kroner and Ng, 1998), VIX futures perform the best in normal times, and bonds performed better during the global financial crisis of

2007-08. Once again, gold provides the best risk management performance for the case of the Greek stock market.

Our results for the gold-stock portfolio are consistent with the reported evidence of Ewing and Malik (2013), Creti et al. (2013), Kumar (2014), Gurgun and Unalmiş (2014) and Arouri et al. (2015), that adding gold to the stock portfolio significantly decreases the downside risk of the portfolio; however, we find that this is only true for Greece and Portugal. Our results are also consistent with Park (2016), that a long position in VIX futures or options can reduce the losses of a stock portfolio. We infer that expansion in volatility derivatives over the last decade is considered a great deal of financial innovation in volatility trading markets. Our results are also consistent with the reported literature (e.g., Brenner and Zhang, 2006; Szado, 2009 and Chen et al., 2011) that the remarkable negative correlation with global stock markets during market stresses is the specific feature of VIX that makes its derivative more attractive and very appealing hedge tools.

Finally, the results of portfolio (III), designed for the variance minimizing strategy, are in line with the hedge effectiveness results as shown in Figure-2. Here we find that oil performs best, in particular, during the Euro-zone crisis of 2011-12. Overall, VIX futures outperform oil, gold and bonds for the majority of cases. Oil performs better for Norway, whereas bonds perform better for the Danish, Finnish and Greek stock markets.

Table-4
The risk performance of assets for European stock markets

Stock markets	Risk Strategies	Portfolio II					Portfolio III					Portfolio IV				
		Pre-GFC	GFC	Post-GFC	EZC	Post-EZC	Pre-GFC	GFC	Post-GFC	EZC	Post-EZC	Pre-GFC	GFC	Post-GFC	EZC	Post-EZC
Austria	VaR	V	B	V	V	V	V	V	O	O	V	B	B	B	B	B
	ES	V	B	V	V	V	G	B	V	O	V	O	V	V	O	B
	RR	V	B	V	V	V	V	V	V	O	V	B	B	B	B	B
	SV	V	B	V	V	V	V	O	V	O	V	B	B	B	B	B
Denmark	VaR	V	B	V	V	V	V	O	B	B	V	B	B	B	B	B
	ES	V	V	V	V	V	V	O	B	B	V	B	V	B	B	B
	RR	V	V	V	V	V	V	V	B	B	V	B	B	B	B	B
	SV	V	B	V	V	V	V	V	B	B	V	B	B	B	B	B
Finland	VaR	V	V	V	V	V	V	B	B	B	V	B	B	B	B	B
	ES	V	V	V	V	O	V	B	B	V	V	B	V	V	B	B
	RR	V	V	V	V	V	V	B	B	B	V	B	B	B	B	B
	SV	V	V	V	V	V	V	V	B	B	V	B	B	B	B	B
Greece	VaR	V	B	G	G	G	V	V	B	B	B	B	G	G	G	G
	ES	B	V	G	O	G	V	V	B	B	B	B	B	V	O	G
	RR	V	V	G	G	G	V	V	B	B	B	B	B	G	G	G
	SV	V	B	G	G	V	V	V	B	B	B	B	B	G	G	G
Ireland	VaR	V	B	V	V	V	V	V	V	O	V	B	B	G	B	B
	ES	V	B	V	V	V	V	V	V	O	V	B	V	V	B	B
	RR	V	B	V	V	V	V	V	V	O	V	B	B	G	B	B
	SV	V	B	V	V	V	V	V	V	O	V	B	B	V	B	B

Note: V= VIX futures; B = benchmark bonds; O= oil futures and G = gold futures. In each cell, we provide the sign of best performing asset. VaR=value-at-risk reduction; ES= expected shortfall reduction; RR= regret reduction; and SV= semi-variance reduction. The GFC indicates the global financial crisis of 2007-08 dated by the National Bureau of Economic Research (NBER), and EZC indicates the Eurozone crisis of 2011-12 dated by the Centre for Economic Policy Research (CEPR).

Table-4
Continued

Stock markets	Risk Strategies	Portfolio II					Portfolio III					Portfolio IV				
		Pre-GFC	GFC	Post-GFC	EZC	Post-EZC	Pre-GFC	GFC	Post-GFC	EZC	Post-EZC	Pre-GFC	GFC	Post-GFC	EZC	Post-EZC
Ireland	VaR	V	B	V	V	V	V	V	V	O	V	B	B	G	B	B
	ES	V	B	V	V	V	V	V	V	O	V	B	V	V	B	B
	RR	V	B	V	V	V	V	V	V	O	V	B	B	G	B	B
	SV	V	B	V	V	V	V	V	V	O	V	B	B	V	B	B
Norway	VaR	V	B	V	V	V	G	O	O	O	V	B	B	G	B	B
	ES	G	V	V	V	O	G	O	O	O	G	B	V	B	B	B
	RR	V	B	V	V	V	V	O	O	O	B	B	B	B	B	B
	SV	V	B	V	V	V	G	O	O	O	V	B	B	B	B	B
Portugal	VaR	V	B	V	V	V	V	O	O	O	B	B	B	G	G	G
	ES	V	V	V	V	V	B	O	V	O	B	B	B	V	O	G
	RR	V	V	V	V	V	V	V	O	O	V	B	B	G	B	B
	SV	V	B	V	V	V	V	O	O	O	B	B	B	G	G	G
Spain	VaR	V	B	V	V	V	V	V	V	B	V	B	B	B	B	B
	ES	O	V	V	V	G	V	V	O	B	V	B	V	V	O	G
	RR	V	V	V	V	V	V	V	V	B	V	B	B	B	B	B
	SV	V	B	V	V	V	V	V	V	B	V	B	B	B	B	B
Czech Republic	VaR	V	B	V	V	V	V	V	V	V	B	B	B	B	B	B
	ES	V	B	V	V	V	V	V	O	O	G	B	V	B	O	B
	RR	V	B	V	V	V	V	V	V	O	V	B	B	B	B	B
	SV	V	B	B	V	V	V	V	O	O	V	B	B	B	B	B
Poland	VaR	V	V	V	V	V	V	V	B	B	O	B	B	B	B	B
	ES	V	V	V	V	V	O	V	V	B	B	O	V	V	G	B
	RR	V	V	V	G	V	V	V	O	B	O	B	B	B	B	B
	SV	V	V	V	V	V	V	V	B	B	V	B	B	B	B	B

Note: V= VIX futures; B = benchmark bonds; O= oil futures; and G = gold futures. In each cell, we provide the sign of best performing asset. VaR=value-at-risk reduction; ES= expected shortfall reduction; RR= regret reduction; and SV= semi-variance reduction. The GFC indicates the global financial crisis of 2007-08 dated by the National Bureau of Economic Research (NBER), and EZC indicates the Eurozone crisis of 2011-12 dated by the Centre for Economic Policy Research (CEPR).

6. Conclusion

We examine the hedging, diversification and risk reduction properties of bonds, oil, gold and VIX for the Eurozone stock markets portfolio. In doing so, we use different specifications of the dynamic correlation models to estimate the dependence between stocks and alternate investments. The asymmetric dynamic correlations vary over the sample period; in particular, especially ups and downs are observed during the global financial crisis of 2007-08 and the Eurozone crisis of 2011-12. Oil and gold (bonds and VIX) have positive correlations with stock markets; however, the dynamic of the Greek stock market is different. The hedging effectiveness is estimated using dynamic correlation estimates under different market conditions, i.e., crisis and non-crisis situations. Furthermore, various risk and downside risk reduction measures are calculated for a comparative analysis. We find that hedging and portfolio diversification opportunities vary when different portfolio strategies are executed. Specifically, bonds perform better in an equally weighted portfolio except for the Greek and Portuguese stock markets, where gold provides better results. In a portfolio with no-shorting constraint, VIX futures outperform other assets, while bonds performed better during the global financial crisis of 2007-08. Again, gold provides the best risk management performance for the case of the Greek stock market. In a hedged portfolio, commodities performed better during the Eurozone crisis of 2011-12. In sum, we suggest that there is no single solution to hedging and portfolio diversification, as normally reported in the literature focusing on a single stock market; rather, investors and portfolio managers must revise their investment decisions considering changing market conditions.

References

Aït-Sahalia, Y., Hurd, T.R., (2015). Portfolio choice in markets with contagion. *Journal of Financial Econometrics*, 14 (1), 1–28.

Alexander, C., & Korovilas, D. (2013). Volatility exchange-traded notes: curse or cure?.*The Journal of Alternative Investments*, 16(2), 52.

Alexander, C., Korovilas, D., & Kapraun, J. (2016). Diversification with volatility products. *Journal of International Money and Finance*, *65*, 213-235.

Arouri, M.H., Lahiani, A., Nguyen, D.K., (2015). World gold prices and stock returns in China: Insights for hedging and diversification strategies. *Economic Modelling*, 44, 273-282.

Baillie, R. T., & Myers, R. J. (1991). Bivariate GARCH estimation of the optimal commodity futures hedge. *Journal of Applied Econometrics*, *6*(2), 109-124.

Basher, S. A., & Sadorsky, P. (2016). Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH. *Energy Economics*, 54, 235-247.

Bessler, W., Opfer, H., & Wolff, D. (2014). Multi-asset portfolio optimization and out-of-sample performance: an evaluation of Black–Litterman, mean-variance, and naïve diversification approaches. *The European Journal of Finance*, 1-30.

Brenner, M., Ou, E.Y., Zhang, J., (2006). Hedging volatility risk. *Journal of Banking & Finance*, 30, 811–821.

Cappiello, L., Engle, R.F., Sheppard, K., (2006). Asymmetric correlations in the dynamics of global equity and bond returns. *Journal of Financial Econometrics*, 4 (4), 537–572.

Chang, C.L., McAleer, M., Tansuchat R., (2010). Analyzing and forecasting volatility spillovers, asymmetries and hedging in major oil markets. *Energy Economics*, 32, 1446-1455.

Chang, C.-L.,McAleer, M., Tansuchat, R., (2011). Crude oil hedging strategies using dynamic multivariate GARCH. *Energy Economics*, 33, 912–923.

Chen, H. C., Chung, S. L., & Ho, K. Y. (2011). The diversification effects of volatility-related assets. *Journal of Banking & Finance*, 35(5), 1179-1189.

Cheung, C. and P. Miu, (2010). Diversication benefits of commodity futures.*Journal of International Financial Markets, Institutions and Money*, 20, 451-474.

Chkili, W., Aloui, C., Masood, O., Fry, J., (2011). Stock market volatility and exchange rates in emerging countries: a Markov-state switching approach. *Emerging Markets Review*, 12, 272–292.

Chkili, W. (2016). Dynamic correlations and hedging effectiveness between gold and stock markets: Evidence for BRICS countries. *Research in International Business and Finance*, *38*, 22-34.

Creti, A., Joëts, M., Mignon, V., (2013). On the links between stock and commodity markets' volatility. *Energy Economics*, 37, 16-28.

Daskalaki, C. and G. Skiadopoulos, (2011). Should investors include commodities in their portfolios after all? New evidence. *Journal of Banking & Finance*, 35, 2606-2626.

DeMiguel, V., Garlappi, L., Uppal, R., (2009). Optimal versus naive diversification: how inefficient is the 1/N portfolio strategy? *Review of Financial Studies*, 22, 1915–1953.

Deng, G., McCann, C. J., & Wang, O. (2012). Are VIX futures ETPs effective hedges?. *The Journal of Index Investing*, *3*(3), 35-48.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3), 339-350.

Ewing, B.T., Malik, F., (2013). Volatility transmission between gold and oil futures under structural breaks. *International Review of Economics and Finance*, 25, 113-121.

Fernandes, M., Medeiros, M. C., & Scharth, M. (2014). Modeling and predicting the CBOE market volatility index. *Journal of Banking & Finance*, 40, 1-10.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, *48*(5), 1779-1801.

Gueyie, J. P., & Amvella, S. P. (2006). Optimal portfolio allocation using funds of hedge funds. *The Journal of Wealth Management*, *9*(2), 85-95.

Guobuzaite, R. and L. Martellini, 2012. The Benefits of Volatility Derivatives in Equity Portfolio Management. EDHEC-Risk Institute publication.

Gurgun, G., Unalmiş, I., (2014). Is gold a safe haven against equity market investment in emerging and developing countries. *Finance Research Letters*, 11, 341-348.

Hammoudeh, S., Nguyen, D. K., Reboredo, J. C., & Wen, X. (2014). Dependence of stock and commodity futures markets in China: Implications for portfolio investment. *Emerging Markets Review*, 21, 183-200.

Hancock, G. D. (2013). Hedging with VIX futures: What is the optimal hedge ratio? *Review of Futures Markets*, *21*(2), 221-245.

Harrathi, N., Aloui, C., Houfi, M. A., & Majdoub, J. (2016). Emerging Equity Markets Connectedness, Portfolio Hedging Strategies and Effectiveness. *International Journal of Financial Research*, *7*(2), 189.

Hill, J. M. (2013). The Different Faces of Volatility Exposure in Portfolio Management (Digest Summary). *Journal of Alternative Investments*, *15*(3), 9-31.

Hood, M., & Malik, F. (2013). Is gold the best hedge and a safe haven under changing stock market volatility? *Review of Financial Economics*, 22(2), 47-52.

Husson, T., & McCann, C. J. (2011). The VXXETN and Volatility Exposure. *PIABA Bar Journal*, *18*(2).

Jung, Y. C. (2016). A portfolio insurance strategy for volatility index (VIX) futures. *The Quarterly Review of Economics and Finance*, 60, 189-200.

Kokholm, T. (2016). Pricing and Hedging of Derivatives in Contagious Markets. *Journal of Banking & Finance*, 66 (2016) 19–34.

Konstantinidi, E., & Skiadopoulos, G. (2011). Are VIX futures prices predictable? An empirical investigation. *International Journal of Forecasting*, 27(2), 543-560.

Kroencke, T. A., & Schindler, F. (2012). International diversification with securitized real estate and the veiling glare from currency risk. *Journal of International Money and Finance*, *31*(7), 1851-1866.

Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. *Review of Financial Studies*, *11*(4), 817-844.

Ku, Y. H. H., Chen, H. C., & Chen, K. H. (2007). On the application of the dynamic conditional correlation model in estimating optimal time-varying hedge ratios. *Applied Economics Letters*, *14*(7), 503-509.

Kumar, D. (2014). Return and volatility transmission between gold and stock sectors: Application of portfolio management and hedging effectiveness. *IIMB Management Review*, *26*(1), 5-16.
Lin, Y. N., & Lin, A. Y. (2016). Using VIX futures to hedge forward implied volatility risk. *International Review of Economics & Finance*, *43*, 88-106.
Liu, T., Hammoudeh, S., & Santos, P. A. (2014). Downside risk and portfolio diversification in the euro-zone equity markets with special consideration of the crisis period. *Journal of International Money and Finance*, *44*, 47-68.
Lu, Z., & Zhu, Y. (2010). Volatility components: The term structure dynamics of VIX futures. *Journal of Futures Markets*, *30*(3), 230-256.
McFarren T., (2013). VIX Your Portfolio. Selling Volatility to Improve Performance. Investment Insights, The Investment Research Journal from BlackRock, 16(2).
Moran, M. T. (2014). Thirty Volatility Indexes: Worldwide Tools to Gauge Sentiment and Diversify Portfolios. *The Journal of Index Investing*, *4*(4), 69-87.
Mull, S. R., & Soenen, L. A. (1997). US REITs as an asset class in international investment portfolios. *Financial Analysts Journal*, *53*(2), 55-61.
Nossman, M., & Wilhelmsson, A. (2009). Is the VIX Futures Market Able to Predict the VIX Index? A Test of the Expectation Hypothesis (Digest Summary). Journal of Alternative Investments, 12(2), 54-67.
Park, Y. H. (2016). The effects of asymmetric volatility and jumps on the pricing of VIX derivatives. *Journal of Econometrics*, *192*(1), 313-328.
Rahim, A. M., & Masih, M. (2016). Portfolio diversification benefits of Islamic investors with their major trading partners: Evidence from Malaysia based on MGARCH-DCC and wavelet approaches. *Economic Modelling*, 54, 425-438.
Reboredo, J. C. (2013). Is gold a safe haven or a hedge for the US dollar? Implications for risk management. *Journal of Banking & Finance*, 37(8), 2665-2676.
Rudolf, M., Zimmermann, H., & Zogg, C., (1993). Anlage-und Portfolioeigenschaften von Commodities am Beispiel des GSCI*Finanzmarkt und Portfolio Management*, 7(3), 339-364.
Shu, J.& Zhang, J.E. (2012). Causality in the VIX Futures Market. *Journal of Futures Markets*, 32 (1), 24-46.
Signori, O., Briere, M., & Burgues, A. (2010). Volatility exposure for strategic asset allocation. *Journal of Portfolio Management*, *36*(3), 105-116.
Stanescu, S., & Tunaru, R. (2012). *Investment Strategies with VIX and VSTOXX*. Unpublished paper, Kent Business School.
Szado, E. (2009). VIX futures and options: A case study of portfolio diversification during the 2008 financial crisis. *Journal of Alternative Investments*, 12, 68–85.
Van der Weide, R. (2002). GO‐GARCH: a multivariate generalized orthogonal GARCH model. *Journal of Applied Econometrics*, *17*(5), 549-564.
Warren, G. J. (2012). Can Investing in Volatility Help Meet Your Portfolio Objectives?. *Journal of Portfolio Management*, *38*(2), 82.
Whaley, R.E., (2013). Trading volatility: At what cost. *Journal of Portfolio Management,* 40, 95–108.
Whaley, R. E. (2009). Understanding the VIX. *The Journal of Portfolio Management*, *35*(3), 98-105.
Whaley, R. E., (2000). The investor fear gauge. *The Journal of Portfolio Management*, 26(3), 12-17.

Whaley, R. E. (1993). Derivatives on market volatility: Hedging tools long overdue. *The journal of Derivatives*, *1*(1), 71-84.

Zhang, J. E. & Zhu, Y. (2006). VIX Futures. *Journal of Futures Markets*, 26, 521–531.

Zhang, J. E., Zhu,Y. & Brenner, M. (2010). The New Market for Volatility Trading. *Journal of Futures Markets*, 30(9), 809-833.