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Essays on heterogeneous news flow on volatility

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Julkaisun nimike

Esseitä heterogeenisen tietovirran vaikutuksesta volatiliteettiin

Tiivistelmä

Tämän väitöskirjan neljä esseetä käsittelevät finanssikriisin vaikutusta rahoitusinstrumenttien tuoton keskiarvolle sekä varianssille. Esseissä tarkastellaan eri strategioiden vaikutusta sijoitus-portfolion suorituskykyyn korkean ja matalan volatiliteetin ajanjaksoina. Ensimmäisessä esseessä tarkastellaan tuottojakauman ensimmäistä momenttia ja hedge-rahastojen parempaa suorituskykyä. Toisessa esseessä, kontrolloimalla tuottojakauman toisen momentin tasoa, hyödynnetään 50 osakemarkkinan indeksituottojen kovarianssimatriisia dynaamisten ehdollisten korrelaatioiden estimointiin. Kolmannessa esseessä S&P 500 -indeksin sekä futuurien päivänsisäisiä havaintoja hyödynnetään varianssin ennustamisessa, jossa huomioidaan tuottojakauman kolmannen sekä neljännen momentin vaikutus ennusteille. Neljännessä esseessä tarkastellaan estimoidun realisoituneen varianssin sisältämän informaation ominaisuutta selittää valuuttakurssien tuottojakauman toista momenttia, jossa estimoitua copula-mallia hyödynnetään suojautumiseen valuuttakurssiriskiltä.

Väitöskirjan kontribuutio on osoittaa informaation vaikutuksen tärkeyttä tehokkaille sijoitusportfolioille. Erityisesti tutkimus huomioi informaatiosisällön vaikutuksen rahoitusinstrumenttien tuotoille korkean sekä matalan volatiliteetin ajanjaksoina. Tutkimusartikkeleissa hyödynnetään aikasarjamalleja tutkimusaineiston informaatiosisällön havainnointiin. Informatiivisesti tehokkaat volatiliteetin estimaatit ovat hyödynnettävissä muun muassa riskien hallinnassa, optioiden hinnoittelussa ja suojautumisen strategioissa.

Asiasanat

Volatiliteetti, dynaaminen korrelaatio, informaatio, riskin hallinta

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Abstract

In the four essays of this dissertation the effect of financial crisis on the financial instruments' mean and variance of price returns is examined. The essays consider the effect of various strategies on the performance of the investment portfolio during the high and low volatility periods. The first essay examines outperformance of the hedge funds where the first moment of the returns distribution is examined. In the second essay by controlling level of the second moment of the returns distribution, it is utilized the covariance matrix structure of 50 stock market index returns for the dynamic conditional correlation estimation. In the third essay the S&P 500 index and futures intraday observations are utilized, where the feature of the third and fourth moments of the returns distribution on the forecasts is considered. The fourth essay examines information content of the estimated realized variance estimator to explain the second moment of the distribution on the currency markets returns by estimated copula model to hedge the currency risk exposure.

The contribution of this doctoral dissertation is to show the importance of information that affects the efficiency of investment portfolios. Specifically, the research acknowledges the information content to the returns of financial instruments during highly volatile periods. Each of the articles uses time series models to identify the information content of the data used. To account for returns variability the resulting information efficient volatility estimates are beneficial for example in risk management, option pricing and for hedging strategies.

Keywords
Volatility, dynamic correlation, information, risk management

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future to come. Last but not least, I like to warmly remember the best friend of mine, Wendi. Certainly, we will have many entertaining moments together in the future.

Vaasa, October 2016

Juha Kotkatvuori-Örnberg

Contents

This dissertation consists of an introductory section and the following four articles[1]:

[1] Printed with permission of Elsevier.

1 INTRODUCTION

An accurate estimate of expected returns is crucial for the profitability of investments. The returns variability that causes uncertain profitability and determines the risk associated with investments is of similar importance. This variability is generally measured by the standard deviation of returns over a specified time period. In addition, in the case of a portfolio of several investments, the co-movement of the volatility of the investment returns is important to the portfolio optimization process. Consequently, the volatility of financial instruments is of interest to both academics and investors.

In statistics, the expected mean value of continuously compounded returns is specified as a first moment of the return distribution, whereas the second moment is the variance. These two moments of the return distribution are the main issues of interest in this doctoral dissertation. I particularly examine the effect of a financial crisis on returns and the volatility of the financial instruments. In addition, the third and fourth moment of the distribution are examined to forecast stock market futures and index returns variance. I utilize the distributional properties of the measured realized variance series, that is, asymmetry and shape respectively in my forecasts.

The four articles of this dissertation examine returns variability during the recent financial crisis. Each of the articles uses time series models in its examination. Considering that the estimated models are fitted to the times series in attempt to capture features of the data implies that the method used are applicable in general. The data used in these studies is possible to characterize as highly volatile but still has relatively long and stable periods. Hence, the high volatility in financial crisis is the research interest in this doctoral dissertation. The first article examines the outperformance of hedge funds on the broad level, considering the returns in the context of aggregated emerging hedge funds with a geographical focus. The second article considers the conditional variance–covariance structure of 50 stock market index returns. It investigates the level of variance of the index returns from six different regions during the financial crisis. The third article uses the S&P 500 index and futures intraday observations for the variance forecasts. To improve efficiency of the volatility forecasts the realized variance distribution asymmetry and shape in optimized structure of the time series model is utilized. The fourth article examines the hedging performance of the estimated time series models. To hedge the risk exposure of the currency portfolios the correlation between the spot and futures is used during the low and high volatility periods.

The contribution of the articles constituting this doctoral dissertation is to show the importance of information that affects the efficiency of investment portfolios. Obviously, information of profitability of investments in the investment portfolio allocation decision is important. Also, it is shown the importance to take into account other essential aspects in the financial decision making. Consequently, this doctoral dissertation extends the work of Maheu and McCurdy (2004), Cappiello, Engle and Sheppard (2006), Christoffersen, Jacobs and Jin (2014) by examining the level of volatility, efficiency of used data in volatility forecasting and method used to estimate covariance of the financial instruments. Common for these studies are assessments of profitability of investment portfolios, diversification benefits and information that affects covariance of the financial investments. In this doctoral dissertation the issue of information is approached by examining the statistical moments of the returns distribution during the financial crisis period. Specifically, the research acknowledges the importance of information content to the returns of financial instruments during highly volatile periods. Each of the articles uses time series models to identify the information content of the data used. To account for returns variability the resulting information efficient volatility estimates are beneficial also in risk management, option pricing and for hedging strategies.

The first article examines the information content by focusing on hedge fund managers with considerable expertise in their chosen market. These portfolio managers, who are focused geographically on emerging hedge funds, have an information advantage that results in improved investment performance. This means investors invest in better performing emerging-market hedge funds, hence facilitating more profitable portfolio allocation decisions. In the second article, the information content of 50 index returns is compared to estimate the conditional correlations. For the dynamic conditional correlations, the variance–covariance structure of the index returns is used. In the third article, the information content of intraday returns is used to measure the realized variance. In order to improve efficiency of the volatility forecasts the measured realized variance series is utilized in the optimized structure of the ARFIMA model. The rating of efficiency is based on the assumption that the predicted volatility encompasses all relevant information of the future volatility. The fourth article investigates the performance of the time series models applied to hedge the risk exposure of currency portfolios. The estimation results indicate superiority of the of the bivariate Copula-EGARCH-DCC model in portfolio variance reduction. Hedging efficiency can be attributed to the information content of the realized variance estimators included in the variance equation of the model.

Prior research has examined the volatility of financial instruments and the related informational efficiency (e.g., Jiang & Tian, 2005; Becker et al., 2006, Wu et al., 2015). Numerous models have been developed to address volatility including examples to forecast volatility, price options, and those used for risk evaluation. In addition, the information content of the implied volatility inferred from the option prices has been examined (e.g., Canina & Figlewski, 1993; Fleming, 1998). In their research, the predictive content of the implied volatility relative to historical conditional volatility has been considered. This area of research of the information efficiency is commonly related to improvements in the investment portfolio selection and volatility forecasts (e.g., Cao & Jayasuriya, 2011; Chung et al., 2011; Bordignon & Raggi, 2012).

Numerous studies have examined financial asset returns in volatile periods. Abugri and Dutta (2009) examine investment performance differences of hedge funds before and after crisis period. They report that for the post-crisis period the performance of emerging-market hedge funds did not differ from advanced market hedge funds. Ehrmann, Fratzscher and Rigobon (2011) examine the transmission of financial shocks between the U.S.A. and the Eurozone area over the period 1989–2004. They find evidence of domestic and international shock spillovers within different asset classes and across financial assets. Several studies examine the effect of the financial crisis on asset returns (e.g., Baba & Packer 2009; Clements et al., 2014) and particularly the effect of the crisis on volatility. In addition, many studies share common subjects, such as how the advent of new information is considered an information shock to the financial markets. The arrival of new information and changes to the volatility of returns of financial instruments is the subject of several studies (e.g., Kumar, 2013; Ma & Wohar, 2014; Puy, 2016).

The remainder of the introduction is organized as follows. Section 2 discusses the impact of information on returns volatility and the relation of volatility and the interdependence of the financial markets. Section 3 introduces the effect of the global financial crisis on asset returns and cross-market correlations. Section 4 presents the summaries of the three constituent articles, and finally, section 5 unites the discussion of the subject of this dissertation.

2 VOLATILITY IN THE FINANCIAL MARKETS

2.1 Impact of heterogeneous news flow on asset returns volatility

This section introduces the concept of volatility and the impact of information arrival on market uncertainty. In earlier studies, Ederington and Lee (1993) examine information and the effect of uncertainty on interest rates and foreign exchange futures markets. Maheu and McCurdy (2004) examine the dynamics of volatility and the importance of the information arrival process on the price movements of financial assets. Obviously, the impact of new information causes uncertainty and has serious consequences for financial markets during a crisis period (e.g., Bartram & Bodnar, 2009; Dooley & Hutchison, 2009; Billio & Caporin, 2010; Chudik & Fratzscher, 2011; Schwert, 2011; Syllignakis & Kouretas, 2011). Therefore, the impact of financial market volatility on investment decisions such as derivative pricing, risk management, and portfolio selection should be taken seriously.

The uncertainty known as a risk is measured by the standard deviation of continuously compounded returns of a financial instrument over a specified time period. Volatility is generally referred to as the standard deviation of returns in the literature. Typically, volatility is calculated from a time series of historical market values or derived from the market price of a derivative (see e.g., Christensen & Prabhala, 1998; Day & Lewis, 1992). Bollerslev (1986, 1990) introduced the generalized autoregressive conditional heteroscedasticity (GARCH) model to estimate conditional volatility in financial markets. The success of the model in capturing information content for conditional volatility estimation led to the development of several extensions of the model, such as multivariate and asymmetric variance models. The GARCH model showed its superiority in volatility estimation over the traditional unconditional models (see e.g., Kroner & Sultan, 1993; Chakraborty & Barkoulas, 1999; Lien et al., 2002).

Harry Markowitz (1952) in his seminal work of Modern Portfolio Theory (MPT) states that an investor's decision is based solely on the first and second moment of a probability distribution, that is, the mean and the variance.[2] The selection of asset proportions for the portfolio of investments requires that the expected risk-return relation is optimized. To make successful investment decisions, it is essential to capture all relevant information to estimate the asset expected return and variance.

[2] The theory assumes that the asset returns are normally distributed random variables.

2.2 Correlation in the financial markets

This section introduces the unconditional and conditional correlation functions commonly used to describe the interdependence observed in the financial markets (e.g., Hon et al., 2004; Syllignakis & Kouretas, 2011), and the constant conditional correlation (CCC) model proposed by Bollerslev (1990) and the dynamic conditional correlation (DCC) model by Engle (2002) are also worthy of mention. Several procedures exist to aid correlation estimation, hence a brief review of fundamentals is presented below.

The Pearson product moment correlation measures linear dependence between two covariance stationary random variables. As an example, the variables *x* and *y* over a specified time period at time *t*, the time-invariant unconditional correlation is defined as

(1) $$\rho_{x,y,t} = \frac{E\left(x_t - E(x_t)\right)\left(y_t - E(y_t)\right)}{E\left(x_t - E(x_t)\right)^2 E\left(y_t - E(y_t)\right)^2} \; .$$

Linear dependence can be expressed as a conditional on a previous information set. For the variables *x* and *y* at time *t+s* conditional on information available at time *t*, the conditional correlation is defined as

(2) $$\rho_{x,y,t+s/t} = \frac{E\left(x_{t+s} - E(x_{t+s})\right)\left(y_t + s - E(y_{t+s})\right)}{E\left(x_{t+s} - E(x_{t+s})\right)^2 E\left(y_{t+s} - E(y_{t+s})\right)^2} \; .$$

Bollerslev (1990) introduced the constant conditional correlation (CCC) model, where the correlation of the matrix R is a time-invariant constant correlation between each pair of variables. The covariance matrix is defined as

(3) $$H_t = D_t R D_t, \quad \text{where} \quad D_t = diag\left(\sqrt{H_t}\right)$$

is a diagonal matrix of time-variant standard deviations.

Engle (2002) introduced the two-step procedure for the time variant conditional correlation estimation, defined as follows

(4) $$H_t = D_t R_t D_t, \text{ where } \quad D_t = diag\left(\sqrt{H_t}\right)$$

is a diagonal matrix of time-varying standard deviations, R_t is a conditional correlation matrix of the standardized residuals from the first-step estimation and is obtained as follows,

(5) $$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}$$

(6) $$Q_t = (1 - \alpha - \beta)\hat{Q} + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta Q_{t-1},$$

where $\hat{Q}$ is the $N \times N$ matrix constructed from the unconditional covariance of standardized residuals ε_t.

The advantage of the DCC model is its ability to capture the dynamics of the covariance between variables (e.g., Bauwens et al., 2006; Pelletier, 2006; Christoffersen et al., 2014). This property can be seen as the model's superiority over the CCC model. However, some controversial results suggest an outperformance for the constant correlation model (see Baillie & Myers, 1991; Kroner & Sultan, 1993; Park & Switzer, 1995; Choudhry, 2004).

2.3 Realized variance

This section introduces the concept of realized variance of returns that both academics and practitioners utilize in risk estimation. The asset returns variance or its square root, the standard deviation, is a common measure of risk. Generally, high-frequency observations computed as a sum of squared intraday returns are used to measure realized variance (Andersen & Bollerslev, 1998; Barndorff-Nielsen & Shephard, 2002). Intraday returns within a defined time interval, such as one hour, a minute or a number of seconds can be used. The efficiency of the risk measure is commonly attributed to the information content, that is, whether the measured volatility incorporates all relevant information on the underlying asset return's variability (see e.g., Jiang & Tian, 2005; Becker et al., 2006, 2007).

The general approach found in the literature to estimate volatility involves modeling the logarithm of the realized variance series directly in the autoregressive fractionally integrated moving average (ARFIMA) model (Andersen et al., 2001, Areal & Taylor, 2002; Andersen et al., 2003; Martens & Zein, 2004). The long memory properties inherent in the logarithm of the series in process of the model are utilized. Another method is to include measured realized variance series as an external additional explanatory variable in some already existing volatility model, such as the GARCH model (Martens, 2002; Zhang & Hu, 2013). In these studies, the realized variance series property to incorporate information for more efficient volatility estimates is generally utilized.

The autocorrelation effect on the realized variance has been widely investigated. The market microstructure effect, such as the effect of non-synchronous trading, bid-ask spread, and discreteness of the data causes bias to the measured realized variance series. The bias in turn adversely affects the accuracy of volatility estimates. Microstructure effects are not common at lower frequencies within the defined time interval, for example daily or weekly observations. However, autocorrelation at higher frequencies is very common (Stoll & Whaley, 1990; Zhou 1996; Campbell et al., 1997; Hansen & Lunde, 2006).

Extant research addresses various methods available for estimating volatility in the context of realized variance (Zhou 1996; Campbell et al., 1997; Hansen & Lunde, 2006; Bandi & Russell, 2008; Andersen et al., 2011). The object of the current research is to measure volatility efficiently to obtain accurate estimates of the underlying asset returns variability. In highly volatile financial periods such as during a financial crisis or in more tranquil periods, it is essential to achieve accurate estimates of volatility for profitable financial decision making.

3 IMPACT OF THE FINANCIAL CRISIS ON ASSET RETURNS

3.1 Asset returns in volatile markets

This section introduces empirical findings on and the implications of the global financial crisis on asset returns. The effect of the financial crisis has been widely reported, for example, research has examined the effect on stock markets (e.g., Kenourgios et al., 2011), foreign exchange markets (Baba & Packer, 2009; Melvin & Taylor, 2009; Fratzscher, 2009) and fixed income markets (Dwyer & Tkac, 2009; Acharya et al., 2009; Hartmann, 2010). The volatility of expected returns is commonly associated with the risk of returns. Investors expect to be compensated for bearing the risk of uncertain returns, suggesting that the level of returns is dependent on its variance. Recognition of this phenomenon prompted substantial interest in the variance-in-mean model (Engle et al., 1987) that enables the risk-return relationship of the financial instruments to be estimated simultaneously (French et al., 1987; Bali & Engle, 2010).

Accurate estimates of an expected returns, volatility and recognition of the risk-return relation are essential for investors' financial decision making. In addition, the literature cited above documents increased volatility in the financial markets during crisis periods. In addition, the co-movement of the market's volatility adversely affects diversification benefits, which are observed especially in the equity markets (Braun et al., 1995; Christiansen, 2000; Cappiello et al., 2006). Hence, several studies have specialized in modeling time-varying dynamics purposefully to account for the changes in variance and the co-movement of markets in the volatility estimation (e.g., Engle & Colacito, 2006; Kearney & Potì, 2006; Syllignakis & Kouretas, 2011).

The interdependence of international financial markets gave rise to several studies examining cross-market spillover effects, and the development of multivariate autoregressive models. The Vector Autoregressive (VAR) model is utilized for the initial examination of financial markets (Cha & Cheung, 1998; Janakiramanan & Lamba, 1998). Hamao et al., (1990) estimate the univariate GARCH-in-mean model to examine the spillover effect between the U.S., UK, and Japanese stock markets. The multivariate GARCH models allow for the modeling of causalities in variances. In the model estimation a positive semi-definite covariance matrix is not guaranteed and the problem related to a huge number of parameters is recognized. However, to resolve the problem, Bollerslev et al. (1988) introduced their VECH model and Engle and Kroner (1995) developed the BEKK model to ensure the positivity of the covariance matrix with a reasonable number of the parameter estimates.

3.2 Effect of the crisis on cross-correlation of the financial markets

This section introduces the effect of the recent financial crisis on the correlations of the global financial markets. Previous studies show that a financial crisis intensifies the volatility of the market where the crisis originates and causes a contagion effect to other financial markets. The contagion effect can be inferred from a statistically significant correlation relationship between markets that can be observed during the crisis period. A high incidence of cross-market relationships is referred to as a contagion that influences the dynamics of the financial markets (e.g., Lee & Kim, 1993; Bartram & Bodnar, 2009; Syllignakis & Kouretas, 2011.)

Accurate estimates of dynamic correlation are important to investors, for example in their decisions on portfolio hedging. In addition, owing to the effect of the crisis, it is interesting to analyze the transmission direction and the duration of the contagion. Briefly, the concept of information flow, first introduced by Ross (1989), reveals the properties of the dynamics of the volatility and the effect of contagion. The multivariate generalized autoregressive conditional heteroskedasticity GARCH model and its several varieties can be utilized to model dynamics of the returns variability and the interdependence of the financial markets (Bollerslev, 1986, 1990.)

Futures contracts are utilized to minimize variance in a hedged portfolio. The number of contracts required for an efficient hedging strategy depends on the estimated variance of the asset and the underlying futures contract. The conventional method for a hedge is the time-invariant hedging strategy, where the estimated second moment of the variables is constant over time (e.g., Figlewski, 1985; Geppert, 1995). Engle (2002) introduced the dynamic conditional correlation (DCC) model to account for the dynamic of the covariance between the estimated variables. The model serves as a flexible and efficient tool to capture dynamic properties of cross-correlations of the financial markets.

The advantage of the multivariate GARCH models is their flexibility in estimation of dynamics of the conditional volatility. The model allows for the investigation of the dynamics of the conditional volatility, spillover effects between financial instruments, the effect of contagion, asset pricing, the information asymmetry effect, and volatility prediction among others. The prominent feature of the financial market is that the market volatilities and correlations increase substantially during a financial crisis simultaneously. This co-movement of the financial markets is widely examined (e.g., Forbes & Rigobon, 2002; Fratzscher, 2009; Kenourgios et al., 2011; Hartmann, 2010; Syllignakis & Kouretas, 2011).

3.3 Information transmission effect on volatility

This section introduces information flow through volatility transmission. A large number of studies have focused on the influence of structural changes in their examination of volatility.

The effect of the transmission of volatility across financial markets is of particular interest. An information shock experienced in any financial market can have a strong impact on other stock markets around the world. The impact of volatility on stock market co-movements during periods of financial crisis is one of the most vibrant areas in research. (see e.g., Bekaert & Harvey, 2000; Aragó-Manzana & Fernández-Izquierdo, 2007; Bubák et al., 2011; Ehrmann et al., 2011; Clements et al., 2014.)

The literature also relates stock market co-movement to the concept of stock market contagion. The concept of contagion is not unambiguously defined, and accordingly in the current research contagion is presented as a significant increase in cross-market linkages after a shock affecting one country or a group of countries. These linkages are measured as a correlation of asset returns between different markets. The co-movement implies high correlation of the markets after a shock i.e. contagion. Though, an insignificant increase in correlation of the markets implies interdependence. (Forbes & Rigobon, 2002.)

Hamao, Masulis, and Ng (1990) reveal the relation of the contagion and spillover effects observed in the financial markets. In general, two issues are of interest: First, the time that elapses before spillover effects are reflected in stock prices, and second, differences between the market reactions to information flows. To examine the spillover effects, Engle and Kroner (1995) present the following multivariate BEKK GARCH model. The advantage of the model is the feature that guarantees the estimated conditional variance–covariance matrix H is positive semi-definite in the optimization process. The equation of the model can be represented as below

(7) $$H_t = C_0 C_0^T + \sum_{k=1}^{K} \sum_{i=1}^{q} A_{ki}^T \varepsilon_{t-i} \varepsilon_{t-i}^T A_{ki} + \sum_{k=1}^{K} \sum_{j=1}^{p} G_{kj}^T H_{t-j} G_{kj}$$

$$\varepsilon_t \mid \Omega_{t-i} \sim N(0, H_t)$$

that is a specification for the conditional variance–covariance matrix H_t estimation. In the equation Ω_{t-1} the information is set at time $t-i$ and ε_t is assumed to be normally distributed. The entries C_0, $A_{k,i}$ and $G_{k,j}$ in the equation are $n*n$ parameter matrices, noting that C_0 is a lower triangular matrix. The estimates of the parameters of the matrix A measure the degree of volatility spillovers from one market to another and in the matrix G, the estimated parameters indicate the persistence in conditional volatility between the markets.

4 SUMMARY OF THE ARTICLES

4.1 Geographical focus in emerging markets and hedge fund performance

The purpose of the first article is to analyze the aggregate performance of emerging-market hedge funds, and in particular the outperformance among the hedge funds with a geographical focus. In addition, the effect of the recent financial crisis of 2008 on emerging-market hedge funds is examined. The earlier studies (e.g., Strömqvist, 2007; Peltomäki, 2008; Abugri & Dutta: 2009) suggest that the emerging hedge funds do not outperform their underlying indexes. However, in the present study, the aggregated performances on a broad level show that the hedge funds focused geographically do have an information advantage that permits them to outperform their underlying benchmark indexes.

Prior studies related to the emerging-market hedge funds have focused on portfolios of hedge funds. The portfolios constructed are specialized in particular characters of existing emerging hedge funds. Chen (2007) reports evidence of the market timing ability of hedge funds in their market focus. Borensztein and Gelos (2003) show that country funds have an information advantage over global funds because their fund flows can precede that of the global funds. In addition, specification in portfolios construction within REIT investment trusts and mutual funds is utilized to analyze the property specialization and industry concentration, respectively. As a whole, the outcomes of the studies show evidence of outperformance with regard to the portfolios in question.

The monthly data used in the analysis of this article cover the period January 1995–September 2009, and were obtained from the EurekaHedge emerging-market hedge funds database. The base currency for all funds is the U.S. dollar. The five different equally-weighted portfolios for geographically different emerging markets are formed as follows:

- India (52 funds).

- Eastern Europe and Russia (87 funds).

- Middle East and Northern Africa (53 funds).

- Latin America (101 funds), having a focus indicated as “Argentina,” “Brazil,” and “Latin America.”

- Asia excluding Japan (321 funds), having a focus indicated as “Asia ex Japan,” “Greater China,” “Taiwan,” and “Korea.”

In addition, the following equally-weighted portfolios were investigated:

- Focus (all hedge funds indicating their focuses).

- Global (172 funds indicating their investment geography as “Emerging Markets”).

The performance of the emerging-market hedge funds is considered in various versions of the model and periods of time. For instance, to test robustness of the results a sub-sample period from April 2000 to June 2007 is examined.

The empirical findings of this article suggest the emerging hedge funds performed better before the financial crisis of 2008. For the investors, this implies that the hedge funds in focus are becoming more attractive while idiosyncratic risk in emerging-market hedge funds is decreasing. The specific characteristic of the estimated model for a multiple emerging-market hedge fund is applied. In the estimation, the performance of the hedge funds with a geographical focus is analyzed in aggregate. The aggregation increases the explanatory power of the model and alters the results significantly. Overall, the results are convincing and suggest that analysts should utilize geographical equity indexes in their work.

4.2 Stock market correlations during the financial crisis of 2008–2009: Evidence from 50 equity markets

The second article of this doctoral dissertation examines the correlations between 50 international stock markets. To do so it examines specific events in the world of banking—JP Morgan Chase's acquisition of the Bear Stearns investment bank and the collapse of the Lehman Brothers investment bank—during the crisis period 2008–2009. The study examines the effect of the events on the unconditional and dynamic conditional correlations. In particular, the changing level of the stock market variance during the financial crisis period is analyzed.

Earlier studies of the stock markets during the financial crisis (e.g., Bartram & Bodnar, 2009; Dooley & Hutchison, 2009; Billio & Caporin, 2010; Chudik & Fratzscher, 2011; Schwert, 2011; Syllignakis & Kouretas, 2011) demonstrate that the markets move together, hence diminishing the diversification benefits of equity investments. However, in this article, by controlling the level of variance, the information content of the conditional variance–covariance of 50 stock market index returns in correlation estimation is utilized. The estimation results confirm the feasibility of the proposed method to capture the dynamics of stock market variance, which in turn additionally enhances the efficiency of portfolio optimization.

Financial or economic crises interest academics because they have serious consequences for investments in equity markets. In addition to the equity markets, the effect of the 2008–09 financial crisis on foreign exchange markets (Baba & Packer, 2009; Melvin & Taylor, 2009; Fratzscher, 2009) and on fixed income markets (Dwyer & Tkac, 2009; Acharya et al., 2009;

Hartmann, 2010) have attracted researchers in their fields of study. A common aspect of all these studies is the observation that the volatility in the financial markets co-move during a crisis period.

The study is carried out with 50 different stock market indexes from six different regions collected from the Datastream database. The data periods investigated are as follows;

- one year before the Bear Stearns event (March 15, 2007, to March 14, 2008)

- 6 months thereafter (March 17, 2008 to September 12, 2008) and

- 6 months after the collapse of Lehman Brothers (September 15, 2008 to March 16, 2009).

The empirical findings indicate that the JP Morgan acquisition of Bear Stearns had only a minor effect on the correlations between the six regions examined. However, the collapse of Lehman Brothers had a significant effect on the interdependences between both the regions and the stock markets, which is evident from both the unconditional and conditional correlation estimates. In addition, the portfolio variance estimated by the DCC model with the controlled variance equation improves the model. The model is more efficient at accounting for the change in level of variance in periods of high volatility. Overall, by controlling level of variance the information content of the conditional variance–covariance structure efficiently captures the index returns variance in the model estimation.

4.3 Measuring actual daily volatility from high frequency intraday returns of the S&P futures and index observations

The third article of this doctoral dissertation considers the information content of the S&P 500 futures (ES) and index (SPX) intraday observations on the estimated variance forecasts. The time period surveyed in the evaluation of forecasts covers the highly volatile financial crisis period as well as more tranquil periods. In the AR(FI)MA model specification, the characteristics of the estimated realized variance distribution, that is, the distribution asymmetry and shape, of the efficiency of the forecasts is considered. The results of this article show that the most accurate forecasts produced are based on the seasonally adjusted realized variance series from the S&P 500 index futures high-frequency observations.

The seminal study of Andersen and Bollerslev (1998) shows that asset price can be assumed to follow a continuous time diffusion process. The study proposes that daily volatility, estimated as the sum of cumulative intraday squared returns, is an unbiased and consistent approximation of actual volatility, called realized volatility. The proposition is widely acknowledged to be an accurate method in the case of unobserved volatility measurement (e.g., Barndorff-Nielsen & Shephard, 2002).

The purpose of this article is to show that the AR(FI)MA model and distribution characteristics of the logarithm-transformed realized variance series can be utilized in efficient volatility forecast estimations. In this article, the S&P 500 futures (ES) and index (SPX) high-frequency observations are utilized to calculate the realized variances. The findings include that the returns of the high-frequency observations generally exhibit seasonality in volatility (e.g., Taylor & Xu, 1997). Hence, the seasonality effect is adjusted by utilizing a filtration method to form more efficient estimates of the volatility forecasts.

This article covers the period June 1, 2007–December 30, 2011. The analysis utilizes the 10-minute frequency of the S&P 500 index (SPX) and the E-mini S&P 500 index futures (ES) intraday observations in its realized variance estimation. The evaluation accuracy of the forecasts of the S&P 500 (SPX) index closing values are used as a proxy for the ex post variance. The VIX volatility index's daily closing values are utilized to assess the degree of bias of the volatility forecast. The aforementioned data used in this article are produced by Pi Trading and the VIX data are from the Chicago Board Options Exchange.

The empirical findings of this article show that the information content of the de-seasonalized filtered returns of the realized variance series produced the most accurate out-of-sample volatility forecasts. However, it is evident that the optimal fit structure and the best performing model for the forecasts at 1-, 10-, and 22-minute horizons was associated with the ARMA model. This is observable for both the futures and index based forecasts. In addition, the encompassing test indicates that the forecasts based on the futures observations contain incremental information over that of the forecasts based on the index observations.

4.4 Dynamic conditional Copula correlation and optimal hedge ratios with currency futures

The fourth essay of this doctoral dissertation examines performance of the time series models applied to hedge the risk exposure of the currency portfolios. The hedging performance of the estimated models is evaluated by noting the time-varying characteristic of the exchange rate volatility. The risk hedging models compare the dynamics of the spot and futures data of the Australian dollar, Canadian dollar, Euro, British pound and Japanese yen. The results of this article show that the bivariate conditional copula correlation model is superior in portfolio variance reduction. The estimated model is efficient in accounting for the clustered nature of the data variance in low and high volatility periods. That efficiency is attributable to the information content of the realized variance estimators which are included in the variance equation of the model.

The method of ordinary least squares (OLS) regression is commonly utilized to derive the optimal hedge ratio. (e.g., Ederington, 1979; Figlewski, 1985; Malliaris & Urrutia, 1991; Benet, 1992: Geppert, 1995). However, the optimal hedge ratio founded on the constant variance is not undisputed. Hence, the DCC model proposed by Engle (2002) is commonly utilized in dynamic hedging strategies to capture the time-varying characteristics of the spot and futures price changes (e.g., Bauwens et al., 2006; Pelletier, 2006; Christoffersen et al., 2014). Studies presented by Hsu et al. (2008), Lai & Sheu (2010) and Sheu & Lai (2014) examine characteristics of the GARCH model to estimate risk-minimizing hedge ratios. Similarly, this study is interested in examining the performance of the Copula-EGARCH-DCC model in terms of portfolio variance reduction.

The article collates data on weekly closing prices from the Datastream database. First, the currency spot and futures data of the Euro, British pound and Japanese yen are used for the model estimation. The return series calculated covers the period 14 January 2000–27 December 2013. In addition, to compare the performance of the estimated models, an artificial data with the utilized bootstrap method is simulated. In the data simulation procedure for each of the currencies and futures a one thousand artificial data is generated. Then all the models are fitted to the simulated returns i.e. each of the model is one thousand times estimated. Second, to test the robustness of the initial findings, the longer time period of the currency and spot and futures returns of the Australian dollar, Canadian dollar, British pound and Japanese yen from 12 June 1987 to 27 December 2013 is examined. The futures non-adjusted settlement data observations are based on the spot-month continuous contract calculations. The series of weekly returns are calculated as the first difference of the natural logarithm for the spot and futures prices.

The results of the current research show the efficiency of the estimated bivariate model accounts for the evolution of the dynamic conditional correlation between the spot and futures markets in low and high volatility periods. The best performing model is the dynamic conditional correlation model estimated, that is, the Copula-EGARCH-DCC model with the external realized volatility estimators included in the variance equation of the model. It is argued that hedging efficiency is based on the ability of the model to account for the clustered characteristics of the data variance. In addition, the empirical findings show that the constant correlation model hedging performance is weak, suggesting that the model is inadequate when used to minimize variance of a portfolio.

5 DISCUSSION

The functioning of the financial markets and the observed prevalence of highly volatile periods is of particular interest to researchers and investors. The high levels of volatility during the global financial crisis increased interest in the co-movement of financial markets. The financial crisis also reduced the opportunity to reap diversification benefits in the area of risk management, hence alternative investment strategies are crucial. Portfolio managers' search for more profitable investment can be based on some geographically segmented market criteria, or some other form. Overall in investment decision making, the uncertainty of the expected returns from an investment should be compensated with higher expected returns. The risk-return relationship in investment decisions justifies the importance of estimating the expected variance of an investment. Hence, in efficient portfolio management, all relevant information on the first and second moments of the returns distribution is utilized.

For hedging purposes, the derivatives, such as options and futures contracts, allow portfolio managers to minimize variance in their portfolios. The dynamic conditional correlation models, and also the univariate multivariate GARCH models have shown their diverse ability to capture the dynamics of the variance–covariance structure of the variables and so to minimize variance. In general, the conditional volatility models and availability of the high-frequency data have increased opportunities for the portfolio managers to hedge more efficiently against the risk of return fluctuations. The efficiency observed is partly accountable for the advantages of the developed methods to estimate the variance. An addition is the availability of high-frequency data that provide supplemental information for more accurate variance estimation.

An interesting subject for future research would be to consider conditional cross-correlation effects on hedge fund portfolios, or in addition, portfolios of mutual funds during periods of financial crisis. Portfolios with different allocation strategies could be evaluated across different countries. For example, we could enhance the knowledge of portfolio diversification by comparing activity in emerging and developed economies. In addition, the multivariate models applied enable the utilization of the variance–covariance structure of the estimated variables. The estimation results of the information flow through volatility transmission could be used to inform investment decisions. An interesting extension for the research method applied would be the realized variance measure calculated from the high-frequency observations. Accordingly, the realized variance measures could be used as external variables in the model.

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Geographical focus in emerging markets and hedge fund performance

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ABSTRACT

Emerging market hedge funds are an asset class which does not seem to outperform the market benchmarks. We hypothesize that the poor aggregate performance may be due to lack of focus of these funds. Our results suggest that a portfolio of emerging market hedge funds, which have geographical focuses, outperform their underlying stock markets. Hedge funds which focus on Eastern Europe appear to have the best outperformance. However, we also find that the performance of all emerging market hedge funds has reduced after the start of the 2008 Crisis.

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1. Introduction

Hedge fund investors can benefit from the skills of a hedge fund manager allowed by their free and flexible investment policies of hedge funds. When investing in emerging markets, which are both risky and challenging, investors can invest in hedge funds as well. But the study by Strömqvist (2007) presents evidence that emerging market hedge funds are not capable of outperforming their underlying benchmarks. This evidence is further supported by Peltomäki (2008) and Abugri and Dutta (2009).

The objective of our study is to further analyze the performance of emerging market hedge funds with a consideration that the term "hedge fund" is most of all a legal definition. Consequently, within the industry some funds may be more alternative investments than other funds. The "true alternatives" can possibly produce superior performance than the others. To pick outperforming funds we propose an investment style for investing in emerging market hedge funds in each geographical location by investing in funds which have reported geographical focuses.

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Given the above reasoning, the purpose of our study is to focus on analyzing the aggregate performance of emerging market hedge funds with geographical focuses. The research problem of this study is two-folded: first, whether geographical portfolios of emerging market hedge funds outperform their underlying geographical focus markets. Second, whether the aggregate portfolio of focused emerging market hedge funds outperform the underlying indexes.

We argue that the investment focus is the key in finding skilled managers within the industry beyond the term "hedge fund" with the following reasoning. As emerging market hedge funds carry a relatively high market risk, it is an opportunity for less skilled managers to infiltrate in the hedge fund industry to collect high fees. A solution to select the skilled managers would be to have a signal of their expertise in some emerging market. Indeed, Chen (2007) presents evidence for market timing ability of hedge funds in their focus market. The result leads us to expect that in their focus market emerging market hedge funds would also show better performance due to their profound expertise in the market.

In fact, our approach of finding information advantage is closely associated with the local information advantage in Teo (2009) but the approach is different. Teo (2009) finds that especially for emerging market and event-driven funds local information advantage (i.e. fund operates close to its focus market) leads to better performance. We assume that market focus likewise to information advantage as does local information advantage. Our study also differs from Cao and Jayasuria (2010a), who examine the performance of individual emerging market hedge funds against their matched regional benchmarks (1 regional benchmark per fund) since they do not consider how the focus relates to the performance. In the following study, Cao and Jayasuria (2010b) study the performance of different geographical hedge fund portfolios and a global hedge fund index against their matched equity and bond benchmarks. In relation to these both studies, we consider all hedge funds that have geographical focuses as a group and we also adjust to the exposures of hedge funds to equity returns of multiple geographical focuses.

To investigate the performance of emerging market hedge funds, we use the emerging market hedge fund database obtained from the EurekaHedge. Our analysis period starts in April 2000 and ends in September 2009. The data for performance analysis includes 786 funds. Our results suggest that a portfolio of emerging market hedge funds that have geographical focuses is able to show statistically significant and positive abnormal performance unlike the portfolio of other emerging market hedge funds. Therefore, a profitable investment style for emerging market investors is to allocate their funds toward emerging market hedge funds which have a distinct geographical focus. For data vendors, we propose that creating focused country benchmarks of emerging market hedge funds could be an interesting and well motivated benchmark style given the results by Teo (2009) and our study.

The remainder if this paper is organized as follows: In Section 2 we review the literature on the market timing ability of hedge funds. Section 3 presents our hypotheses. In Section 4 we present the data used for this study followed by Section 5 for the methods used in this study. Section 6 presents our results and Section 7 concludes the study.

2. Literature review

The question whether hedge funds truly outperform their underlying benchmarks and are able to produce abnormal performance is stressed in the academic research, but is also difficult to answer. Using a robust methodology, Kosowski, Naik and Teo (2007) find that hedge funds outperform their underlying benchmarks. However, Aragon (2007) finds that the performance of hedge funds is associated with share restrictions, and thus the seemingly abnormal performance of hedge funds can be explained by illiquidity premium.

For the emerging market hedge funds, two early studies examine their performance: first, the evidence reported by Strömqvist (2007) suggests that at the broad strategy level emerging market hedge funds have not outperformed their benchmarks over the period 1994–2004. However, her results suggest that the abnormal returns of the strategy may be increasing. For the period 1994–2006, Peltomäki (2008) also examines the performance of emerging market hedge funds and confirms poor performance at the index level. However, he finds that nearly 40% of emerging market hedge funds shows statistically significant and positive abnormal returns. He also finds that higher performance among emerging market hedge funds is associated with the use of auditing services and higher management fees. Both of these studies use the Lipper TASS database.

A further study by Abugri and Dutta (2009) examines whether emerging market hedge funds are managed like advanced markets hedge funds. Their results suggest that for the post-2006 period emerging market hedge funds behave like advanced markets hedge funds. Their results regarding the performance of emerging market hedge funds also suggest that they do not consistently outperform their underlying benchmarks.

Cao and Jayasuria (2010a) use a sample of 287 emerging market hedge funds obtained from CISDM Hedge Fund/CTA database and analyze the performances of emerging market hedge funds in different locations. Their results suggest that 56 (16) of the funds presented statistically significant and positive (negative) abnormal performance.

Cao and Jayasuria (2010b) examine market timing and performance of emerging market hedge funds in different regions using a sample of 541 funds. Specifically, the authors examine the performances of the following portfolios: Asia/Pacific (excl Japan), Eastern Europe, Global and Latin America. After considering bond and stock market volatilities, the results of the study suggest that only the Global portfolio of emerging market hedge funds is capable to produce positive and statistically significant abnormal returns.

The evidence by Huij and Post (2011) on the performance of emerging market equity mutual funds suggests that the funds perform better than funds investing in USA. This evidence is contradictory to the evidence by Strömqvist (2007), Peltomäki (2008) and Abugri and Dutta (2009).

3. Hypothesis development

The emerge of the hedge fund industry over the past two decades has driven investors and researchers to focus on emerging market hedge funds. For emerging market hedge fund indexes, Strömqvist (2007) and Peltomäki (2008) do not find strong evidence for abnormal performance of emerging market hedge funds. But to exploit the opportunity to build well performing portfolios of emerging market hedge funds, a distinct specialization of a hedge fund could be undertaken and four academic studies advocate this view: first, Chen (2007) reports evidence for the market timing ability of hedge funds in their market focus. Second, Eichhold, Veld and Schweitzer (2000) examine the performance of REIT investment trusts and find evidence that their property specialization can lead to outperformance. For mutual funds, Kacperczyk, Sialm and Zheng (2005) present evidence those funds with greater industry concentration show better performance on average. For emerging market equity funds, Borensztein and Gelos (2003) present evidence that country funds have an information advantage over global funds as their fund flows of the former ones can precede that of the latter ones. Therefore, it is also reasonable to expect that geographical focuses of emerging market hedge funds would lead to better performance. Specifically, those hedge funds that report their market focuses or have a marker focus should have more profound knowledge and expertise in their focus markets than funds without focus, and thus be able to beat the market. As a result, we hypothesize that:

H. *Emerging market hedge funds with geographical focus show abnormal performance.*

4. Data

The data for the time-series analysis of this study begin from January 1995 and last until September 2009. Data are downloaded in September 2009. The portfolios for hedge funds are constructed using the EurekaHedge emerging market hedge funds database. Including only the most recent data could lead to less biased data as EurekaHedge started collecting data in the beginning of the 2000s. However, excluding the 1990s, a relatively weak decade for emerging markets, and including 2000s, a relatively strong decade for emerging markets, would in turn lead to testing hedge fund performance over secular bull market. Therefore, we use as long period of data as available. We use both the live and dead hedge funds to mitigate survivorship bias in our sample. Base currency for all funds used in the analysis is U.S. dollar.

All in all, 5 different equally-weighted portfolios for geographically different emerging market are formed: India (52 funds), Eastern Europe and Russia (87 funds), Middle East and Northern Africa (53 funds), Latin America (101 funds), and Asia excluding Japan (321 funds). Funds included in the Asia ex Japan sample have the following focuses indicated: “Asia ex Japan,” “Greater China,” “Taiwan,” and “Korea.” Funds included in the Latin America sample are indicated either “Argentina,” “Brazil,” and “Latin America.” In addition, Greater China (115 funds), a subsample of Asia excluding Japan sample, is investigated separately given growing importance of the Chinese economy which leads the significance of its capital markets as well. Equally weighted portfolio of all hedge funds indicating their focuses is also used. We refer to this fund category as "Focus." The final equally-weighted portfolio used is the portfolio of emerging market hedge funds (172 funds) which indicate their investment geography as "Emerging Markets." This fund category includes 172 funds and we refer to this portfolio as "Global." The characteristics of funds included in Focus and Global categories are also presented after the analysis as they may indicate some differences in the investment strategies.

It must be noticed that the practice of indicating geographical focuses may vary across database vendors. The most notable difference is that all hedge funds in EurekaHedge database indicate their statuses of geographical focus. In the Lipper TASS database, hedge funds in turn as may indicate more focuses than one geographical focuses or they do not report any. Hence, there indicating geographical focuses appears to be more or less voluntary in some cases, and thereby results for voluntary reporting can be expected to be stronger given if the focus is more requested it may encourage some funds to report it even though signification of the focus is little. In consequence, we also report our analysis using the Lipper TASS database.

To be included in the analysis a hedge fund must report its returns in U.S. dollars. All returns are in excess of the 1-month U.S. T-bill rate of return obtained from Ibbotson Associates, Inc. The returns are expressed in percentages. The returns of international total return indexes and an emerging market bond return index presented in Table 1 denoted in U.S. dollars are chosen as proxies for the returns of emerging markets.

In addition to the above presented indexes in Table 1, Table 2 presents the descriptive statistics for the full time-series sample of the data of our study (Panel A) and the descriptive statistics for one common and recent sample of the data (Panel B), which is used in the most analyses of our study. From a geographical point of view, the highest returns of the common sample are generated from China. The stock market index used in this study shows an average return of 2.33% and the portfolio of Greater China hedge funds shows an average return of 1.41%. FTSE RAFI index shows a competitive average return, 1.50%, in relation to the hedge fund portfolios although with pretty high standard deviation of its returns, 7.48%.

A considerable difference in Panels A and B is for the Lehman Brothers emerging market bond index. The statistics show 2.47% average return for the full return series and only 0.94% average return for the return series of common sample. When considering individual samples, the global portfolio of emerging market hedge funds shows higher average returns than the focus portfolio (1.06% vs. 0.92%). However, when the common sample, which is more recent, is considered, the focus portfolio in turn shows higher average returns (0.93% vs. 0.75%).

5. Methods

In this paper, we use two different models to study market timing ability and performance of emerging market hedge funds. To test the hypothesis of this study we examine the performance of hedge funds in comparison to geographical markets and other benchmarks using the following model:

$$r_p - r_f = \alpha + \beta_i \sum_{n=1}^{N} \left(r_i - r_f\right) + \beta_{p,RAFI}\left(r_{RAFI} - r_f\right) + \beta_{p,b}\left(r_b - r_f\right) + e, \quad (1)$$

Table 1
Emerging market indexes.

Objective	Index	Datastream ticker	Abbreviation
Russia	MSCI Russia	(MSRUSS$(RI))	MSRUSS
Europe	MSCI Emerging Markets Europe	(MSEEUR$(RI))	MSEEUR
Asia	MSCI Emerging Markets Asia	(MSEMFA$(RI))	MSEMFA
Africa	FTSE All World Middle East and Africa	(AWMEAF$(RI))	AWMEAF
India	MSCI India	(MSINDI$(RI))	MSINDI
Latin America	MSCI Emerging Markets Latin America	(MSEFLA$(RI))	MSEFLA
China	FTSE China	(WICINA$(RI))	WICINA
RAFI	FTSE RAFI US Emerging Market	(FTREMR$(RI))	FTREMR
Bond	Barclays EM World All Series	LHEMAME(IN)	LHEMAME

Table 2
Descriptive statistics. This table presents monthly data of this study. Individual return series start from January 1995 onwards and the last month is August 2009. Common sample is from March 2000 to August 2009 and includes 113 observations. Returns are in percentages. JB refers to Jarque–Bera test for normality of a distribution.

	Asia all	Asia ex. Japan	Global	Eastern Europe	Focus	Greater China	India	Latin America	Middle East/Africa	RAFI	LHEMAME	AWMEAF	MSEEUR	WICINA	MSRUSS	MSINDI	MSEMFA	MSEFLA
Panel A: Individual series																		
Mean	0.79	0.63	1.06	1.69	0.92	1.25	0.56	0.64	0.52	1.43	2.47	0.79	1.08	1.61	2.51	0.84	0.17	1.10
Median	0.53	0.80	1.48	1.79	1.47	1.09	1.76	1.21	−0.38	2.49	1.84	0.83	1.71	0.44	2.54	1.25	−0.22	2.34
Std. dev.	4.69	4.70	3.76	9.65	5.09	5.82	7.98	5.19	2.88	7.43	16.55	7.39	9.45	11.06	17.12	9.32	7.91	8.66
Skewness	0.29	0.48	−1.17	−0.38	−0.49	0.26	−0.06	−0.48	−0.62	−0.43	7.20	−0.68	−0.64	0.67	0.19	0.06	−0.18	−0.84
Kurtosis	4.80	5.07	7.34	5.97	5.04	5.78	3.50	6.19	7.52	3.91	82.05	4.20	4.68	5.36	4.67	3.65	3.34	4.96
JB	26.08	38.08	178.12	69.08	37.69	58.62	1.94	81.24	160.73	7.57	47,339.10	24.27	32.74	54.13	21.26	3.22	1.81	49.03
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.378	0.000	0.000	0.023	0.000	0.000	0.000	0.000	0.000	0.200	0.404	0.000
N	176	176	176	176	176	176	176	176	176	115	176	176	176	176	175	176	176	176
Panel B: Common sample																		
Mean	0.84	0.51	0.75	1.43	0.93	1.36	0.41	0.73	1.04	1.50	0.93	1.22	0.84	2.33	1.31	1.09	0.52	1.34
Median	1.20	1.12	1.34	1.89	1.58	1.52	2.24	1.17	0.99	2.52	1.22	1.75	1.91	1.68	2.32	2.11	0.10	2.56
Std. dev.	3.90	3.65	3.38	6.33	4.02	5.13	7.57	3.82	3.49	7.48	4.44	6.98	9.80	9.41	11.28	9.51	7.69	8.49
Skewness	−0.54	−0.54	−1.24	−0.78	−0.77	0.31	−0.21	−0.75	−0.99	−0.45	−1.62	−0.67	−0.43	−0.19	−0.37	−0.10	−0.26	−0.68
Kurtosis	3.34	3.76	6.69	4.29	4.39	5.26	3.78	4.84	5.91	3.89	11.13	3.63	3.77	3.70	3.52	4.29	3.19	4.33
JB	6.05	8.31	92.83	19.19	20.08	25.81	3.68	26.73	58.12	7.62	361.11	10.33	6.30	2.95	3.90	7.98	1.41	17.01
Prob.	0.049	0.016	0.000	0.000	0.000	0.000	0.158	0.000	0.000	0.022	0.000	0.006	0.043	0.229	0.142	0.019	0.493	0.000

Table 3
Time-series analysis of global and focus portfolios. Newey–West (lag = 6) regressions of excess returns on hedge fund portfolios using the following model:

$$r_p - r_f = \alpha + \beta_i \sum_{n=1}^{N} \left(r_i - r_f\right) + \beta_{p,RAFI}\left(r_{RAFI} - r_f\right) + \beta_{p,b}\left(r_b - r_f\right) + e,$$

where r_p defines the return of a hedge fund portfolio; r_i defines the return of a geographical stock index; r_f defines the risk-free rate; r_m defines the return of an emerging market stock index; r_b defines the return of an emerging market bond index; r_{RAFI} defines the return on the FTSE RAFI emerging index, which is a fundamentally weighted-index (lagged value also included). AR(1) is also included in the model. AIC refers to Akaike Information Criterion, SIC refers to Schwarz Information Criterion. This table also presents Durbin–Watson test for first-order serial correlation. See Table 1 for definitions of the variables. Notes: (standard errors in parentheses), ***, ** and * denote statistically significant at 0.1%, 1% and 5% respectively. The estimation period is from March 1995 to August 2009 and includes 114 observations.

Variable	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.
Panel A: Focus portfolio						
C	0.298**	*2.23*	0.201	*0.64*	0.351**	*2.29*
MSEEUR	−0.088***	*−2.63*			−0.086***	*−2.94*
MSEFLA	0.061**	*2.31*			0.055**	*2.08*
MSEMFA	0.199***	*5.38*			0.193***	*5.25*
MSINDI	0.060***	*3.45*			0.069***	*4.57*
MSRUSS	0.168***	*8.92*			0.172***	*10.26*
WICINA	0.054***	*2.76*			0.049**	*2.54*
AWMEAF	0.021	*1.07*			0.019	*0.96*
LHEMAME	0.044*	*1.86*	0.201***	*5.16*	0.047*	*1.89*
FTREMR	0.031*	*1.90*	0.517***	*8.72*		
AR(1)	0.223***	*2.72*	−0.186	*−1.20*	0.277***	*3.56*
Adjusted R^2	0.93		0.43		0.93	
AIC	3.09		5.11		3.12	
SIC	3.36		5.20		3.36	
Durbin–Watson	2.00		1.86		2.01	
F-statistic	147.24		29.51		158.59	
Prob(F-statistic)	0.00		0.00		0.00	
Panel B: Global portfolio						
C	0.193	*1.16*	0.079	*0.29*	0.263	*1.39*
MSEEUR	0.009	*0.35*			0.009	*0.44*
MSEFLA	0.108***	*4.97*			0.101***	*4.15*
MSEMFA	0.098***	*2.88*			0.089***	*2.64*
MSINDI	0.030*	*1.87*			0.041***	*2.71*
MSRUSS	0.080***	*4.90*			0.083***	*5.69*
WICINA	0.025*	*1.70*			0.019	*1.38*
AWMEAF	0.025	*1.19*			0.021	*0.94*
LHEMAME	0.073***	*2.65*	0.164***	*5.03*	0.075**	*2.54*
FTREMR	0.040***	*3.24*	0.486***	*9.48*		
AR(1)	0.302***	*3.82*	−0.164	*−0.96*	0.367***	*3.91*
Adjusted R^2	0.92		0.52		0.92	
AIC	2.79		4.57		2.86	
SIC	3.06		4.67		3.10	
Durbin–Watson	2.03		1.92		2.04	
F-statistic	137.32		41.83		140.63	
Prob (F-statistic)	0.00		0.00		0.00	

where r_p defines the return of a hedge fund portfolio; r_i defines the return of a geographical stock index; r_f defines the risk-free rate; r_m defines the return of an emerging market stock index; r_b defines the return of an emerging market bond index; r_{RAFI} defines the return on the FTSE RAFI emerging index, which is a fundamentally weighted-index. In addition to the above presented model, first-order serial correlation is considered using AR(1) term.

The use of the FTSE RAFI emerging index in analyzing emerging market hedge funds performance is well founded. The results by Arnott, Hsu and Moore (2005) imply that the fundamental weighting can produce positive abnormal returns given that fundamentally weighted indexes are more efficient over-weighting undervalued stocks and under-weighting overvalued stocks. The criticism against the fundamental weighting by Kaplan (2008) and Blitz and Swinkels (2008) argue that the outperformance of these indexes is mere compensation for value bias. Nevertheless, this is a little importance for our study as we use the FTSE RAFI emerging index to account for passive security selection which can be considered as alternative choice for hedge funds.

We also provide our results without using the FTSE RAFI emerging index so that one can evaluate the effect of using the benchmark. As the data for the FTSE RAFI emerging benchmark begins in April 2000, our analyses are mainly limited for this time period. The use of this late sub-sample may also provide better and more relevant insight for current emerging market investors. The reason is that emerging markets were only at the very preliminary phase before that time.[1]

The performance of emerging market hedge funds is analyzed using various versions of the model used so that one can see the factors for which the results may be sensitive. In addition to the above analysis, we consider the recent financial crisis of 2008 which may have affected emerging market hedge funds. This additional analysis is reasonable as the results by Abugri and Dutta (2009) suggest that the characteristics of emerging markets hedge funds are different for the post-2006 period. As such, we repeat our results using a sub-sample from April 2000 to June 2007.

6. Empirical results

Table 3 presents our results for performance analysis of the Focus and Global portfolios. The results suggest that if all factors are included in the model, the Focus portfolio shows statistically significant abnormal performance (0.298% per month). This result supports the hypothesis of this study and implies that if an investor holds a portfolio of hedge funds which have geographical focuses the portfolio held is likely to outperform the underlying markets. What is more, the information criteria (AIC and SIC) presented in Table 3 suggest that the full model has the best fit among the other models. It is also reasonable to note that the model without specific geographical portfolios does not support the result but the model may not consider the allocation of hedge funds in different countries sufficiently. Moreover, the explanatory power of the model is weak in comparison to the full model used, and therefore adjustment for different geographical equity indexes is seemingly needed. The results for the Global portfolio in turn do not provide statistically significant evidence implying that it is important for hedge funds to focus on specific geographical locations. Overall, the results are consistent with the evidence by Borensztein and Gelos (2003) on the information advantage of country funds over global funds.

The use of geographical equity indexes may explain the difference between our results and those Cao and Jayasuria (2010b), who present evidence that it is particularly the global hedge funds that outperform the market. These authors do not adjust for specific exposure of hedge funds returns to the returns of multiple geographical equity indexes as we do. The explanatory power our model in analyzing global emerging market hedge funds is approximately 9 percentage points higher that of theirs (83% vs. 92%).

The results in Table 4 are denoted for analyzing each geographical location separately. The results can be considered presenting strong evidence for the outperformance of Eastern Europe and Russia hedge funds. As the explanatory power of the model for this portfolio is high, 91%, it means that there is less chance that there are benchmarks which explain this outperformance. This clearly suggests that best performing hedge funds are focused on Eastern Europe markets. Highest abnormal returns (0.644%) are provided by the focus portfolio of Middle East/Africa focused hedge funds but the result is not statistically significant. The weakest performance is evinced for the portfolio of India hedge funds for which the abnormal performance is found to be as low as −0.385% per month. Admittedly, the result is not statistically significant.

Table 5 presents pre-2008 crisis analysis of hedge fund performance. In comparison to the results presented in Table 3, the performance of emerging market hedge funds appears to be much stronger before the crisis. For a sample from March 2000 to December 2007, both of the Focus and Global portfolios show statistically significant outperformance with abnormal performance. The abnormal returns are higher when the returns on fundamental index are excluded from the analysis. The exclusion alters especially the

[1] See e.g. Fig. 1 by Abugri and Dutta (2009) for the market capitalization of emerging market hedge funds.

Table 4
Time-series analysis of geographical portfolios. Newey–West (lag = 6) regressions of excess returns on hedge fund portfolios using the following model:

$$r_p - r_f = \alpha + \beta_i \sum_{n=1}^{N} \left(r_i - r_f\right) + \beta_{p,RAFI}\left(r_{RAFI} - r_f\right) + \beta_{p,b}\left(r_b - r_f\right) + e,$$

where r_p defines the return of a hedge fund portfolio; r_i defines the return of a geographical stock index; r_f defines the risk-free rate; r_m defines the return of an emerging market stock index; r_b defines the return of an emerging market bond index; r_{RAFI} defines the return on the FTSE RAFI US index, which is a fundamentally weighted-index (lagged value also included). AR(1) is also included in the model. AIC refers to Akaike Information Criterion, SIC refers to Schwarz Information Criterion. This table also presents Durbin–Watson test for first-order serial correlation. See Table 1 for definitions of the variables. The estimation period is from March 1995 to August 2009 and includes 114 observations. Notes: (standard errors in parentheses), ***, ** and * denote statistically significant at 0.1%, 1% and 5% respectively.

	Asia all		Asia ex. Japan		Eastern Europe		GChina		India		Latin America		Middle East/Africa	
Variable	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.
C	0.258	*1.54*	0.067	*0.39*	0.607**	*2.08*	0.288	*1.11*	−0.385	*−1.02*	0.115	*0.91*	0.644	*1.65*
MSEEUR	−0.120***	*−2.91*	−0.092**	*−2.42*	0.023	*0.55*	−0.183**	*−2.30*	−0.027	*−0.34*	−0.032	*−0.93*	0.028	*0.49*
MSEFLA	0.006	*0.15*	−0.008	*−0.24*	0.031	*0.79*	0.078	*1.09*	−0.065	*−1.01*	0.365***	*8.92*	0.088	*1.56*
MSEMFA	0.310***	*5.85*	0.286***	*6.53*	0.079	*1.56*	0.120	*1.14*	0.087	*1.28*	0.020	*0.50*	0.065	*0.87*
MSINDI	0.050**	*2.12*	0.079***	*4.46*	−0.037	*−1.06*	−0.011	*−0.19*	0.715***	*13.41*	0.020	*0.91*	0.003	*0.08*
MSRUSS	0.103***	*5.77*	0.100***	*4.20*	0.437***	*11.96*	0.130***	*3.43*	0.063	*1.11*	0.016	*0.65*	−0.009	*−0.27*
WICINA	0.097***	*3.25*	0.019	*0.98*	0.015	*0.60*	0.408***	*4.39*	−0.074	*−1.64*	−0.002	*−0.09*	−0.012	*−0.44*
AWMEAF	0.032	*1.41*	0.057	*1.63*	−0.014	*−0.32*	−0.054	*−0.54*	−0.007	*−0.11*	−0.014	*−0.50*	0.151***	*2.74*
LHEMAME	0.019	*0.64*	0.019	*0.62*	0.075	*1.45*	0.002	*0.02*	0.034	*0.48*	0.111***	*2.91*	−0.029	*−0.37*
FTREMR	0.021	*1.13*	0.032**	*2.16*	0.080***	*3.19*	0.002	*0.05*	0.068	*1.44*	0.023	*1.17*	0.067*	*1.96*
AR(1)	0.220**	*2.06*	0.243**	*2.28*	0.219**	*2.04*	0.056	*0.68*	0.145	*1.53*	0.082	*0.95*	0.156*	*1.81*
Adjusted R^2	0.88		0.88		0.91		0.70		0.85		0.87		0.40	
AIC	3.57		3.41		4.25		5.01		5.10		3.59		4.90	
SIC	3.83		3.67		4.52		5.27		5.36		3.85		5.16	
Durbin–Watson	1.97		2.00		2.03		1.96		1.97		1.95		2.07	
F-statistic	80.27		83.09		118.41		26.90		64.45		74.34		8.69	
Prob (F-statistic)	0.000		0.000		0.000		0.000		0.000		0.000		0.000	

Table 5
Pre-crisis analysis of global and focus portfolios. Newey–West (lag = 6) regressions of excess returns on hedge fund portfolios using the following model:

$$r_p - r_f = \alpha + \beta_i \sum_{n=1}^{N} \left(r_i - r_f\right) + \beta_{p,RAFI}\left(r_{RAFI} - r_f\right) + \beta_{p,b}\left(r_b - r_f\right) + e,$$

where r_p defines the return of a hedge fund portfolio; r_i defines the return of a geographical stock index; r_f defines the risk-free rate; r_m defines the return of an emerging market stock index; r_b defines the return of an emerging market bond index; r_{RAFI} defines the return on the FTSE RAFI US index, which is a fundamentally weighted-index (lagged value also included). See Table 1 for definitions of the variables. AR(1) is also included in the model. AIC refers to Akaike Information Criterion, SIC refers to Schwarz Information Criterion. This table also presents Durbin–Watson test for first-order serial correlation. See Table 1 for definitions of the variables. Notes: (standard errors in parentheses), ***, ** and * denote statistically significant at 0.1%, 1% and 5% respectively.

	Focus portfolio		Global portfolio		Focus portfolio		Global portfolio	
	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.
March 2000–December 2007; N: 94								
C	0.404***	*2.61*	0.357**	*2.22*	0.468***	*2.92*	0.443***	*2.73*
MSEEUR	−0.076**	*−2.43*	0.012	*0.49*	−0.077***	*−2.71*	0.009	*0.36*
MSEFLA	0.048*	*1.78*	0.096***	*4.89*	0.039	*1.47*	0.085***	*3.85*
MSEMFA	0.216***	*5.53*	0.107***	*3.09*	0.218***	*5.54*	0.109***	*3.26*
MSINDI	0.064***	*3.38*	0.038**	*2.36*	0.069***	*3.63*	0.043**	*2.56*
MSRUSS	0.167***	*8.73*	0.080***	*4.91*	0.169***	*9.34*	0.083***	*5.44*
WICINA	0.050**	*2.41*	0.011	*0.83*	0.047**	*2.23*	0.007	*0.55*
AWMEAF	0.016	*0.86*	0.031*	*1.67*	0.018	*0.91*	0.034*	*1.74*
LHEMAME	0.056	*1.65*	0.054*	*1.72*	0.056	*1.56*	0.052	*1.60*
FTREMR	0.028	*1.55*	0.038***	*2.77*				
AR(1)	0.242**	*2.52*	0.287***	*3.52*	0.273***	*3.02*	0.290***	*3.34*
Adjusted R^2	0.90		0.89		0.90		0.88	
AIC	3.04		2.69		3.04		2.74	
SIC	3.34		2.99		3.31		3.01	
Durbin–Watson	1.97		1.99		1.98		1.96	
F-statistic	*86.83*		*74.03*		*94.85*		*77.07*	
Prob (F-statistic)	0.00		0.00		0.00		0.00	

	Focus portfolio		Global portfolio	
	Coef.	*t*-Stat.	Coef.	*t*-Stat.
March 1995–December 2007; N = 154				
C	0.403**	*2.15*	0.698***	*3.27*
MSEEUR	−0.018	*−0.58*	0.061***	*2.87*
MSEFLA	0.061**	*2.28*	0.076***	*3.22*
MSEMFA	0.286***	*7.51*	0.094***	*4.63*
MSINDI	0.028	*1.06*	0.029**	*2.01*
MSRUSS	0.123***	*6.02*	0.051***	*4.08*
WICINA	0.053**	*2.56*	0.002	*0.17*
AWMEAF	0.045	*1.48*	0.050***	*2.87*
LHEMAME	0.017**	*2.27*	0.046***	*10.72*
AR(1)	0.234**	*2.29*	0.467***	*4.75*
Adjusted R^2	0.87		0.85	
AIC	4.01		3.46	
SIC	4.20		3.66	
Durbin–Watson	1.95		2.03	
F-statistic	*118.10*		*96.10*	
Prob (F-statistic)	0.00		0.00	
March 1995–February 2000; N = 60				
C	0.445	*1.12*	1.130**	*1.99*
MSEEUR	0.061	*1.61*	0.110***	*3.26*
MSEFLA	0.116*	*1.89*	0.050	*0.99*
MSEMFA	0.339***	*6.16*	0.082***	*2.78*

(continued on next page)

Table 5 (*continued*)

	Focus portfolio		Global portfolio	
	Coef.	*t*-Stat.	Coef.	*t*-Stat.
MSINDI	0.017	*0.44*	0.004	*0.20*
MSRUSS	0.090***	*3.91*	0.042***	*2.67*
WICINA	0.067**	*2.34*	0.010	*0.49*
AWMEAF	0.028	*0.43*	0.067*	*1.86*
LHEMAME	0.000	*−0.04*	0.043***	*5.36*
AR(1)	0.238	*1.34*	0.574***	*3.84*
Adjusted R^2	0.88		0.83	
AIC	4.63		4.13	
SIC	4.98		4.48	
Durbin–Watson	1.95		2.01	
F-statistic	50.33		33.69	
Prob (F-statistic)	0.000		0.000	

Global portfolio for which the abnormal returns increase 24% (0.443/0.357-1) in comparison to the increase of 16% (0.468/0.404-1) for the Focus portfolio.

The explanation power in the analysis model increases after the crisis implying that once the crisis unfolded emerging market hedge funds appeared to be less alternative. Nevertheless, when the difference between Focus and Global portfolios is considered, the Focus portfolio delivered 0.103% better abnormal performance over the pre-crisis period from March 2000 to December 2007. However, when the earliest period from March 1995 to February 2000 is considered, only the Global portfolio of emerging market hedge funds shows statistically significant abnormal returns. The explanation power of the model is also lower in comparison to the corresponding analysis in Table 3. Taken together, the results imply that the outperformance of emerging market hedge funds has shifted from Global hedge funds to more focused hedge funds. The risk in emerging market hedge funds has become less idiosyncratic.

Table 6 presents the associated characteristics of hedge funds which have either local of global focus. Global hedge funds are on average bigger and they have higher investment capacity implying that focused

Table 6
Fund characteristics. This table presents fund characteristics for focused and global hedge funds as of September 2009. The full sample includes 869 funds including those which do not report return data.

	Fund capacity US$M1		Fund size US$M1	
Variable	Count	Mean	Count	Mean
Global	96	608.85	176	208.12
Focus	391	489.41	575	80.69
All	487	512.96	751	110.55
t	1.71		5.55	
Prob.	0.089		0.000	
	High watermark (1 if yes)		**Listed in exchange (1 if yes)**	
Variable	Count	%	Count	%
Global	195	85.13%	195	28.72%
Focus	674	78.49%	674	15.43%
All	869	79.98%	869	18.41%
z	4.38		4.20	
Prob.	0.000		0.000	
	Fund closed (1 if yes)		**Lock-up (1 if yes)**	
Variable	Count	%	Count	%
Global	195	7.69%	195	53.33%
Focus	674	5.49%	674	45.25%
All	869	5.98%	869	47.07%
z	0.66		3.27	
Prob.	0.254		0.001	

hedge funds are the ones rather using niche strategies. However, 53.33% of global hedge funds use lock-up periods which is more than 45.25% for focused hedge funds implying that outperformance of focused hedge funds over global hedge funds is not likely to be related to illiquidity premium (see Aragon, 2007). When considering the recent outperformance of focused hedge funds, it is astonishing that global hedge funds on average appear to be more often closed. However, this difference is not statistically significant. In conclusion, the characteristics associated with focused hedge fund imply that is realistic for investors to chase outperformance if focused hedge funds.

We also carried analysis of the performance of emerging market hedge funds using the Lipper TASS database in which all hedge funds do not report their geographical focuses and they may have more focuses than one, which is different from the database of EurekaHedge. Using this database, we found for the Russia portfolio to have statistically significant and highest abnormal performance. Thus, our results appear to be fairly similar although we find outperformance of focused hedge funds to be much more evident in the Lipper TASS database, which is likely to be caused by voluntary nature of hedge funds to report their geographical focuses.

7. Conclusion

This study examines whether emerging market hedge funds outperform their underlying indexes in their respective focus markets. The results by Strömqvist (2007), Peltomäki (2008), and Abugri and Dutta (2009) suggest that emerging market hedge funds at the index level do not outperform their underlying market indexes. In contrast to these earlier findings, the results of this study suggest that emerging market hedge funds on aggregate may be able to outperform their underlying indexes once they have a geographical focus. This geographical focus can be considered such that hedge funds clearly have an information advantage when they have a focus and so they are able to outperform their underlying benchmarks at the broad level. The result implies also that when non-direct investments in emerging markets is considered in the current global situation focused rather than global hedge funds should be used. For geographical portfolios, we find that Eastern Europe and Russia focus portfolio is the only portfolio able to show outperformance over the period March 2000 to August 2009.

Our results suggest that the performance of emerging market hedge funds appeared to look much better before the crisis 2008. Moreover, the extend the emerging market hedge funds represent true alternative investments for investors is less after considering the crisis of 2008 in the analysis as our model is capable of explaining more than 90% of their returns. The specific characteristic of our model to other studies is the use of multiple emerging market regional indexes. The use of multiple indexes increases explanatory power of the model – especially in the case of focused hedge funds – and alters the results significantly as the alpha for focused funds becomes statistically significant. Information criteria also suggest that the analysis of model emerging market hedge funds is better without general emerging market returns. Thus, it is clearly evident that the analysts should use very geographical equity indexes when analyzing emerging market hedge funds.

Overall, we find that focused hedge funds are becoming more attractive while idiosyncratic risk in emerging market hedge funds is decreasing. This result implies that easy anomalies and profit opportunities in emerging markets are decreasing and finding them requires more specialization. Without the profound expertise and knowledge of the underlying markets emerging market hedge funds would be conventional mutual funds rather than alternative investments and abnormal performance producers.

It may be noted that the results may depend on the Database and the practice of reporting geographical focuses as our results using the Lipper TASS database provided much stronger evidence for outperformance of focused hedge funds. It is very likely that the difference in the results is altered by voluntary nature of reporting geographical focuses to the database.

The results of this study may be applicable to mutual funds, particularly the performance shift from global funds to focused funds but this would be a considerable avenue for further research. Also, it would be interesting to find out whether geographical focus is important for other hedge funds than emerging market hedge funds. However, geographical focus in emerging markets may be more important as the markets are not as developed and transparent as in the developed economies. In further studies, it would be also interesting to test hedge fund performance against some country allocation strategies. As Naranjo and Porter (2007) confirm profitability of momentum strategies on emerging market country portfolios, one could use such a strategy as a hedge fund performance benchmark.

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Stock market correlations during the financial crisis of 2008–2009: Evidence from 50 equity markets

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Using data from 50 equity markets we examine conditional and unconditional correlations around two major banking events during the financial crisis of 2008–09. To measure the value of covariance information on the augmented DCC model used in the study, a portfolio in-sample estimation is performed. We show that by taking into account the change in the level of variance in high volatility periods, the estimates of the conditional covariance are more efficient in capturing the dynamics of the stock markets variance. Furthermore, in a two-asset allocation framework, the model consistently generates relatively low portfolio variances, implying substantial benefits in portfolio diversification.

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1. Introduction

Financial or economical crises can have serious consequences for investors and as a result the topic issue has attracted considerable amount of interests among academic researchers. For example, the crash of 1987 (Forbes & Rigobon, 2002), the Russian, Brasilian and Asian crises of 1997–98 (Forbes & Rigobon, 2002; Kenourgios et al., 2011), the terrorist attacks of 9.11 (Hon et al., 2004) and the "tech bubble" (Kenourgios et al., 2011) have been widely examined. More recently, scholarship has addressed the impact of the 2008–09 financial crisis on foreign exchange markets (Baba & Packer, 2009; Melvin & Taylor, 2009; Fratzscher, 2009), on fixed income markets (Dwyer & Tkac, 2009; Acharya et al., 2009; Hartmann, 2010) and on stock markets (Bartman & Bodnar, 2009; Dooley & Hutchison, 2009; Billio & Caporin, 2010; Chudik & Fratzscher, 2011; Schwert, 2011; Syllignakis & Kouretas, 2011). All these studies demonstrate that financial markets' volatilities increase substantially during crisis, which further implies that both financial markets' volatilities and correlations move together over time.[1] This co-movement diminishes the diversification benefits and it is commonly known to be apparent especially in the equity markets.

In this study we investigate the effects of two major banking events, i.e. JP Morgan Chase's acquisition of the Bear Stearns investment bank and the collapse of the Lehman Brothers Holding Inc. investment bank, on the time-varying correlations of international stock markets. Our objective is to examine the impact of these events on a total of 50 international stock markets from 6 different regions using an augmented dynamic conditional correlation (hereafter DCC) model. In particular, the model allows us to examine the effect of the financial crisis of 2008–09 on the conditional correlations across all investigated stock markets, while simultaneously controlling for changes in the conditional variances.

Our study contributes to the earlier studies on the financial crisis by examining time varying covariance structure between global stock indexes during the financial crisis. Like Syllignakis and Kouretas (2011) we also analyze dynamic correlations, but unlike them we do not focus on the contagion issue. Instead, we examine the dynamic correlations from the portfolio manager's point of view across global stock markets. Specifically, in addition to modeling the conditional covariance matrix we evaluate the performance of the estimated conditional correlations in the asset allocation framework, evaluating in-sample portfolio optimization and hedging performance.

We also extend the work of Syllignakis and Kouretas (2011) by reporting the results for all major economic areas, namely Developed Europe, G7, Asia Pacific, Middle East, Latin America, and Emerging Europe. Our study also adds to the earlier literature on DCC models by modeling simultaneously 50 stock index return series (i.e. the 49 stock markets' correlations against the U.S. market). The characteristics of the DCC models make it possible to take into account the effect of

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[1] The arrival of bad news causes significant increase in cross-market variances and correlations (Braun et al., 1995; Christiansen, 2000; Cappiello, Engle and Sheppard, 2003).

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heteroscedasticity on the variance of the fifty return series over the estimation periods. By allowing correlation to change over time, we are able to demonstrate in a portfolio framework that the conditional model estimates outperform simple models.

Our empirical findings show that the impact of the Lehman Brothers' collapse resulted in significant increases in correlations, whereas the acquisition of Bear Stearns had negligible effects on correlations. We find that the effect of the Lehman Brothers' collapse on global stock markets is prominent for all the regions, which is evident from both the unconditional and conditional correlation estimates. Furthermore, when evaluating the performance of the conditional correlations in the asset allocation framework, in which portfolio optimization and hedging performance are considered in-sample, we find that the augmented DCC model outperforms all the other models. The augmented DCC model constitutes the lowest portfolio variances within all crisis periods implying that the augmented DCC model is efficient in capturing the dynamics of the stock market variances during high volatility periods.

2. Data and preliminary analysis

The study is carried out with 50 different stock market indexes from six different regions. The data set is obtained from Datastream. The data periods investigated are as follows; (*preBS*) one year before the Bear Stearns event (March 15, 2007, to March 14, 2008), (*postBS*) 6 months thereafter (March 17, 2008 to September 12, 2008) and (*postLB*) 6 months after the Lehman Brothers' collapse (September 15, 2008 to March 16, 2009). Following, for example, Forbes and Rigobon (2002) and Hon et al. (2004), we use two-day rolling-average returns denominated in dollars in our analysis. Two-day average returns are utilized mindful that the markets around the world are not open at the same times.

As a first step, we follow Hon et al. (2004) and conduct a simple correlation analysis to examine the relationship of each of the 49 countries with the U.S. stock markets. As a next step, we examine the impacts of Bear Stearns and Lehman Brothers on global stock markets by using an augmented dynamic conditional correlation (DCC) model. We report the results dividing the countries into six different regions, namely G7, Developed Europe, Emerging Europe, Asia-Pacific, Latin America and Middle East. Table 1 presents the countries investigated in the study, with descriptive statistics on the two-day rolling average stock index returns.

Next, we constitute the Fisher transformed correlations as in similar to Hon et al. (2004). These transformed correlations are then compared between the periods defined. For the analysis, the statistical values of the Fisher z transformations for the Pearson product moment correlations are obtained as follows:

$$\hat{\rho}_{i,t} = 0.5\left[\ln\left(\rho^*_{i,t}+1\right)-\ln\left(\rho^*_{i,t}-1\right)\right] \tag{1}$$

where $\hat{\rho}_{i,t}$ and $\rho^*_{i,t}$ denote the transformed and untransformed Pearson product moment correlations for country *i*, respectively. The transformed pairs of correlations enable us to perform a test to decide whether the two correlations have different strengths. To obtain approximately standard normal distributed z-statistic values the difference is formed as follows:

$$z = \left(\hat{\rho}_{1,t}-\hat{\rho}_{2,t}\right)/\sqrt{1/(n_1-3)+1/(n_2-3)} \tag{2}$$

where n_i is the sample size.

In Table 2 we report the results of the preliminary analysis of the unconditional correlation analysis. Significant test statistic values indicate the difference in return series correlation strength between the compared time periods. Column z-stat (1) presents the test statistics comparing the unconditional correlations between the *preBS* and *postBS* periods. The results suggest that the unconditional correlations decline after the event of JP Morgan's acquisition of Bear Stearns. The decline in correlation can be observed within the period of *postBS* for all the countries (the only exceptions are Korea, Taiwan, and Japan).

Column z-stat (2) in Table 2 presents the test statistics comparing the unconditional correlations between the *preBS* and *postLB* periods (i.e. a comparison of the post period correlations against the 12-month period) and Column z-stat (3) gives the test statistics between *postBS* and *postLB*.

Table 1
Descriptive statistic on two-day rolling average stock index returns.

Region/country	Mean	Std. dev.	Skewness	Kurtosis	LB(16)
Asia Pacific					
Australia (AUST)	−0.001	0.018	−0.318	6.068	173.997***
China (CHIN)	0.000	0.020	−0.207	5.624	182.171***
Hong Kong (HGKG)	0.000	0.015	−0.205	6.577	186.321***
Indonesia (INDF)	0.000	0.020	−0.494	7.570	298.176***
India (INDI)	0.000	0.020	−0.022	6.798	236.703***
Korea (KORE)	−0.001	0.021	−0.313	11.49	217.811***
Malaysia (MALF)	0.000	0.011	−0.339	4.787	193.503***
New Zealand (NZEA)	−0.001	0.015	−0.498	5.357	171.903***
Pakistan (PAKI)	−0.001	0.017	−0.677	5.988	404.502***
Philippines (PHLF)	0.000	0.016	−0.381	5.676	228.005***
Singapore (SING)	0.000	0.015	−0.282	5.230	205.519***
Sri Lanka (SRIL)	−0.001	0.013	2.355	18.625	365.755***
Taiwan (TAIW)	0.000	0.014	−0.068	3.974	281.963***
Thailand (THAF)	0.000	0.016	−0.636	9.022	254.814***
Middle East					
Bahrain (BAHR)	−0.001	0.013	−2.79	23.815	260.993***
Egypt (EGYT)	0.000	0.016	−1.626	12.793	246.925***
Israel (ISRA)	0.000	0.010	−0.708	5.940	193.362***
Jordan (JORD)	0.000	0.011	−0.967	8.178	307.815***
Kuwait (KUWA)	0.000	0.014	−0.784	8.747	295.148***
Morocco (MORC)	0.000	0.011	−0.695	7.117	247.024***
Latin America					
Argentina (ARGT)	−0.001	0.021	−0.745	7.349	187.209***
Brazil (BRAZ)	0.000	0.024	−0.374	6.634	182.477***
Chile (CHIL)	0.000	0.015	−0.220	9.663	234.08***
Columbia (COLM)	0.000	0.016	−0.637	6.316	198.519***
Mexico (MEXF)	−0.001	0.019	−0.329	6.610	197.748***
Peru (PERU)	0.001	0.021	−0.224	5.498	182.403***
Developed Europe					
Austria (ASTR)	−0.002	0.021	−0.272	7.935	189.668***
Belgium (BELG)	−0.002	0.017	−0.961	8.320	227.832***
Denmark (DNMK)	0.000	0.016	−0.401	7.452	202.998***
Ireland (EIRE)	−0.002	0.022	−0.532	5.910	188.609***
Finland (FIND)	−0.001	0.018	0.009	4.860	162.223***
Greece (GDEE)	−0.001	0.018	−0.371	6.812	209.517***
Netherlands (NETH)	−0.001	0.015	−0.478	6.855	175.16***
Norway (NWAY)	−0.001	0.022	−0.528	6.029	167.088***
Portugal (PORD)	−0.001	0.014	−0.090	8.467	251.794***
Spain (SPAN)	−0.001	0.016	−0.262	7.300	196.805***
Sweden (SWDN)	−0.001	0.019	0.194	5.597	166.81***
Switzerland (SWIT)	−0.001	0.012	−0.159	7.330	172.86***
G7					
Canada (CNDA)	0.000	0.017	−0.606	8.626	177.225***
France (FRNC)	−0.001	0.015	−0.019	6.907	170.54***
Germany (GERM)	−0.001	0.015	−0.165	6.431	156.842***
Italy (ITAL)	−0.001	0.016	−0.166	6.752	203.363***
Japan (JPAN)	−0.001	0.013	0.155	6.878	150.766***
United Kingdom (UTDK)	−0.001	0.016	−0.105	7.378	170.601***
United States (US)	−0.001	0.013	−0.344	7.307	112.217***
Emerging Europe					
Czech Republic (CZCH)	0.000	0.020	−0.057	11.927	183.217***
Hungary (HUNG)	−0.001	0.024	−0.064	12.104	221.622***
Poland (PLND)	−0.001	0.021	−0.199	6.892	221.661***
Russia (RUSS)	−0.001	0.027	−0.238	12.82	277.679***
Turkey (TURK)	0.000	0.023	−0.214	5.229	220.543***

Notes: LB(16) refers to Ljung–Box statistic with up to 16-day lags. ***, ** and * denote statistical significance at 0.1%, 1% and 5%, respectively.

Table 2
Unconditional correlations around the Bearn Stearns and Lehman Brothers events. The table presents the Pearson product moment correlations. z-stat (1) is the test statistics of correlation strength between *preBS* and *postBS*. z-stat (2) is the test statistics of correlation strength between *preBS* and *postLB*. z-stat (3) is the test statistics of correlation strength between *postBS* and *postLB*. z-statistics are based on the Fisher transformed correlations. ***, ** and * denote statistical significance at 0.1%, 1% and 5%, respectively.

Region/ country	12 months *preBS*	6 months *postBS*	z-stat (1)	6 months *postLB*	z-stat (2)	z-stat (3)
	ρ	ρ		ρ		
Asia Pacific						
AUST	0.420	0.224	−2.023*	0.581	2.005*	3.481***
CHIN	0.263	0.164	−0.957	0.551	3.243**	3.627***
HGKG	0.341	0.189	−1.513	0.509	1.901	2.951**
INDF	0.326	0.112	−2.082*	0.354	0.298	2.059*
INDI	0.285	0.153	−1.280	0.566	3.230**	3.896***
KORE	0.286	0.300	0.136	0.494	2.288*	1.858
MALF	0.237	0.063	−1.645	0.340	1.039	2.321*
NZEA	0.385	0.256	−1.330	0.515	1.519	2.462*
PAKI	0.118	0.014	−0.964	−0.042	−1.483	−0.445
PHLF	0.388	0.206	−1.851	0.311	−0.816	0.898
SING	0.385	0.277	−1.116	0.591	2.535*	3.154**
SRIL	0.153	−0.115	−2.491*	−0.019	−1.610	0.766
TAIW	0.233	0.362	1.312	0.396	1.679	0.314
THAF	0.286	0.043	−2.313*	0.506	2.433*	4.102***
Middle East						
BAHR	−0.116	0.032	1.371	−0.085	0.293	−0.934
EGYT	0.146	0.016	−1.209	0.342	1.929	2.712**
ISRA	0.454	0.255	−2.116*	0.421	−0.384	1.500
JORD	−0.014	−0.083	−0.635	0.144	1.473	1.821
KUWA	−0.070	−0.083	−0.121	0.022	0.851	0.839
MORC	0.028	−0.083	−1.021	0.341	3.032**	3.501***
Latin America						
ARGT	0.591	0.178	−4.603***	0.653	0.941	4.797***
BRAZ	0.701	0.490	−3.071**	0.804	2.237*	4.589***
CHIL	0.614	0.378	−2.927**	0.706	1.516	3.842***
COLM	0.444	0.319	−1.360	0.575	1.644	2.595**
MEXF	0.814	0.668	−3.078**	0.845	0.901	3.442***
PERU	0.588	0.233	−4.042***	0.761	2.993**	6.082***
Developed Europe						
ASTR	0.523	0.395	−1.499	0.616	1.283	2.405*
BELG	0.637	0.481	−2.111*	0.630	−0.098	1.742
DNMK	0.540	0.371	−1.975*	0.699	2.422*	3.800***
EIRE	0.551	0.472	−0.991	0.610	0.833	1.577
FIND	0.525	0.321	−2.306*	0.723	3.057**	4.634***
GDEE	0.480	0.163	−3.303***	0.592	1.462	4.120***
NETH	0.611	0.549	−0.863	0.723	1.887	2.375*
NWAY	0.444	0.239	−2.154*	0.678	3.225**	4.647***
PORD	0.387	0.239	−1.521	0.624	2.982**	3.890***
SPAN	0.527	0.512	−0.197	0.715	2.878**	2.655**
SWDN	0.585	0.427	−1.971*	0.713	2.078*	3.500***
SWIT	0.585	0.420	−2.056*	0.724	2.263*	3.733***
G7						
CNDA	0.741	0.385	−5.032***	0.781	0.898	5.130***
FRNC	0.640	0.522	−1.657	0.764	2.298*	3.418***
GERM	0.569	0.483	−1.097	0.802	4.254***	4.622***
ITAL	0.599	0.382	−2.659**	0.703	1.689	3.759***
JPAN	0.174	0.191	0.163	0.266	0.896	0.632
UTDK	0.635	0.559	−1.092	0.756	2.188*	2.834**
Emerging Europe						
CZCH	0.320	0.054	−2.555*	0.565	2.858**	4.678***
HUNG	0.469	0.232	−2.513*	0.636	2.248*	4.116***
PLND	0.562	0.209	−3.912***	0.557	−0.075	3.321***
RUSS	0.467	0.262	−2.196*	0.551	1.051	2.808**
TURK	0.555	0.340	−2.511*	0.660	1.541	3.504***

The results indicate that contrary to the Bear Stearns event (*postBS*) the correlations exhibit a significant increase after the event of Lehman Brothers' collapse.

3. Analysis of dynamic conditional correlations

3.1. Estimation of the DCC model

We estimate the time varying conditional correlations from the standard two-step specification of the DCC model proposed by Engle (2002). In the first step, a diagonal vech parametrization proposed by Bollerslev, Engle and Wooldridge (1988) is modeled by assuming that the market returns follow a simple AR(1) dependency structure (Eq. (3)) and the conditional volatility follows a GARCH(1,1) structure (Eq. (4)). According to the diagonal vech model it is assumed that each covariance depends only on its past values and innovations, i.e., α and β are diagonal. Then each element of covariance variance matrix H_t follows a GARCH structure driven by the corresponding cross product $\varepsilon_t\varepsilon'_t$. The mean equation of the model is as follows:

$$r_t = \varphi_0 + \varphi_1 r_{t-1} + \varepsilon_t \quad ; \quad \varepsilon_t | I_{t-1} \sim (0, H_t) \tag{3}$$

where $r_t = (r_{1,t}, r_{2,t}, \ldots, r_{50,t})$ is an 50×1 vector of two-day rolling-average returns at time t and the vector $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \ldots, \varepsilon_{50,t})'$ is the unconditional error component of r_t. It is also assumed that the time varying covariance variance matrix H_t consists of normally distributed errors ε_t conditional on the given information set I_{t-1}.

To examine the impact of the two banking events on conditional volatilities, we estimate the following augmented conditional variance equation:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1} + \beta_i h_{i,t-1} + \gamma_1 postBS_t + \gamma_2 postLB_t \tag{4}$$

where the dummy variables *postBS* and *postLB* are included into the variance equation for the time periods 3/17/2008–9/12/2008 and 9/15/2008–3/16/2009, respectively. This structure of the model in stage one adequately captures the volatility clustering in the data.

In the second part of the model, we use the estimates of the conditional standard deviations to standardize the returns. Then the standardized returns are used to model the correlation dynamics. Thus, $H_t = D_t R_t D$ is the time varying covariance matrix where R_t is a simple estimate of the unconditional correlation matrix of the standardized errors and $D_t = diag\{\sqrt{h_{ii,t}}\}$ is the diagonal matrix in which h_{iit} is the conditional standard deviations from the individually modeled GARCH variance processes. Assuming that the standardized residual vector $z = D_t^{-1}\varepsilon_t$ has zero mean and variance one the conditional correlation matrix (Eq. (5)) can be specified further:

$$\begin{gathered} r_t | I_{t-1} \sim N(0, D_t R_t D_t) \\ R_t = (diag(Q_t))^{-\frac{1}{2}} Q (diag(Q_t))^{-\frac{1}{2}} \\ Q_t = \left(q_{ij,t}\right) \\ (diag(Q_t))^{-\frac{1}{2}} = diag\left(\frac{1}{\sqrt{q_{11,t}}}, \ldots, \frac{1}{\sqrt{q_{nn,t}}}\right) \\ q_{ij,t} = \overline{\rho}_{ij} + \alpha\left(z_{i,t-1} z_{j,t-1} - \overline{\rho}_{ij}\right) + \beta\left(q_{ij,t-1} - \overline{\rho}_{ij}\right) \end{gathered} \tag{5}$$

where $\overline{\rho}_{ij,t} = [R_t]_{ij}$ is the unconditional correlation coefficient. The model can be estimated by using a two-stage approach to maximize the log-likelihood function. Let the parameters in D be denoted by θ and the additional parameter in R be denoted by φ. The log likelihood can be stated as the sum of a volatility part and a correlation part as follows:

$$L(\theta, \varphi) = L_V(\theta) + L_C(\theta, \varphi) \tag{6}$$

where the volatility part is

$$L_V(\theta) = -\frac{1}{2}\sum_t \left(n\log(2\pi) + \log|D_t|2 + r^{'}D_t^{-2}r_t\right) \tag{7}$$

and the correlation part is

$$L_C(\theta,\varphi) = -\frac{1}{2}\sum \left(n\log|R_t| + \varepsilon^{'}_t R_t^{-1}\varepsilon_t - \varepsilon^{'}_t\varepsilon_t\right). \tag{8}$$

The first part of the likelihood function in Eq. (6), i.e. the volatility part, is the sum of individual GARCH likelihoods. The log-likelihood function can be maximized in the first stage over the parameters D_t (see Eq. (7)). Given the parameters estimated in the first stage, the second stage estimates the parameters in the conditional correlation equation by maximizing the likelihood function equation (see Eq. (8)).

3.2. Conditional variances and conditional correlations around the crisis events

3.2.1. Behavior of conditional variances around the crisis events

In Table 3 we present the estimation results of the augmented variance equation, i.e., the results of the Eq. (4) of the DCC's two step estimation. The results indicate that the coefficients γ_1 weights on the dummy variable *postBS* are effectively zero indicating that conditional variance does not increase after the Bear Stearns event. Although that 14 coefficients out of 49 appear to be statistically significant, the coefficients in absolute value are very low for all the stock markets. The opposite is true when considering the results of the post period event of the Lehman Brothers' collapse. The coefficients γ_2, are positive and statistically significant (47 out of 49 coefficients) suggesting that the conditional variance increases markedly after the Lehman Brothers' collapse.

Additionally, the DCC model estimates show that the constant term values in the mean equation are not statistically significant at the conventional 5% level suggesting that our model is correctly specified. Additionally, AR(1) terms are all highly significant at the 1% level in the mean equation, thus the result suggests a positive autocorrelation in the index returns structure.[2]

3.2.2. Behavior of conditional correlations around the crisis events

Given that the empirical evidence shows that during periods of stock market fluctuation correlations between international asset returns tend to increase, the existing results also suggest a time varying correlation. Thus, the preliminary perception of the dynamics of the pair-wise conditional correlations over the time periods is interesting and it is consistent with the empirical research, e.g. by Longin and Solnik (2001), Ang and Chen (2002), and Kearney and Poti (2006). Therefore, we further investigate the dynamic features of the correlation changes during the previously defined time periods of financial crisis by regressing Fisher transformed conditional correlations against two dummy variables by using a structure of a GARCH(1,1) model in a diagonal vech formation. This allows us to investigate dynamic feature of conditional variance changes during the various phases of the financial crisis. The model is as follows:

$$\rho_{i,t} = \varphi_i + DM_i postBS_t + DM_i postLB_t + \varepsilon_{ij,t} \quad ; \quad \varepsilon_{ij;t}|I_{t-1}\sim N(0,H_t) \tag{9}$$

$$h_{i,t} = \omega_i + \alpha_i\varepsilon_{ij,t-1} + \beta_i h_{ij,t-1} + DV_1 postBS_t + DV_2 postLB_t \tag{10}$$

where $\rho_{i,t} = (\rho_{1,t}, \rho_{2,t}, \ldots, \rho_{49;t})'$ is an 49×1 vector of pair-wise Fisher transformed conditional correlations between U.S. and 49 country stock index returns. To capture structural changes in the conditional correlation coefficients due to external shocks, the dummy variables *postBS* and *postLB* are included into the mean and variance equations.

[2] However, the estimates of the mean equation are not reported. They are available from the authors upon request.

Table 3
Conditional variances around the two banking events. Estimation results from the DCC–GARCH model.

	Variance equations				
	ω	α	β	γ_1	γ_2
Asia Pacific					
AUST	0.077***	0.239***	0.715***	0.046**	0.272***
	(0.014)	(0.023)	(0.023)	(0.016)	(0.054)
CHIN	0.132***	0.207***	0.730***	0.060*	0.345**
	(0.031)	(0.022)	(0.024)	(0.025)	(0.121)
HGKG	0.026**	0.166***	0.813***	0.013	0.086**
	(0.010)	(0.018)	(0.018)	(0.015)	(0.027)
INDF	0.252***	0.202***	0.660***	0.031	0.473***
	(0.038)	(0.022)	(0.026)	(0.025)	(0.077)
INDI	0.124***	0.280***	0.689***	−0.034	0.376***
	(0.017)	(0.026)	(0.024)	(0.023)	(0.068)
KORE	0.050**	0.179***	0.793***	0.027	0.397***
	(0.018)	(0.015)	(0.017)	(0.026)	(0.098)
MALF	0.158***	0.238***	0.588***	−0.026**	0.031*
	(0.019)	(0.027)	(0.041)	(0.010)	(0.015)
NZEA	0.143***	0.330***	0.522***	0.117**	0.608***
	(0.021)	(0.039)	(0.047)	(0.039)	(0.079)
PAKI	0.086***	0.329***	0.650***	−0.055**	−0.025
	(0.015)	(0.027)	(0.024)	(0.019)	(0.025)
PHLF	0.213***	0.203***	0.663***	−0.065**	0.233***
	(0.040)	(0.032)	(0.054)	(0.021)	(0.055)
SING	0.042***	0.179***	0.781***	0.003	0.328***
	(0.010)	(0.023)	(0.024)	(0.011)	(0.075)
SRIL	0.109***	0.158***	0.758***	0.018	0.949***
	(0.018)	(0.016)	(0.024)	(0.010)	(0.131)
TAIW	0.107***	0.176***	0.741***	−0.013	0.240***
	(0.016)	(0.016)	(0.027)	(0.016)	(0.048)
THAF	0.269***	0.181***	0.732***	−0.040*	0.432***
	(0.033)	(0.016)	(0.019)	(0.018)	(0.084)
Middle East					
BAHR	0.050***	0.346***	0.591***	−0.011	0.495**
	(0.010)	(0.058)	(0.041)	(0.011)	(0.182)
EGYT	0.152**	0.262***	0.540***	0.069*	1.078**
	(0.053)	(0.055)	(0.112)	(0.033)	(0.381)
ISRA	0.078*	0.160***	0.646***	0.031	0.266*
	(0.033)	(0.037)	(0.118)	(0.023)	(0.132)
JORD	0.024**	0.159***	0.783***	0.036	0.137**
	(0.008)	(0.026)	(0.028)	(0.019)	(0.049)
KUWA	0.059***	0.152***	0.709***	0.009	0.804***
	(0.014)	(0.018)	(0.042)	(0.012)	(0.192)
MORC	0.131***	0.236***	0.482***	−0.021	0.492***
	(0.015)	(0.018)	(0.034)	(0.014)	(0.059)
Latin America					
ARGT	0.146***	0.267***	0.657***	0.097**	0.422***
	(0.039)	(0.032)	(0.036)	(0.034)	(0.122)
BRAZ	0.305***	0.225***	0.658***	−0.048	1.073***
	(0.056)	(0.028)	(0.045)	(0.036)	(0.299)
CHIL	0.062***	0.195***	0.755***	0.001	0.043
	(0.016)	(0.024)	(0.024)	(0.017)	(0.034)
COLM	0.093***	0.225***	0.707***	0.001	0.097
	(0.017)	(0.024)	(0.022)	(0.023)	(0.057)
MEXF	0.108***	0.151***	0.770***	−0.037*	0.478***
	(0.021)	(0.016)	(0.025)	(0.017)	(0.098)
PERU	0.128***	0.172***	0.746***	0.034	0.885***
	(0.027)	(0.016)	(0.019)	(0.02)	(0.121)
Developed Europe					
ASTR	0.037***	0.192***	0.772***	0.035	0.766***
	(0.008)	(0.016)	(0.015)	(0.024)	(0.093)
BELG	0.033***	0.206***	0.777***	0.011	0.215***
	(0.007)	(0.022)	(0.019)	(0.014)	(0.032)
DNMK	0.053***	0.217***	0.722***	0.034	0.425***
	(0.012)	(0.026)	(0.027)	(0.022)	(0.075)
EIRE	0.089***	0.235***	0.716***	0.089***	0.830***
	(0.015)	(0.018)	(0.020)	(0.018)	(0.110)
FIND	0.123***	0.212***	0.694***	0.071***	0.709***
	(0.024)	(0.020)	(0.029)	(0.015)	(0.116)
GDEE	0.053***	0.222***	0.723***	0.072*	0.499***
	(0.012)	(0.021)	(0.023)	(0.031)	(0.072)

(*continued on next page*)

Table 3 (*continued*)

	Variance equations				
	ω	α	β	γ_1	γ_2
NETH	0.036***	0.183***	0.764***	0.017	0.461***
	(0.009)	(0.021)	(0.029)	(0.016)	(0.101)
NWAY	0.103***	0.173***	0.753***	0.070	1.199***
	(0.024)	(0.022)	(0.028)	(0.040)	(0.295)
PORD	0.032***	0.163***	0.785***	0.018	0.251***
	(0.009)	(0.012)	(0.019)	(0.014)	(0.036)
SPAN	0.042***	0.179***	0.781***	0.003	0.328***
	(0.010)	(0.023)	(0.024)	(0.011)	(0.075)
SWDN	0.109***	0.158***	0.758***	0.018	0.949***
	(0.018)	(0.016)	(0.024)	(0.010)	(0.131)
SWIT	0.029***	0.146***	0.799***	0.000	0.234***
	(0.008)	(0.016)	(0.026)	(0.009)	(0.070)
G7					
CNDA	0.031**	0.173***	0.789***	0.020	0.434***
	(0.010)	(0.016)	(0.020)	(0.014)	(0.075)
FRNC	0.036***	0.163***	0.795***	0.008	0.342***
	(0.008)	(0.022)	(0.026)	(0.014)	(0.081)
GERM	0.036***	0.136***	0.819***	−0.007	0.326**
	(0.011)	(0.026)	(0.024)	(0.011)	(0.114)
ITAL	0.032***	0.145***	0.807***	0.012	0.380***
	(0.008)	(0.020)	(0.020)	(0.010)	(0.079)
JPAN	0.036***	0.135***	0.813***	0.024	0.140***
	(0.009)	(0.015)	(0.021)	(0.015)	(0.034)
USAML	0.024**	0.144***	0.812***	0.011	0.214***
	(0.009)	(0.017)	(0.021)	(0.009)	(0.046)
UTDK	0.026**	0.195***	0.782***	0.017	0.265*
	(0.008)	(0.032)	(0.031)	(0.016)	(0.103)
Emerging Europe					
CZCH	0.037***	0.227***	0.749***	0.021	0.424***
	(0.009)	(0.022)	(0.019)	(0.012)	(0.059)
HUNG	0.095***	0.192***	0.752***	−0.001	0.932***
	(0.018)	(0.018)	(0.021)	(0.021)	(0.111)
PLND	0.092***	0.156***	0.788***	−0.015	0.509***
	(0.017)	(0.017)	(0.019)	(0.022)	(0.114)
RUSS	0.117***	0.222***	0.713***	0.012	1.227***
	(0.017)	(0.015)	(0.018)	(0.015)	(0.205)
TURK	0.269***	0.181***	0.732***	−0.040*	0.432***
	(0.033)	(0.016)	(0.019)	(0.018)	(0.084)

Notes: The mean equations of the dynamic conditional correlation model are estimated as follows:

$$r_{i,t} = c_i + \varphi r_{i,t-1} + \varepsilon_{i,t}, \quad \text{where} \quad \varepsilon_t | I_{t-1} \tilde{} N(0, H_t), i = 1, 2, \ldots, 50.$$

The table reports the estimates of the following variance equations:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1} + \beta_i h_{i,t-1} + \gamma_1 postBS_t + \gamma_2 postLB_t.$$

In the model, the estimates of the mean-reverting process are $\alpha = 0.103^{***}$ (0.001) and $\beta = 0.554^{***}$ (0.007).
The table presents the coefficient White's heteroscedastic consistent robust standard errors in the parenthesis and the signs ***, ** and * denote statistical significance at 0.1%, 1% and 5%, respectively.

The results in Table 4 show that the global pair-wise correlations between U.S. stock index returns decreased after the Bear Stearns acquisition, as 22 out of 49 coefficients (DM_1) in the mean equation (Eq. (9)) are negative and statistically significant. These results are consistent with the decrease in conditional volatility reported previously. Instead, the results from the second phase of the financial crisis (i.e. the Lehman Brothers' collapse) show that 34 out of 49 coefficients (DM_2) are positive and statistically significant indicating that the conditional correlations increased significantly. Moreover, these results are consistent with the increase in conditional volatility reported previously in Table 3.

Finally, the coefficients on the dummy variables DV_1 and DV_2 do not indicate variance shifts of the correlation coefficients during the periods of financial crisis indicating that our results are robust. Thus, the results show that the overall effect of the acquisition of Bear Stearns on the correlations between the U.S. and the other stock markets was negligible, while the collapse of Lehman Brothers had a significant effect on global stock market interdependencies.

The regional conditional correlations are illustrated in Fig. 1, where the three periods of crisis are added to visualize regional differences in the stock market correlations during the financial crisis. As can be seen from the figure, the overall correlations seem to increase after the Lehman Brothers event, while the Bear Stearns event has less impact. These findings are consistent with the results represented in Table 4.

4. Portfolio in-sample estimation

As a specification check for the method we propose in our study, we construct two asset portfolios to evaluate the performance of the model estimates. The properties of the estimated conditional correlation in the asset allocation framework are introduced to measure the value of covariance information. Specifically, the evaluation of portfolio optimization and hedging performance is considered in-sample i.e., where the hedges are evaluated and constructed using the same set of data.[3] Generally, the optimal portfolio return r of two assets (i, j) is the minimum-variance combination of each asset as follows:

$$r_{portfolio,t} = w_t r_{i,t} + (1 - w_t) r_{j,t} \tag{11}$$

$$w_t = \frac{\sigma^2{}_{j,t} - Cov\left(r_{i,t}, r_{j,t}\right)}{\sigma^2{}_{i,t} + \sigma^2{}_{j,t} - 2Cov\left(r_{i,t}, r_{j,t}\right)}, \quad \text{where} \quad V_{t-1}(r_t) = H_t$$

where time-varying weights w_t specify the optimal proportion of each asset in a portfolio based on the forecast of the time-varying variance covariance matrix H_t.

The optimal hedges are constructed by following the criterion of the smallest variance of the portfolio return. Typically the optimal hedge of the portfolio is presented as a combination of some particular commodity and future contract to minimize portfolio's variance (see Myers & Thompson, 1989). We use the same approach for the pair-wise assets by holding one asset and shorting another asset to obtain a hedged portfolio with the optimal minimum variance as follows:

$$r_{portfolio,t} = r_{i,t} - \beta_{i,j,t} r_{j,t}, \quad \text{where} \quad \beta_{i,j,t} = \frac{Cov\left(r_{i,t}, r_{j,t}\right)}{\sigma^2{}_{j,t}}. \tag{12}$$

The portfolios' efficiency is estimated using in-sample evaluation framework in which the smallest variance of portfolio return is the criterion for success. The portfolios are constituted of all possible combinations of pairs of the fifty stock market indexes i.e. a total of 1225 portfolios. The performance of the minimum-variance and the optimal hedge procedures are examined in all the different phases of the financial crisis by computing the covariance matrixes with four different estimation models. The models can be classified into two different groups according to their estimates of the model variances (see Table 5), i.e. unconditional variance [Models (1) and (2)] and conditional variances estimates [Models (3) and (4)]. In the construction of the portfolios it is assumed for the Model (1) that the optimal weights on each asset are simply constant throughout an estimation period. In the same manner for the Model (2), the optimal weights are constant but time periods are considered individually. The estimated conditional covariance matrixes are based on the DCC model with dummy variables in the variance equation [Model (3)] and the same model without

[3] A considerable amount of empirical research has concentrated on MGARCH models to capture time-variation in the covariance matrix. For example, Engle and Colacito (2006) introduce an optimal portfolio asset allocation by minimizing predicted variance, likewise Baillie and Myers (1991) consider the optimal futures hedge ratios, and Antoniou et al. (2003) focus on the benefits of the international diversification in stock index and stock index futures markets.

Table 4
Conditional correlations around the two banking events. Estimation results from the diagonal VEC model.

	Mean equations			Variance equations				
	φ	DM_1	DM_2	ω	α	β	DV_1	DV_2
Asia Pacific								
AUST	0.341***	−0.039*	0.043***	0.007***	0.284***	0.117	−0.001	−0.002**
	(0.007)	(0.015)	(0.012)	(0.001)	(0.028)	(0.075)	(0.001)	(0.001)
CHIN	0.244***	−0.002	0.071***	0.005***	0.325***	0.259	0.001	0.000
	(0.006)	(0.013)	(0.015)	(0.001)	(0.066)	(0.145)	(0.001)	(0.001)
HGKG	0.256***	−0.017	0.051***	0.007***	0.393***	0.043	0.001	−0.001
	(0.007)	(0.016)	(0.014)	(0.001)	(0.064)	(0.085)	(0.001)	(0.001)
INDF	0.229***	−0.008	0.032**	0.007***	0.347***	0.053	0.003	−0.003**
	(0.007)	(0.014)	(0.012)	(0.001)	(0.052)	(0.132)	(0.002)	(0.001)
INDI	0.284***	−0.012	0.064***	0.008***	0.372***	0.000***	0.001	−0.001
	(0.007)	(0.016)	(0.015)	(0.001)	(0.055)	(0.000)	(0.002)	(0.002)
KORE	0.308***	0.013	0.023	0.003	0.242**	0.474	0.000	−0.001
	(0.007)	(0.013)	(0.012)	(0.002)	(0.080)	(0.258)	(0.001)	(0.001)
MALF	0.254***	−0.033*	0.033*	0.008***	0.350***	0.014	−0.002	−0.001
	(0.007)	(0.014)	(0.016)	(0.002)	(0.077)	(0.128)	(0.002)	(0.002)
NZEA	0.286***	−0.003	0.045**	0.008***	0.335***	0.000***	−0.001	−0.002
	(0.007)	(0.014)	(0.015)	(0.001)	(0.049)	(0.000)	(0.001)	(0.001)
PAKI	0.079***	−0.004	−0.006	0.006***	0.297***	0.000***	0.003	−0.001
	(0.006)	(0.015)	(0.010)	(0.001)	(0.038)	(0.000)	(0.002)	(0.002)
PHLF	0.260***	−0.018	0.001	0.003	0.159*	0.551	0.000	−0.001
	(0.007)	(0.012)	(0.011)	(0.002)	(0.076)	(0.299)	(0.001)	(0.001)
SING	0.367***	−0.018	0.060***	0.003*	0.318**	0.390	0.001	−0.001
	(0.007)	(0.014)	(0.013)	(0.002)	(0.105)	(0.221)	(0.001)	(0.001)
SRIL	0.025***	−0.023	−0.011	0.005***	0.311***	0.114	0.003	0.002
	(0.005)	(0.012)	(0.013)	(0.001)	(0.044)	(0.098)	(0.002)	(0.001)
TAIW	0.219***	0.035**	0.044***	0.006***	0.304***	0.247*	0.000	−0.001
	(0.007)	(0.013)	(0.012)	(0.001)	(0.051)	(0.106)	(0.001)	(0.001)
THAF	0.230***	−0.035*	0.059***	0.002	0.142***	0.739***	0.000	−0.001
	(0.008)	(0.015)	(0.012)	(0.001)	(0.037)	(0.097)	(0.001)	(0.001)
Developed Europe								
ASTR	0.487***	−0.028	0.038*	0.002	0.238***	0.590***	0.000	0.000
	(0.009)	(0.017)	(0.018)	(0.002)	(0.065)	(0.178)	(0.001)	(0.001)
BELG	0.630***	−0.019	0.026	0.007***	0.411***	0.008	0.002	0.002
	(0.007)	(0.016)	(0.017)	(0.001)	(0.061)	(0.072)	(0.002)	(0.002)
DNMK	0.494***	−0.035*	0.060***	0.004**	0.289***	0.471***	0.000	0.000
	(0.009)	(0.018)	(0.017)	(0.001)	(0.051)	(0.101)	(0.001)	(0.001)
EIRE	0.531***	0.025	0.033*	0.001*	0.099***	0.806***	0.001	0.000
	(0.007)	(0.018)	(0.013)	(0.001)	(0.022)	(0.058)	(0.000)	(0.000)
FIND	0.537***	−0.030	0.067***	0.009***	0.327***	0.000***	0.000	−0.002
	(0.008)	(0.017)	(0.014)	(0.001)	(0.040)	(0.000)	(0.002)	(0.001)
GDEE	0.436***	−0.076***	0.028*	0.010***	0.247***	0.116	0.000	−0.002*
	(0.008)	(0.012)	(0.012)	(0.002)	(0.060)	(0.113)	(0.001)	(0.001)
NETH	0.636***	0.001	0.059***	0.007***	0.364***	0.051	0.001	0.000
	(0.008)	(0.014)	(0.016)	(0.001)	(0.058)	(0.114)	(0.002)	(0.001)
NWAY	0.443***	−0.051**	0.065***	0.009***	0.425***	0.000***	−0.002	−0.002
	(0.008)	(0.016)	(0.015)	(0.001)	(0.058)	(0.000)	(0.001)	(0.001)
PORD	0.386***	−0.048***	0.053***	0.004	0.301***	0.357	0.001	0.000
	(0.008)	(0.014)	(0.014)	(0.002)	(0.082)	(0.255)	(0.001)	(0.001)
SPAN	0.584***	−0.010	0.064***	0.004	0.253*	0.424	−0.001	0.000
	(0.009)	(0.018)	(0.016)	(0.007)	(0.126)	(0.642)	(0.002)	(0.002)
SWDN	0.565***	−0.045**	0.055***	0.008***	0.377***	0.043	0.000	−0.001
	(0.008)	(0.016)	(0.015)	(0.001)	(0.075)	(0.132)	(0.002)	(0.001)
SWIT	0.536***	−0.004	0.061***	0.006***	0.389***	0.140	−0.001	0.001
	(0.008)	(0.012)	(0.017)	(0.001)	(0.068)	(0.116)	(0.001)	(0.001)
Middle East								
BAHR	−0.016	0.055***	0.018	0.008***	0.404***	0.166*	−0.003*	−0.003*
	(0.009)	(0.014)	(0.015)	(0.001)	(0.065)	(0.065)	(0.001)	(0.001)
EGYT	0.131***	0.002	0.030**	0.006***	0.593***	0.000***	0.000	0.000
	(0.008)	(0.014)	(0.011)	(0.001)	(0.093)	(0.000)	(0.002)	(0.001)
ISRA	0.424***	−0.045***	−0.022	0.008***	0.476***	0.000***	−0.003**	−0.001
	(0.008)	(0.013)	(0.014)	(0.001)	(0.083)	(0.000)	(0.001)	(0.002)
JORD	−0.008	−0.025*	0.020	0.006***	0.358***	0.000***	0.002	0.001
	(0.005)	(0.010)	(0.010)	(0.001)	(0.048)	(0.000)	(0.001)	(0.002)
KUWA	0.017**	−0.025	−0.001	0.005***	0.363***	0.107	0.001	−0.001
	(0.006)	(0.013)	(0.012)	(0.001)	(0.055)	(0.156)	(0.001)	(0.001)
MORC	0.032***	0.001	0.070***	0.006*	0.206***	0.316	0.000	0.000
	(0.007)	(0.012)	(0.014)	(0.003)	(0.051)	(0.245)	(0.001)	(0.001)
G7								
CNDA	0.874***	−0.128***	0.020	0.006***	0.302***	0.206*	0.000	−0.001
	(0.008)	(0.015)	(0.015)	(0.001)	(0.053)	(0.098)	(0.001)	(0.001)

(continued on next page)

Table 4 (*continued*)

	Mean equations			Variance equations				
	φ	DM_1	DM_2	ω	α	β	DV_1	DV_2
FRNC	0.677***	−0.047**	0.049**	0.007***	0.367***	0.109	0.000	−0.002
	(0.010)	(0.016)	(0.015)	(0.002)	(0.072)	(0.114)	(0.002)	(0.001)
GERM	0.639***	−0.019	0.074***	0.007***	0.449***	0.071	−0.001	−0.002
	(0.009)	(0.015)	(0.014)	(0.002)	(0.071)	(0.107)	(0.002)	(0.001)
ITAL	0.591***	−0.046***	0.041**	0.007***	0.378***	0.073	0.000	−0.001
	(0.008)	(0.014)	(0.016)	(0.001)	(0.063)	(0.099)	(0.002)	(0.001)
JPAN	0.027***	0.021*	0.015	0.006	0.198*	0.338	−0.001	−0.002
	(0.007)	(0.010)	(0.009)	(0.003)	(0.080)	(0.348)	(0.001)	(0.001)
UTDK	0.658***	−0.009	0.047**	0.006***	0.351***	0.247	−0.001	−0.001
	(0.008)	(0.012)	(0.015)	(0.002)	(0.078)	(0.157)	(0.001)	(0.001)
Latin America								
ARGT	0.622***	−0.087***	0.026	0.007***	0.467***	0.000***	0.003	0.002
	(0.008)	(0.019)	(0.017)	(0.001)	(0.082)	(0.000)	(0.002)	(0.002)
BRAZ	0.874***	−0.070***	0.018	0.001*	0.151***	0.795***	0.000	0.000
	(0.008)	(0.016)	(0.013)	(0.000)	(0.035)	(0.046)	(0.001)	(0.000)
CHIL	0.610***	−0.015	0.067***	0.008***	0.509***	0.012	0.000	0.000
	(0.008)	(0.015)	(0.020)	(0.001)	(0.062)	(0.088)	(0.001)	(0.002)
COLM	0.469***	−0.045**	0.041*	0.007***	0.372***	0.136	0.000	0.001
	(0.007)	(0.015)	(0.017)	(0.002)	(0.047)	(0.097)	(0.002)	(0.002)
MEXF	1.059***	−0.028	0.041**	0.009***	0.391***	0.000***	0.003	−0.002
	(0.008)	(0.017)	(0.014)	(0.001)	(0.044)	(0.000)	(0.003)	(0.002)
PERU	0.592***	−0.102***	0.052**	0.007***	0.417***	0.190	0.000	−0.002
	(0.010)	(0.017)	(0.016)	(0.002)	(0.087)	(0.155)	(0.002)	(0.002)
Emerging Europe								
CZCH	0.319***	−0.075***	0.052***	0.002	0.147***	0.740***	0.000	−0.001
	(0.008)	(0.013)	(0.012)	(0.001)	(0.032)	(0.055)	(0.001)	(0.001)
HUNG	0.442***	−0.034*	0.035	0.006***	0.419***	0.189*	0.000	0.000
	(0.008)	(0.016)	(0.019)	(0.001)	(0.051)	(0.091)	(0.001)	(0.001)
PLND	0.471***	−0.076***	0.007	0.006***	0.285***	0.208*	−0.001	0.000
	(0.007)	(0.012)	(0.014)	(0.001)	(0.054)	(0.096)	(0.001)	(0.001)
RUSS	0.446***	−0.057***	0.037*	0.007***	0.452***	0.015	0.002	0.000
	(0.007)	(0.017)	(0.016)	(0.001)	(0.055)	(0.059)	(0.001)	(0.001)
TURK	0.549***	−0.039*	0.034*	0.003**	0.219***	0.596***	0.001	0.000
	(0.008)	(0.016)	(0.016)	(0.001)	(0.047)	(0.101)	(0.001)	(0.001)

Notes: The results of the diagonal VEC model (MGARCH) proposed by Bollerslev, Engle, and Wooldridge (1988) are presented in the table. In the model the estimated conditional correlations (Fisher transformed correlations) are the dependent variables in the mean equation:

$$\rho_{i,t} = c_i + DM_1 postBS_t + DM_2 postLB_t + \varepsilon_{i,t} \quad \text{where } \varepsilon_t | I_{t-1} \sim N(0, H_t) i = 1, 2, ..., 49.$$

The variance equation is as follows:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1} + \beta_i h_{i,t-1} + DV_1 postBS_t + DV_2 postLB_t.$$

The table presents the coefficient White's heteroscedastic consistent robust standard errors in the parenthesis and the signs ***, ** and * denote statistical significance at 0.1%, 1% and 5%, respectively.

dummies [Model (4)]. Finally, the single number of annualized volatility reported is an average of volatility of all the pairs of the portfolios.

The results of the optimized portfolios are reported in Table 5. The accounted annualized volatility is 27.7% for the stock index returns over the whole estimation period and the respective volatilities are 18.4%, 19.4% and 45.9% over the periods *preBS*, *postBS* and *postLB*. Obviously, all the hedges of the portfolios have decreased the overall variance. The results of Table 5 further demonstrate that the estimated DCC model with dummy variables included in the variance equation, i.e., Model (3), is the best fitting model in the estimated data period. The model outperforms all the other models and the results are consistent in all the time periods studied. Furthermore, it is possible to infer that the model without dummy variable, i.e., Model (4), does not take into account of the change in level of variance in high volatility periods, hence the estimates of the conditional covariance are inefficient in capturing the dynamics of the stock markets variance.

During the financial crisis it is evident that the combination of the pair-wise assets by holding one asset and shorting another performs better than the minimum-variance combination of the same assets. Overall, the differences between the portfolio variances are quite small and it is, therefore, important to examine whether the differences should be considered as random. This issue is addressed by comparing portfolios' variances achieved using Models (1)–(4).

Table 6 presents the results from the abovementioned analysis. The number of the lower variance portfolios constitutes the value of the fraction such that the model in row is compared to the model in column. The results support the assumption that portfolio variance constructed by the DCC model with dummies in the variance equation, i.e., Model (3), is the best fitting model in the data in all the time periods estimated. These findings indicate that by taking into account the change in the level of variance in high volatility periods, the model is more efficient in capturing the dynamics of stock market variance.

5. Conclusions

In this study we investigate the impact of recent financial crises on global stock market interdependence. For this purpose we use data from 50 equity markets and examine the stock market correlations around two significant events, namely around JP Morgan's acquisition of Bear Stearns and the Lehman Brothers' collapse, using an augmented dynamic conditional correlation model. In particular, the model allows

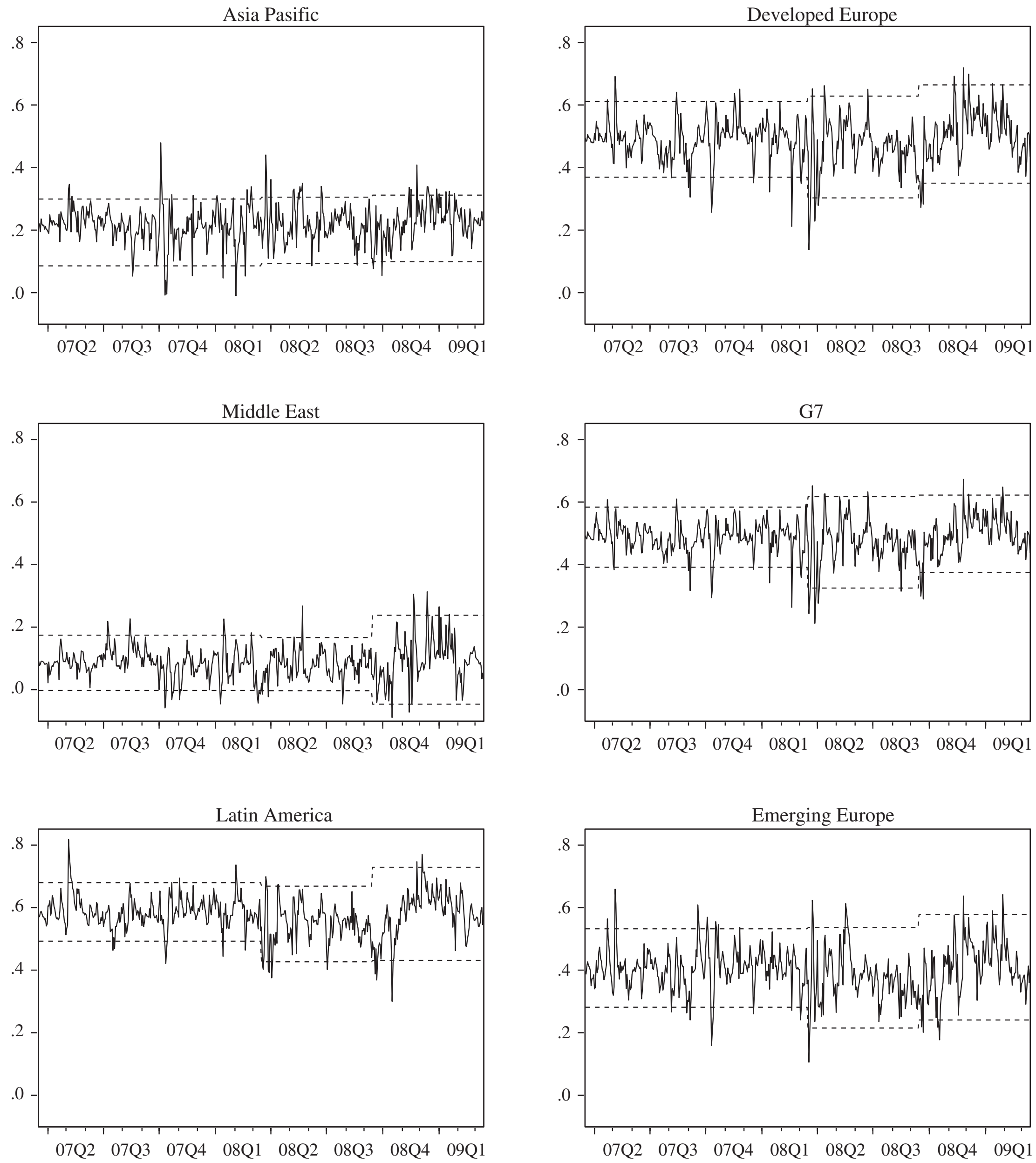

Fig. 1. Dynamic regional correlations with U.S. The solid lines illustrate the dynamic correlations (average value for the regions) between U.S. and the 49 countries. The correlations are dynamic conditional correlations estimated by the augmented DCC–MGARCH(1,1) model. The dashed line depicts 95% confidence intervals for the correlations. The interval on the figure are grouped into the three time periods; *preBS*, *postBS*, and *postLB*.

us to examine the effect of the financial crisis of 2008–09 on the conditional correlations across all investigated stock markets while simultaneously controlling for changes in the conditional variances. Our conclusion is that while the JP Morgan's acquisition of Bear Stearns had only a negligible impact on stock market correlations across all regions, the effect on interdependence of the Lehman Brothers' collapse was considerable. The results from both the unconditional and conditional correlation analyses suggest that the impact of the financial crisis on stock markets is significant for all regions.

The performance of the augmented dynamic conditional correlations model estimates is further analyzed by applying a two-asset portfolio allocation framework. The portfolios' efficiency is estimated in-sample in which the smallest variance in portfolio return is the criterion for success. The results support the assumption that portfolio variance constructed by the DCC model with dummies in the variance equation is the best fitting model in the data and that the model outperforms all the other models within all the investigated time periods. Overall, the differences between the portfolio variances are quite small but consistent. It is evident that including dummy variables in the variance equation improves the model efficiency since they take into account the change in level of variance in high volatility periods. In a two-asset allocation framework, the model generates relatively low portfolio variances within all time periods investigated.

Table 5
Averaged annualized standard deviations of the optimized portfolios.

Portfolio annualized std.	Model (1)	Model (2)	Model (3)	Model (4)
	Optimal constant weight	Constant weight per period	DCC-model with dummies	DCC-model
Full estimation period				
Min. var.	0.221	0.218	0.211	0.222
Hedge	0.191	0.186	0.177	0.193
PreBS period				
Min. var.	0.147	0.142	0.137	0.146
Hedge	0.133	0.126	0.120	0.132
PostBS period				
Min. var.	0.147	0.143	0.136	0.145
Hedge	0.155	0.148	0.136	0.147
PostLB period				
Min. var.	0.364	0.360	0.351	0.367
Hedge	0.293	0.289	0.282	0.304

Notes: The portfolios are constituted of all possible combinations of pairs of the index returns accounting to total amount of 1225 portfolios for each period.

Table 6
Fraction of lower variance portfolios.

Min. var./hedge	Model (1)	Model (2)	Model (3)	Model (4)
	Optimal constant weight	Constant weight per period	DCC model with dummies	DCC model
Full estimation period				
Optimal constant weight	–	0.118/0.193	0.070/0.136	0.578/0.638
Constant weight per period	0.882/0.820	–	0.122/0.211	0.813/0.807
DCC model with dummies	0.930/0.864	0.878/0.789	–	0.988/0.961
DCC model	0.422/0.362	0.187/0.193	0.012/0.039	–
PreBS period				
Optimal constant weight	–	0.145/0.278	0.060/0.098	0.509/0.522
Constant weight per period	0.855/0.782	–	0.143/0.173	0.804/0.756
DCC model with dummies	0.940/0.902	0.857/0.827	–	0.940/0.927
DCC model	0.491/0.478	0.196/0.244	0.060/0.073	–
PostBS period				
Optimal constant weight	–	0.541/0.372	0.089/0.095	0.476/0.367
Constant weight per period	0.459/0.694	–	0.294/0.118	0.404/0.501
DCC model with dummies	0.911/0.905	0.706/0.882	–	0.934/0.885
DCC model	0.524/0.633	0.596/0.499	0.066/0.115	–
PostLB period				
Optimal constant weight	–	0.161/0.515	0.178/0.410	0.605/0.758
Constant weight per period	0.839/0.554	–	0.256/0.450	0.732/0.808
DCC model with dummies	0.822/0.590	0.744/0.550	–	0.931/0.870
DCC model	0.395/0.242	0.268/0.192	0.069/0.130	–

Notes: This table contains the fractions of the portfolios, which have lower variance in the combined pair-wise asset allocations (the optimization methods; Min. var./hedge). The model in row is compared to the model in column. The portfolio variance constructed by the DCC model with dummies proves to be the best model with the highest value of fraction in all the time periods.

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Measuring actual daily volatility from high frequency intraday returns of the S&P futures and index observations

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ABSTRACT

In this study 10 min frequency realized variance series are used to forecast the volatility of S&P 500 index (SPX) daily returns. The logarithm-transformed realized variances are modeled directly in the *AR(FI)MA* model specification in which the structure of the model is optimized using the AICc criterion. As reported in previous literature, the approximately normal structure of distribution of the logarithm-transformed realized variance series can be modeled directly in structure of the *AR(FI)MA* process. However, in this study, it is recognized the statistically significant non-normal property of the logarithm-transformed realized variances. Hence, to forecast volatility the non-normality is exploited to improve efficiency of volatility forecasts. It is also observed that in the context of the *AR(FI)MA* model specification the futures and index based deseasonalized returns for the realized variance estimates improve the forecast performance. Considering the seasonality effect and the distributional properties of the estimated realized variance series, it is evident that the information content of the futures (ES) high frequency observations produces the most accurate forecasts.

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1. Introduction

Recognition of the importance of measuring financial volatility and the availability of high frequency data observations has increased research interest in volatility modeling and led to more efficient volatility forecasts. For investors looking to obtain an accurate price for an option contract, it is essential to have an efficient volatility forecast for underlying asset returns over the maturity of the option. The issue of efficiency is based on assumptions about the information content of the forecast, *i.e.*, whether the estimate of volatility incorporates all relevant information of the underlying asset's future return volatility (see *e.g.* Jiang & Tian, 2005; Becker, Clements, & White, 2006, 2007). The efficiency of the volatility forecast is certainly crucial for option pricing, but also in many areas of finance, such as in risk management and portfolio selection.

The purpose of this study is to show that by utilizing the *AR(FI)MA* model and distribution characteristics of the logarithm-transformed realized variance series it is possible to enhance the information content of the volatility forecasts produced. To utilize the information content of the high frequency observations actual daily volatility, *i.e.*, the realized volatility, is measured to produce the volatility forecasts.[1] In this study, the S&P 500 futures (ES) and index (SPX) high frequency observations are used to calculate the intraday returns (see *e.g.* Andersen & Bollerslev, 1998; Martens & Zein, 2004; Becker et al., 2006; Patton, 2011; Bordignon & Raggi, 2012).

This paper contributes to the previous literature of Areal and Taylor (2002), Andersen, Bollerslev, Diebold, and Ebens (2001a), (2003) and Martens and Zein (2004). Those studies establish that logarithm values of a realized variance series are approximately normally distributed and suitable to model directly in a fractionally integrated long memory process. Similarly, this study utilizes logarithm-transformed realized variances and the *AR(FI)MA* model to analyze the long memory properties of the *AR(FI)MA* process, *i.e.*, the autocorrelation of the process that slowly hyperbolically dies to zero, unlike the *ARMA* process that decays exponentially (Pong, Shackelton, Taylor, & Xu, 2004; Koopman, Jungbacker, & Hol, 2005; Becker, Clements, & White, 2007, 2009). It is shown that it is possible to improve the efficiency of the forecasts in the *AR(FI)MA* model specification by taking into account the characteristics of the distribution of the estimated realized variances. Considering the seasonality effect and the information content of the returns volatility makes

[1] Actual volatility by definition is a measure of actual daily variability of the unobserved volatility estimated as a sum of cumulative intraday squared returns (Andersen & Bollerslev, 1998; Andersen et al., 2001b, 2003; Barndorff-Nielsen & Shephard, 2002a; Poon & Granger, 2003).

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it possible to observe that the most accurate forecasts produced are based on the realized variance series from the futures high frequency observations. In the model estimation it is evident that the skewed conditional distribution densities employed for the innovations contribute to the fit of the model and the efficiency of the forecasts.

Andersen et al. (2001a) support the rationale for use the long memory model for logarithm transformed realized volatilities. Hence, for the volatility forecasts in this study the *AR(FI)MA* model is utilized to capture autocorrelation process of the logarithm-transformed realized variances. The strength of the model is its property that enables to model realized variance directly within the structure of the *AR(FI)MA* specification. In addition, the model efficiently captures the autocorrelation process that slowly hyperbolically dies to zero. Similarly, to capture long memory properties of realized variance Andersen, Bollerslev, Diebold, and Labys (2003) introduced a multivariate fractionally-integrated Gaussian vector autoregression (VAR) model. Substantial number of various *GARCH* type models, in addition to stochastic volatility models is proposed. In comparison, the widely utilized *GARCH* models for volatility forecasts, the model is applicable to analyzes of autocorrelation processes that decay exponentially. In addition, the multivariate models and stochastic volatility models generally suffers from multidimensionality structure of matrices in the model estimation. The univariate *AR(FI)MA* model cannot capture subtleties of variance–covariance structures inherent in the multivariate models. However, for recognized efficiency of the model several studies support the use of the *AR(FI)MA* model for realized volatilities (see *e.g.* Areal & Taylor, 2002; Andersen et al., 2001a, 2003; Martens & Zein, 2004).

The recent availability of high frequency financial observations is of interest in several studies for the model-free realized variance estimation (*e.g.* Andersen & Bollerslev, 1998, Bordignon & Raggi, 2012). The realized variance as a sum of cumulative intraday squared returns provides consistent approximation of the quadratic variation of the semi-martingale that drives continuous price of an asset (Andersen et al., 2001a). The accuracy of the approximation is dependent on the choice of a frequency of the intraday returns *i.e.* a higher frequency improves accuracy of the realized variance estimates. However, the issue of autocorrelation is related to the high frequency observations which suffer from the effect of microstructure frictions as well as the effect of seasonality (see Taylor & Xu, 1997). Particularly, in this study to adjust for the first-order autocorrelation a method proposed by Hansen and Lunde (2006) is applied. In addition, the effect of seasonality inherent in the high frequency observations is considered (see Taylor & Xu, 1997). The forecasts of daily realized volatility are implemented in the optimal structure of the *AR(FI)MA* model, where the AICc information criterion in the selection procedure is utilized. The specific of this study is the iterative method used in the selection procedure that also accounts for the symmetric and skewed conditional distribution densities for the innovation of the estimated *AR(FI)MA* model.

The remaining sections of this study are organized as follows. Section 2 presents an overview of the previous literature. Section 3 introduces the data employed in this paper and the methods used to calculate the realized variance series, including the descriptive statistics for the daily returns and realized variance series. Section 4 provides an introduction to the *AR(FI)MA* model and the skewed distributions utilized. Section 5 introduces the methodology applied to estimate the models and the performance criteria to evaluate the forecasts. Section 6 presents the empirical results and the final section concludes the study.

2. Previous literature

Interest in high frequency observations emerged largely from the study of Andersen and Bollerslev (1998) which showed that asset price can be assumed to follow a continuous time diffusion process (see Eq. 1). The study proposed that daily volatility

$$\sigma_{t,1}^2 = \int_0^1 \sigma_{t+\tau}^2 \, d\tau \tag{1}$$

is an integrated variance over one day. This is widely acknowledged (*e.g.* Barndorff-Nielsen & Shephard, 2002b) to be more accurate procedure in estimation of the unobserved volatility than the estimates of volatility based solely on squared returns (Day & Lewis, 1992; Fleming, 1998; Poon & Granger, 2003). However, in reality the price quotes are not continuous. Hence, Barndorff-Nielsen and Shephard (2002b) outlined the semi-martingale process for the methodology of actual daily variability noting that variation of integrated volatility measure is a consistent estimator of quadratic variation. The Barndorff-Nielsen and Shephard (2002b) study shows that the discrete daily sum of squared returns constitutes an unbiased and consistent approximation of the actual volatility, termed realized volatility (RV).

It is expected that intraday returns are not serially correlated and consequently violate the semi-martingale assumption. However, the findings of the serial correlation related to high frequency stock index observations are obvious. The autocorrelation and its effect on the realized variance has been addressed in many studies (see *e.g.* Stoll & Whaley, 1990; Zhou, 1996; Cambell, Lo, & Mackinlay, 1997; Hansen & Lunde, 2006) suggesting that the issue of market microstructure frictions such as the effect of non-synchronous trading, bid-ask spread and the discreteness of the data have serious implications for the estimated realized volatility. It has been shown that the effect of microstructure frictions causes autocorrelation in the intra-day returns and hence, realized variance estimates are biased (Zhou, 1996; Cambell et al., 1997; Hansen & Lunde, 2006; Bandi & Russell, 2008; Andersen, Bollerslev, & Meddahi, 2011).

The specification of the *AR(FI)MA* model structure and its influence on forecast accuracy was previously examined by Barkoulas and Baum (1997) for Eurocurrency return series. The study showed that the selection of the model structure improved the accuracy of the forecasts. In simulation studies, Andersson (1998) compared the forecast performances of the *AR(FI)MA* and *ARMA* models and concluded that in general it is worse to ignore than to impose the long memory parameter in the model structure. In contrast Ellis and Wilson (2004) show that the *AR(FI)MA(0,d,0)* structure for out-of-sample forecasts performance is weak. In addition, Kanellopoulou and Panas (2008) examined the accuracy specification of the distribution on the returns and the long memory properties of the *AR(FI)MA* model. They argue that the specification of the model structure and the distributional assumptions, both influence the approximations of return distributions.

During the last decades a considerable amount of research covering volatility forecasts is devoted to an examination of performance differences of forecasts between model-based volatility and implied volatility (IV) derived from the option prices. Generally, the outcome of research applied to options report that information content of IV forecast relative to model-based forecast is more efficient. However, such mutual consensus of outperformance over any method applied does not exist. Earlier research on the issue of forecast efficiency (Christensen & Prabhala, 1998; Day & Lewis, 1992; Canina & Figlewski, 1993; Fleming, 1998) is based on the observed prices of single option series for a particular underlying asset. The implication of this method is that the induced IVs of the consecutive series of options results in multiple period forecasts with varying time horizons. The outcome of results can be seen to hinder comparisons of the forecast performances. Since the introduction of the VIX, the advantage of the volatility indices constant 22 day IV forecast horizon is utilized (Blair, Poon, & Taylor, 2001; Becker et al., 2006, 2007, 2009; Chung, Tsai, Wang, & Weng, 2011; Bordignon & Raggi, 2012).

As distinct to the IV, the model-based volatility is estimated from the historical data observations. In the literature, various GARCH model modifications are deployed to enhance ability of the models to forecast volatility. Hajizadeh, Seifi, Zarandi, and Turksen (2012) suggest hybrid models that consider the EGARCH model and Artifical Neural Networks to forecast volatility of the S&P 500 index returns. The optimal structure for the model selected is implemented through the AIC and BIC criteria. Whereas, in this study to achieve more precise forecasts of the volatility the intraday returns of the S&P 500 index and futures observations are utilized. Also, by following Hurvich and Tsai (1989), it is noticed that the AICc criterion is preferable for the autoregressive models in optimal structure selection. Hence, for the best fitted structure of the model selection the unbiased AICc criterion is utilized, where in addition the characteristics of the distribution of the estimated realized variances are considered.

Lux, Morales-Arias, and Sattarhoff (2014) proposed the Markov-switching multifractal (MSM) model that is compared with et al. ARFIMA, GARCH models to forecast the realized volatility. Similarly, Yang, Chen, and Tian (2015) investigate the realized volatility forecasts of several stock indices. They consider nonlinear and linear models with ARFIMA and GARCH model combinations which are designed to forecast realized volatility under structural brakes in the daily realized volatility. Instead, in this study, comparison of the model is implemented within the applied *AR(FI)MA* model by considering distributional characteristics of the innovations in the estimation process. It is approached the issue of approximately normal logarithm values of the realized variances in context of the *AR(FI)MA* model estimation. It is recognized that the distribution of the logarithm-transformed realized variance series indicate non-normality, hence this property is utilized to forecast volatility.

It is common that realized volatility measure is used as an unbiased volatility proxy for purposes of forecast evaluation (*e.g.* Koopman et al., 2005; Corsi, Mittnik, Pigorsch, & Pigorsch, 2008; Liu & Hung, 2010, Cordis & Kirby, 2014). Obviously, biased proxy can lead to incorrect conclusions of volatility performances. Hence, a prominent segment of the literature is focused on the issue of market microstructure noise that causes bias on the realized volatility measure. Degiannakis and Floros (2015) examined intra-day realized volatilities and behavior of correlation between European and USA stock indices. They present that the effect of market microstructure noise in calculation for the realized volatility measures should be considered, hence to minimize the noise the volatility signature plot is utilized in their study (see also Caporin & Velo, 2015; Liu et al., 2015). Also, the empirical findings of intraday seasonal patterns in volatility gave rise in research to take into account seasonality before modelling dynamics of the volatility (see, for *e.g.* Deo, Hurvich, & Lu, 2006). In this study the effect of microstructure frictions is considered and adjusted in the realized variance calculations. In addition, to mitigate the impact of seasonality in volatility, also the deseasonalized filtered returns are considered to form realized variance measures. The empirical results suggest applying the presented method for high frequency returns that exhibit seasonality.

3. Data

In this study, the full data period for all the time series covers the period from June 1, 2007 to December 30, 2011. For the estimates of the actual volatility, first outlined by Andersen and Bollerslev (1998), the method of the current research is to use the S&P 500 index (SPX) and the E-mini S&P 500 index futures (ES) intraday observations. The effect of the microstructure frictions on the realized volatility measures is generally attributed to the high sampling frequency, hence conventional 10 min frequency observations are used to form the realized volatility measures.[2] The full data period of the high frequency observations based on the index produces 1157 actual volatility estimates, following the normal trading hours of the stock exchange. As for the futures, the number of actual volatility estimates is 1423 based on E-mini S&P 500 futures continuous contracts observations incorporating intraday observations from 23.25 h of trading per day from Sunday afternoon to Friday afternoon.

For forecast evaluation purposes, the current research uses 300 out-of-sample daily observations from October 25, 2010 to December 30, 2011, where daily squared returns of the S&P 500 (SPX) index closing values are used as a proxy for the ex post variance. According to the out-of-sample period, the VIX volatility index daily closing values as a measure of implied volatility are used to assess the degree of bias of the volatility forecasts produced. The aforementioned time series used in this study are produced by Pi Trading and the VIX data is extracted from the online database produced by the Chicago Board Options Exchange.

3.1. Measuring realized volatility

It is widely acknowledged that estimates based solely on squared returns provide an extremely noisy proxy of the realized volatility (see Fig. 1).

Adopting the methodology of Andersen and Bollerslev (1998) makes it possible to present a more accurate estimate. For demonstration purposes, 10 min intraday returns $R_{t,d}$ is considered and defined as:

$$R_{t,d} = 100ln\left(\frac{P_{t,d}}{P_{t-1,d}}\right) \tag{2}$$

where P is the asset price, $t = 1, \ldots, T$ is a specific trading day, and $d = 1, \ldots, D$ is a 10-minute tick quantifying a total of $D = 39$ intraday observations. The discrete daily sum of squared returns (see Eq. 3) is an approximation of the realized volatility

$$RV_t = \sum_{d=1}^{D} R_{t,d}^2 \tag{3}$$

that is an unbiased and consistent approximation of the actual volatility. However, it should be remembered that foreign exchange markets are open 24 h a day, while normally stock markets trade for 6.5 h per day Monday through Friday. It is very probable that changes of volatility are larger during the time the stock market is closed. Hence, as proposed by Martens (2002) the intraday returns are scaled by

$$(1+c)RV_t = \frac{\hat{\sigma}_{oc}^2 + \hat{\sigma}_{co}^2}{\hat{\sigma}_{oc}^2} \sum_{d=1}^{D} R_{t,d}^2,$$

$$\text{where} \quad \hat{\sigma}_{oc}^2 = \frac{10,000}{T} \sum_{d=1}^{D} ln\left(\frac{P_{t,D}}{P_{t,0}}\right)^2,$$

$$\text{and} \quad \hat{\sigma}_{co}^2 = \frac{10,000}{T} \sum_{d=1}^{D} ln\left(\frac{P_{t,0}}{P_{t-1,D}}\right)^2 \tag{4}$$

are open-to-close and close-to-open sample variances, respectively. In the equations, the overnight return $P_{t,0}$ is the opening price of 10 min intraday observations, and $P_{t-1,D}$ is the previous day's closing price. The operation of scaling realizes the effect of a noisy overnight return by perceiving it as more volatile than the estimated 10 min intraday returns (Koopman et al., 2005).

Considering the first-order autocorrelation caused by the effect of the microstructure frictions in intraday returns the following correction method

$$RV_t^{AC} = (1+c)\left(\sum_{t=1}^{T} R_{t,d}^2 + \left(\frac{2T}{T-1}\right)\sum_{d=1}^{D-1} R_{t,d}R_{t,d+1}\right) \tag{5}$$

[2] It is common that the realized variance is computed by summing intraday returns at a moderate frequency, such as 5 min or 30 min sampling (see, for example, Andersen et al., 2007).

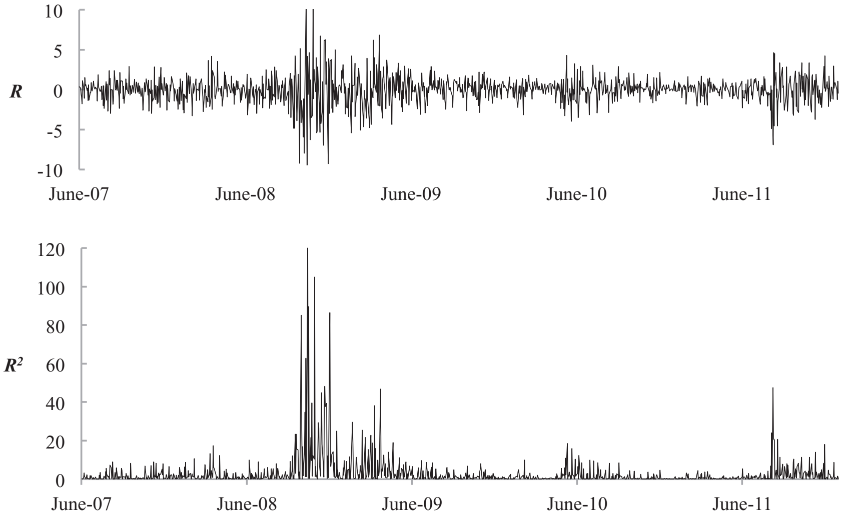

Fig. 1. The daily log return series (R) and squared log returns series (R^2) of the Standard & Poor's 500 index over the period from June 1, 2007 to December 30, 2011.

is proposed to adjust for the first-order autocorrelation in the intraday returns.[3]

Taylor and Xu (1997) introduced the variance multiplier in their study by demonstrating that the high frequency intraday returns exhibit a seasonal volatility pattern.[4] In this study intraday returns over one-minute frequency are used to apply the variance multiplier. It is introduced the sub periods of the intraday returns, where the sum of the one-minute squared returns over a specified intraday interval is indexed by j, as follows:

$$\hat{s}_j^2 = D \sum_{t=1}^{T} \sum_{i=d(j-1)+1}^{dj} R_{t,1}^2 \Bigg/ \left(d \sum_{t=1}^{T} \sum_{t=1}^{t} R^2{}_{t,1} \right) \tag{6}$$

where D is the number of observations per day, $R_{t,i}^2$ is the one-minute squared return on day t, and d is the specified frequency of the data. It follows that the deseasonalized filtered return

$$\tilde{R}_{t,d} = R_{t,d} / \hat{s}_j^2 \tag{7}$$

is an intraday return divided by the variance multiplier, where the sub period j is equivalent to the specified frequency d.

3.2. *Distribution properties of the realized variances*

In an earlier study on equity realized return volatility, Andersen et al. (2001a) showed that dynamic dependence of the volatility property is measurable in mean-reverting fractionally integrated process. Subsequently Andersen et al. (2003) studied exchange rates, and proposed that the distributional properties of the logarithm-transformed realized volatility series can be utilized in a fractionally integrated long memory *AR(FI)MA* modeling process. The Gaussianity of the distribution of the logarithm-transformed series is presumed to have superior properties for realized volatility forecasting. In this study the empirical findings show that the distribution of the logarithm-transformed RV series is approximately normal, but still indicates a statistical significance of non-normality in values of skewness and kurtosis. It is argued that it is possible to utilize the statistical non-normality in the model structure and volatility forecasting by taking into account the characteristics of the distribution.

The descriptive statistics for the SPX daily returns R, squared daily return R^2 and estimates of the logarithm-transformed realized volatility series at 10 min frequency over the full data period are recorded in Table 1. The squared daily return is the generally used estimator serving as an unbiased proxy for ex post volatility, although it is known to be an exceedingly noisy estimator (see *e.g.* Andersen & Bollerslev, 1998). In this study squared daily returns are used as a proxy for the ex post volatility for performance evaluation purposes and to assess predictive ability of the forecasts. The realized variance series RV_I and RV_{II} are constructed by using the futures (ES) intraday high frequency observations and the presented statistics for the series represent unfiltered and filtered logarithm-transformed realized variance series, respectively. It is known that high frequency intraday returns exhibit seasonality in volatility (Taylor & Xu, 1997; Martens, Chang, & Taylor, 2002; Deo et al., 2006). Therefore filtration is used to prevent seasonal effect on returns and ultimately improve the efficiency of the volatility forecasts.

For the realized variance series RV_I and RV_{II} based on the futures intraday observations the critical test statistic values of skewness $\pm\sqrt{6/N} * t\text{-}stat_{.05} = \pm.127$ and excess kurtosis $\pm\sqrt{24/N} * t\text{-}stat_{.05} = \pm 0.255$ are set to assess the normality of the series. It is notable that the test statistics for the series RV_I indicate the non-normality of the distribution. Analyzing the statistic values of the series RV_{II} suggests that the effect of filtering on the distribution of the RV series is strongest on the value of kurtosis, hence the logarithm-transformed RV_{II} series is closer to normal but still statistically different from zero. However, the critical statistic value of skewness indicates normality.[5]

The logarithm-transformed realized variance series $RV_{III} - RV_{IV}$ are estimated from high frequency observations of the SPX data. The test statistics show that for all the RV series the values of skeweness indicate non-normality according to the critical value of $\pm$ .141. Furthermore, the critical statistic value for excess kurtosis $\pm$ .283 indicates that the values of kurtosis are statistically different from zero.

A comparison of the statistics in general reveals that for all the estimated RV series the sample autocorrelation coefficients are high and slowly decaying. These results are also in accordance with the Box–Ljung critical test statistic value of 21.026 on 12 squared

[3] This method is closely related to the method proposed by Hansen and Lunde (2006) and Jiang and Tian (2005).

[4] Taylor and Xu (1997) examined five-minute intraday volatility of exchange rate (DM/$) returns.

[5] All the statistical tests are performed at 5% significance level.

Table 1
Summary statistics for S&P 500 daily returns, squared returns and estimated logarithm-transformed realized volatility series at 10 min frequency over the period June 1, 2007 to December 30, 2011.

	R	R^2	RV_I	RV_{II}	RV_{III}	RV_{IV}	RV_V	RV_{VI}
Obs.	1157	1157	1423	1423	1157	1157	1157	1157
Mean	−0.017	3.030	0.080	0.252	0.170	0.142	0.065	0.362
Var.	3.032	73.284	1.796	1.799	1.306	1.245	1.372	1.363
Skew.	−0.220	7.571	−0.223	−0.043	0.375	0.472	0.389	0.374
Kurt.	8.970	78.528	3.713	3.568	3.243	3.494	3.349	3.260
Min	−9.470	0.000	−4.904	−4.522	−3.264	−2.919	−3.374	−3.147
Max	10.957	120.060	4.619	4.636	4.490	4.481	4.618	4.763
$\hat{\rho}_1$	−0.127	0.174	0.532	0.613	0.723	0.829	0.749	0.734
$\hat{\rho}_2$	−0.067	0.383	0.431	0.472	0.718	0.767	0.696	0.719
$\hat{\rho}_3$	0.049	0.152	0.400	0.419	0.674	0.734	0.667	0.677
$\hat{\rho}_4$	−0.013	0.291	0.394	0.435	0.656	0.718	0.652	0.661
$\hat{\rho}_5$	−0.050	0.322	0.457	0.524	0.642	0.694	0.636	0.645
Q_{12}	38.6	1134.4	4006.4	4560.7	5427.0	6510.5	5410.8	5519.6
JB	1727.7	286053.8	42.0	19.6	30.0	54.8	35.0	30.2

Notes: The table presents the sample autocorrelation coefficients $\hat{\rho}_i$ at lag 1–5, and Box–Ljung portmanteau statistics value $Q_{(i)}$ on 12 squared autocorrelations (the critical value at 5% significance level is 21.026). *JB* is the Jarque Bera normality test statistic value (the critical value at 5% significance level is 5.991).
Daily return series:
$R_t = 100\,ln(\frac{SPX_t}{SPX_{t-1}})$, where SPX_t is closing value of the index on day t, and
R_t^2 t is analogously squared value of the index return.
The futures (ES) high frequency return series:
$RV_I = \sum_{d=1}^{D} R_{t,d}^2$, where $R_{t,d}$ is an intraday log return (see Eq. 3).
$RV_{II} = \sum_{d=1}^{D} \tilde{R}_{t,d}^2$, where $\tilde{R}_{t,d}$ is a filtered intraday log return (see Eqs. 3 and 7).
The index (SPX) high frequency return series:
$RV_{III} = \sum_{d=1}^{D} R_{t,d}^2$, where $R_{t,d}$ is an intraday log return (see Eq. 3).
$RV_{IV} = \sum_{d=1}^{D} R_{t,d}^2$, where $R_{t,d}$ is overnight corrected intraday log return (see Eq. 4)
$RV_V = \sum_{d=1}^{D} R_{t,d}^2$, where $R_{t,d}$ is overnight autocorrelation corrected intraday log return (see Eq. 5).
$RV_{VI} = \sum_{d=1}^{D} \tilde{R}_{t,d}^2$, where $\tilde{R}_{t,d}$ is a filtered intraday log return (see Eqs. 3 and 7).

autocorrelations. The Jarque Bera normality test statistic critical value of 5.991 also rejects the null hypothesis that the RV series are normally distributed. However, as expected, the logarithm-transformed realized variance series RV_V, where the effect of overnight returns and autocorrelation of high frequency returns is adjusted, the values of the sample autocorrelation coefficients are lower.

4. AR(FI)MA model

The autoregressive fractionally integrated moving average *AR(FI)MA(p,d,q)* is estimated for the series to capture the long memory properties of the volatility, formally defined as

$$\phi(L)(1-L)^d(y_t-\mu)=\theta(L)\varepsilon_t, \quad t=1,\dots,T. \tag{8}$$

where d is the degree of long memory fractional integration process with $0<d<1$. In the model the lag operator is L, the AR polynomial on the left-hand side defines the autoregressive component on the demeaned data, the MA polynomial on the right-hand side specifies the component on the residuals, and ε_t is white noise.

Following the method proposed by Andersen and Bollerslev (1998) the logarithm-transformed daily realized volatility series

$$y_t = ln(RV_t), \quad t=1,\dots,T. \tag{9}$$

are directly modeled within the framework of the *AR(FI)MA(p,d,q)* model. The model in more general form, where

$$y_t=\mu+\sum_{i=1}^{\infty}\pi_i(y_{t-i}-\mu), \quad t=1,\dots,T. \quad i<t \tag{10}$$

and the coefficients π_i are a product of the polynomials $\phi(L)$ and $(1-L)^d$, which are specified to produce the forecast known as the long memory forecast.

4.1. Introduction to the skewed distribution

Fernández and Steel (1998) introduced a method to transform a symmetric distribution into a skewed variant. By assumption the skewed univariate probability density function (pdf) $f(\cdot)$, is unimodal and symmetric around 0. The skeweness of a pdf $f(\cdot)$ of a random variable z is introduced with the inverse scale factors $\frac{1}{\gamma}$ and γ in the positive and negative orthant. Indexed skew parameter as a scalar $\gamma \in (0,\infty)$ in the model,

$$\begin{aligned} f(z\mid\gamma) &= \frac{2}{\gamma+\frac{1}{\gamma}}\left\{f\left(\frac{z}{\gamma}\right)I_{[0,\infty)}(z)+f(\gamma z)I_{(-\infty,0)}(z)\right\} \\ &= \frac{2}{\gamma+\frac{1}{\gamma}}f\left(z\gamma^{-sign(z)}\right) \end{aligned} \tag{11}$$

describes the asymmetry of the distribution, and $I_{(\cdot)}$ is the indicator function by having value 1 if the value of the random variable z is specified in the subscript of the indicator function, 0 otherwise.

The moment conditions are used to standardize skew variants of distributions to zero mean and unit variance. The absolute moments are generated by the function

$$M_r = 2\int_0^{\infty} z^r f(z)dz \tag{12}$$

where M_r is the r^{th} order absolute moment of $f(z)$ on the positive real line. The mean $\mu\gamma$ and variance $\sigma\gamma$ of $f(z|\gamma)$ depend on γ are defined by

$$\mu\gamma = M1\left(\gamma-\frac{1}{\gamma}\right) \tag{13}$$

$$\sigma_\gamma^2=\left(M_2-M_1^2\right)\left(\gamma+\frac{1}{\gamma^2}\right)+2M_1^2-M_2. \tag{14}$$

It follows that the probability function $\tilde{f}(z\mid\gamma)$ of a standardized skewed distribution is possible to present as

$$\begin{aligned}\tilde{f}(z\mid\gamma\theta) &= \frac{2\sigma}{\gamma+\frac{1}{\gamma}}\tilde{f}\left(z_{\mu_\gamma\sigma_\gamma}\mid\theta\right), \quad \text{where} \quad z_{\mu_\gamma\sigma_\gamma} \\ &= \gamma^{sign\left(\sigma_\gamma z+\mu_\gamma\right)}\left(\sigma_\gamma z+\mu_\gamma\right), \end{aligned} \tag{15}$$

i.e. $\tilde{f}(z \mid \gamma)$ can be any standardized symmetric distribution function, including the standardized Normal Distribution, the standardized Student-*t* Distribution or the standardized General Error Distribution (GED). In above equation θ represents a set of shape parameters that model higher moments of even order *e.g.* the shape parameter in the GED and Student-t distributions.

5. Methodology

The *AR(FI)MA(p,d,q)* model is used to forecast out-of-sample volatility by considering either the symmetric and skewed conditional distribution densities for the innovations.[6] The employed densities are; the normal norm, the student-t *std*, and the generalized error distributions ged in addition to the skewed variants; the skew-normal snorm, the skew-student-t *sstd*, and the skew-generalized error distribution *sged*. The feature of the leptokurtosis and asymmetry of the distribution of realized variances is scrutinized, as is the assumption that non-normality is successfully eliminated by the logarithm-transformation (Wilhelmsson, 2006; Corsi et al., 2008).

This study assumes that to capture the dynamics of estimated volatility requires determining the most functional structure for the estimated model. The model specification reveals the issue of model overfitting, *i.e.*, the problem related to insignificant extra terms added to the model, hence the forecasts produced may not be optimal. To prevent overfitting of the model, Sugiura (1978) introduced the AICc criterion for linear models, and by Hurvich and Tsai (1989) extension the AICc criterion is suggested for regression and autoregressive model selection to reduce bias and improve the selected model orders. In the selection process version of the Akaike information criterion (AICc) corrected for small sample size prefers the structure of the model that has the smallest value for the criterion. In this study, to prevent overfitting of the model the unbiased information criterion of the AICc is used to select the best fitting *AR(FI)MA(p,d,q)* model structure by considering the distribution densities and all the model structures with combinations of the autoregressive and the mean average parameter orders up to three lags.

According to the AICc criterion and selected best fitted structure of the *AR(FI)MA(p,d,q)* model the realized volatility forecasts are produced by rolling the forecasts. This is a procedure where the starting point of the forecast does not change, *i.e.*, the in-sample period is used to estimate the model and the parameter values remain unchanged throughout the procedure. To compare the forecast performance differences, the realized volatility forecasts are produced at 1-day, 10-day, and 22-day horizons, where a one-day-ahead forecast is based on information content of the previous data, and forecasts further than one day are based on the unconditional mean of the estimated model. The estimation procedure is performed over the in-sample period from June 01, 2007 to October 22, 2010, a period consisting of 857 trading days. For evaluation purposes the out-of-sample period is used to measure the forecast performances of the estimated models, hence a total of 300 trading days is adapted for the out-of-sample period from October 25, 2010 to December 30, 2011.

To evaluate the performance of the produced volatility forecasts the VIX volatility index serves as a reference forecast.[7] However, in line with the findings of Coval, Joshua, and Tyler (2001)), the risk premium that is associated with the option prices is considered. The study mentioned above suggests that investors are willing to pay a risk premium on option prices as a price for a having a hedge against volatile market movements. Hence, the purpose of the VIX as a reference forecast for the volatility forecasts produced is to assess possible forecast bias in the estimation process, instead of assessments of the option market's volatility forecast efficiency per se. Previous studies on the forecast efficiency of the option markets assume that the VIX index contains all relevant information beyond that of any achievable volatility forecast (see *e.g.* Becker et al., 2006, 2007). Like Becker et al. (2006) in their study, the VIX index 22-day trading horizon is utilized as a measure of forecasted volatility of the S&P 500 index.

5.1. Forecast performance measures

The performance measures presented below were used to assess the quality of the forecasts produced. In the equations *N* is the total number of forecasts and *Realized* is the actual volatility, *i.e.*, the squared daily return as a proxy for the true volatility. The Heteroscedasticity Consistent Mean Square Error (*HRMSE*) of the forecasts

$$HRMSE = \sqrt{\frac{1}{N}\sum\nolimits_{t=1}^{N}\left(1-(RV_t/Realized_t)\right)^2} \qquad (16)$$

and

$$MSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(RV_t - Realized_t)^2} \qquad (17)$$

is used as a forecast evaluation criterion to measure the predictive ability and to rank the estimated models.

5.2. Regression test

In addition to the performance measures an OLS linear regression is used to evaluate the predictions. The presence of heteroskedasticity is assumed, hence the Newey–West heteroskedasticity and autocorrelation consistent (HAC) standard errors are estimated. In the predictive regression

$$R^2_{T+f} = \alpha + \beta RV_{T+f} + \varepsilon_T \qquad (18)$$

the squared daily return as a proxy for the true volatility is regressed on the estimated realized volatility forecast, where the lower index *f* denotes the *f*-period ahead forecasts. If the realized volatility forecasts are unbiased, it is expected that $\alpha = 0$ and $\beta = 1$. In Tables 2 and 3, the probability values of the F-test for the Newey–West regression are presented with the hypothesis, including the goodness-of-fit coefficient R^2 of the regression. The value of the *Joint Test* is the *F*-test's probability value, assuming simultaneously $H_0: \alpha = 0,\ \beta = 1$.

6. Empirical results

Forecasts based on the futures observations

Table 2 (in *Panel A*) presents the parameter estimates for the specified *AR(FI)MA* models, where the best fitting structure of the model is fitted to the logarithm-transformed realized variance series over the in-sample period. In the model estimation procedure, the coefficients of the parameters *Skew* and *Shape* are estimated to capture the feature of the realized returns distribution, in other words, asymmetry and leptokurtosis, respectively. All the estimated parameter coefficients of the models are highly significant, except the constant term in the model estimation for the RV_{IV} data. Considering the models that are fitted to the produced realized variance series based on the futures high frequency observations, RV_I and RV_{II}, makes it apparent that according to the Box–Ljung and the ARCH LM tests (in *Panel B*), the residuals and squared residuals are autocorrelated and

[6] The estimated *AR(FI)MA* models are conducted with R software using the rugarch (Ghalanos, 2013) package.

[7] The VIX volatility index, has since 2003, estimated the expected volatility of the S&P 500 index by averaging the weighted prices of SPX put and call options considering a wide range of strike prices. As a continuum for VIX, in 2007 and 2011 CBOE launched the S&P 500 three-month volatility index VXV and VIX volatility term structure data, respectively. For further details relating to the construction of the VIX index see Chicago Board Options Exchange (2003).

Table 2
This table presents the estimation results of the *AR(FI)MA(p,d,q)* models where the best fitting structure of the model is selected using the *AICc* criterion. In selection procedure, it is considered the combinations of the autoregressive and the mean average parameter orders up to three lags and the best fitting distribution density *(Dist.)* for the innovations. The models are fitted to the 10 min data frequency of the S&P 500 realized volatility log returns series over the in-sample period from June 01, 2007 to October 22, 2010. The out-of-sample period is from October 25, 2010 to December 30, 2011, including a total of 300 trading days for the forecasts evaluation.

Data	RV_I	RV_{II}	RV_{III}	RV_{IV}	RV_V	RV_{VI}
Dist.	*sstd*	*sged*	*std*	*sged*	*std*	*std*
AR(FI)MA	(1,0,1)	(2,0,1)	(1,0,1)	(0,d,0)	(0,d,0)	(1,0,1)
***Panel A:** Parameter estimates*						
μ				−0.628		
				(0.545)		
AR(1)	0.976***	1.088***	0.975***			0.979***
	(0.011)	(0.005)	(0.009)			(0.008)
AR(2)		−0.099***				
		(0.003)				
MA(1)	−0.756***	−0.816***	−0.657***			−0.658***
	(0.027)	(0.011)	(0.038)			(0.038)
d				0.500***	0.459***	
				(0.020)	(0.027)	
σ	2.711	1.034***	0.667***	0.570***	0.716***	0.677***
	(2.612)	(0.033)	(0.021)	(0.022)	(0.022)	(0.022)
Skew	0.612***	0.639***		1.086***		
	(0.023)	(0.025)		(0.025)		
Shape	2.129***	1.066***	14.053**	1.328***	11.584**	10.823***
	(0.272)	(0.057)	(5.074)	(0.092)	(3.755)	(3.219)
***Panel B:** Diagnostics*						
LogL	−1391	−1385	−865	−718	−924	−875
AICc	2.667	2.673	2.055	1.702	2.178	2.080
Skewness	−1.317	−1.049	0.132	0.339	0.035	0.096
Kurtosis	4.456	4.073	3.499	4.797	3.744	3.831
JB	0.000	0.000	0.003	0.000	0.000	0.000
$Q_{(3)}$	0.000	0.000	0.328	0.479	0.274	0.328
$Q_{(12)}$	0.000	0.000	0.229	0.034	0.012	0.181
$Q^2_{(3)}$	0.000	0.003	0.070	0.088	0.916	0.315
$Q^2_{(12)}$	0.000	0.000	0.304	0.000	0.033	0.667
$ARCH_{(3)}$	0.000	0.000	0.072	0.102	0.905	0.329
$ARCH_{(12)}$	0.000	0.000	0.410	0.005	0.044	0.715
***Panel C:** Forecast Performance Measures for 1-day ahead forecasts (300 forecasts)*						
HRMSE	2.636	2.074	2.445	2.662	2.734	2.070
MSE	16.66	15.87	16.49	16.41	16.39	15.77
R^2	0.237	0.220	0.226	0.312	0.322	0.228
$Ho: \alpha = 0$	0.317	0.409	0.440	0.277	0.245	0.504
$Ho: \beta = 1$	0.051	0.199	0.101	0.051	0.028	0.213
Joint test	0.001	0.184	0.002	0.000	0.000	0.088
***Panel D:** Forecast performance measures for 10-days ahead forecasts (291 forecasts)*						
HRMSE	4.599	3.714	6.146	7.677	7.675	5.641
MSE	19.77	19.33	20.19	20.66	20.67	20.01
R^2	0.052	0.051	0.027	0.033	0.037	0.026
$Ho: \alpha = 0$	0.261	0.129	0.139	0.415	0.481	0.105
$Ho: \beta = 1$	0.139	0.536	0.697	0.254	0.157	0.211
Joint test	0.010	0.302	0.031	0.000	0.000	0.239
***Panel E:** Forecast Performance Measures for 22-days ahead forecasts (279 forecasts)*						
HRMSE	4.820	4.260	6.151	8.575	8.232	5.770
MSE	21.10	20.56	21.35	21.94	21.92	21.14
R^2	0.036	0.036	0.018	0.016	0.018	0.017
$Ho: \alpha = 0$	0.551	0.134	0.237	0.340	0.396	0.153
$Ho: \beta = 1$	0.046	0.957	0.848	0.534	0.417	0.664
Joint test	0.004	0.170	0.008	0.000	0.000	0.068

Notes: In the table, Panel A, is presented the parameter estimates, and inside the parenthesis, White's (1982) heteroscedastic consistent robust standard errors. The signs ***, ** and * of the two-tailed *t*-test indicate statistical significance at 0.1%, 1% and 5%, respectively. In Panel B, is the value of the log-likelihood *(LogL)* function, and the value of corrected Akaike information criterion *(AICc)*. In Panel B is presented the Box–Ljung test probability values for autocorrelation in residuals, $Q_{(.)}$, and squared residuals, $Q^2_{(.)}$, where the $ARCH_{(.)}$ and *JB* represent the probability values of the ARCH LM and Jarque Bera tests, respectively. The forecast performance measures in Panel C, D, and E, are the heteroscedasticity consistent root mean squared error *(HRMSE)* and the mean square error *(MSE)*. The probability values of the *F*-test for the Newey–West regression are presented with the hypothesis, including the value of R^2 of the regression. The value of the *Joint Test is* the *F*-test's probability value, assuming simultaneously Ho : $\alpha = 0$, $\beta = 1$.

Table 3
This table presents the estimation results of the *ARMA(p,q)* models where the best fitting structure of the model is selected using the *AICc* criterion. In selection procedure, it is considered the combinations of the autoregressive and the mean average parameter orders up to three lags. Here the best fitting distribution density *(Dist.)* for the innovations is restricted to the non-skewed distributions only. The models are fitted to the 10 min data frequency of the S&P 500 realized volatility log returns series over the in-sample period from June 01, 2007 to October 22, 2010. The out-of-sample period is from October 25, 2010 to December 30, 2011, including a total of 300 trading days for the forecasts evaluation.

Data	RV_I	RV_{II}	RV_{III}	RV_{IV}	RV_V	RV_{VI}
Dist.	*std*	*ged*	*std*	*std*	*std*	*std*
AR(FI)MA	(1,1)	(2,3)	(1,1)	(2,1)	(1,1)	(1,1)
***Panel A:** Parameter estimates*						
μ	2.727***	−1.928***		−1.198***		
	(0.704)	(0.342)		(0.181)		
AR(1)	0.973***	0.014	0.975***	1.327***	0.971***	0.979***
	(0.008)	(0.011)	(0.009)	(0.074)	(0.010)	(0.008)
AR(2)		0.986***		−0.332***		
		(0.008)		(0.074)		
AR(3)	−0.773***	0.502***	−0.657***	−0.783***	-0.644***	−0.658***
	(0.022)	(0.073)	(0.038)	(0.047)	(0.042)	(0.038)
MA(2)		−0.826***				
		(0.021)				
MA(3)		−0.397***				
		(0.072)				
σ	2.523**	0.951***	0.667***	0.573***	0.715***	0.677***
	(0.894)	(0.024)	(0.021)	(0.023)	(0.022)	(0.022)
Skew						
Shape	2.100***	1.576***	14.053**	6.564***	10.820***	10.823***
	(0.084)	(0.287)	(5.074)	(1.215)	(3.230)	(3.219)
***Panel B:** Diagnostics*						
LogL	−1475	−1438	−865	−718	−922	−875
AICc	2.825	2.819	2.055	1.737	2.190	2.080
Skewness	−1.375	−0.515	0.132	0.260	−0.055	0.096
Kurtosis	4.918	3.488	3.499	4.767	3.797	3.831
JB	0.000	0.000	0.003	0.000	0.000	0.000
$Q_{(3)}$	0.000	0.002	0.328	0.948	0.050	0.328
$Q_{(12)}$	0.000	0.000	0.229	0.637	0.040	0.181
$Q^2_{(3)}$	0.000	0.002	0.070	0.126	0.971	0.315
$Q^2_{(12)}$	0.000	0.000	0.304	0.008	0.173	0.667
$ARCH_{(3)}$	0.000	0.002	0.072	0.151	0.975	0.329
$ARCH_{(12)}$	0.000	0.000	0.410	0.025	0.189	0.715
***Panel C:** Forecast performance measures for 1-day ahead forecasts (300 forecasts)*						
HRMSE	1.858	1.990	2.445	2.670	2.707	2.070
MSE	15.70	16.15	16.49	15.84	15.82	15.77
R^2	0.231	0.181	0.226	0.312	0.300	0.228
$Ho: \alpha = 0$	0.229	0.905	0.440	0.451	0.627	0.504
$Ho: \beta = 1$	0.166	0.581	0.101	0.070	0.034	0.213
Joint Test	0.334	0.425	0.002	0.000	0.000	0.088
***Panel D:** Forecast performance measures for 10-days ahead forecasts (291 forecasts)*						
HRMSE	1.958	3.856	6.146	8.702	7.353	5.641
MSE	19.55	19.36	20.19	20.46	20.31	20.01
R^2	0.053	0.047	0.027	0.029	0.033	0.026
$Ho: \alpha = 0$	0.389	0.099	0.139	0.064	0.131	0.105
$Ho: \beta = 1$	0.000	0.106	0.697	0.722	0.955	0.211
Joint Test	0.000	0.208	0.031	0.007	0.005	0.239
***Panel E:** Forecast performance measures for 22-days ahead forecasts (279 forecasts)*						
HRMSE	1.309	5.044	6.151	11.857	7.545	5.770
MSE	24.37	20.64	21.35	21.83	21.60	21.14
R^2	0.036	0.031	0.018	0.016	0.015	0.017
$Ho: \alpha = 0$	0.768	0.031	0.237	0.028	0.285	0.153
$Ho: \beta = 1$	0.000	0.019	0.848	0.630	0.856	0.664
Joint test	0.000	0.055	0.008	0.001	0.000	0.068

Notes: In the table, Panel A, is presented the parameter estimates, and inside the parenthesis, White's (1982) heteroscedastic consistent robust standard errors. The signs ***, ** and * of the two-tailed *t*-test indicate statistical significance at 0.1%, 1% and 5%, respectively. In Panel B, is the value of the log-likelihood *(LogL)* function, and the value of corrected Akaike information criterion *(AICc)*. In Panel B is presented the Box–Ljung test probability values for autocorrelation in residuals, $Q_{(.)}$, and squared residuals, $Q^2_{(.)}$, where the $ARCH_{(.)}$ and *JB* represent the probability values of the ARCH LM and Jarque Bera tests, respectively. The forecast performance measures in Panel C, D, and E, are the heteroscedasticity consistent root mean squared error *(HRMSE)* and the mean square error *(MSE)*. The probability values of the *F*-test for the Newey–West regression are presented with the hypothesis, including the value of R^2 of the regression. The value of the *Joint Test is* the *F*-test's probability value, assuming simultaneously Ho : $\alpha = 0$, $\beta = 1$.

heteroscedastic, suggesting that all information is not completely accounted for in the models. However, the test statistics for the modeled high frequency index data, $RV_{III} - RV_{VI}$, indicate the models better fit to the data.

For evaluation purposes and to rank the individual forecasts, the performance measures, in the form of the loss functions of the mean square error *MSE*, and also the heteroscedasticity consistent mean square error *HRMSE*, are presented for the forecasts at 1-day, 10-day, and 22-day horizons in *Panels C, D*, and *E*, respectively. The measured values of the loss functions show that the *AR(FI)MA* models fitted to the produced realized variance series based on the futures high frequency observations, RV_I and RV_{II}, are the best performing. According to the loss function value of the *MSE* it is evident that the *AR(FI)MA* model fitted to the futures realized variance series from filtered returns, RV_{II}, produces the most accurate forecasts. Furthermore, the high probability values of the Newey–West regression tests indicate the forecasts are unbiased. The results are consistent and cover all the produced forecasts within the different forecast horizons.

Furthermore, for the purposes of comparing the forecast performance produced, the loss function value, $MSE = 22.21$ was calculated for the VIX index's 22-day ahead forecasts.[8] In Table 2 (*Panel E*) the *MSE* values of the 22-day ahead volatility forecasts are lower than the performance value for the VIX index. Hence, it is apparent that the volatility forecasts, which are produced from the logarithm realized variance series, $RV_I - RV_{VI}$, performed better than the volatility forecasts of the VIX index.

Forecasts based on the index observations

In addition to the forecasts utilizing the information content of the futures observations (ES) it is interesting to compare the forecasts based on the index (SPX) observations, $RV_{III} - RV_{VI}$, and it appears that the *MSE* value is lowest for the forecasts that are modeled against the realized variance series from filtered returns, RV_{VI}. This finding suggests that deseasonalized returns, that involve the filtration of the high frequency returns, have an effect on the estimated realized variance series, hence in the *AR(FI)MA* model estimation process, the produced volatility forecasts are the most accurate. The consistency of the results at the different forecast horizons is also apparent. In addition, the high probability values of the Newey–West regression tests accord with the observations related to the forecast accuracy and lack of bias of the high frequency futures observations. In general, in the *AR(FI)MA* process the realized variance series from filtrated high frequency returns produced the most accurate forecasts. This effect is more prominent in the estimation process where the model is fitted to the filtered futures observations. In addition to accuracy, the forecasts are unbiased and the findings are consistent over all the forecast horizons.

The effect of the skewed distribution on forecasts

It is also interesting to examine the effect on forecast accuracy of the skewed distributions employed. The process is conducted in the optimal model selection procedure by fitting the optimal model structure separately to models with skewed and non-skewed distributions. It is evident that in the selection process the optimal model is reduced to the *ARMA(p,q)* structure.[9] Table 3 (*Panel A*) presents the parameter estimates for the specified *ARMA* models. Here the best fitting structure for the model in pre-specified fixed form is fitted to the logarithm-transformed realized variance series over the in-sample period. Viewing the estimation results in the table reveals that the parameter coefficients of the models are highly significant as a product of the selection procedure based on the AICc criterion. According to the Box–Ljung and the ARCH LM tests (in *Panel B*) the specified

Table 4
The results of the estimated regressions for the forecast encompassing performance evaluation. The 22-day-horizon forecasts comprise 279 out-of-sample forecasts from October 25, 2010 to December 30, 2011.

Data	RV_I	RV_{II}	RV_{III}	RV_{IV}	RV_V	RV_{VI}
Panel A: *Parameter estimates*						
RV_I vs. RV_{II}	0.615	−0.220				
	(0.653)	(1.016)				
RV_I vs. RV_{III}	0.653*		−0.705			
	(0.285)		(1.048)			
RV_I vs. RV_{IV}	0.649*			−0.572		
	(0.317)			(0.990)		
RV_I vs. RV_V	0.716				−1.076	
	(0.382)				(1.653)	
RV_I vs. RV_{VI}	0.645*					−0.540
	(0.277)					(0.803)
RV_{II} vs. RV_{III}		0.936**	−0.770			
		(0.308)	(0.749)			
RV_{II} vs. RV_{IV}		1.129**		−1.002		
		(0.413)		(0.937)		
RV_{II} vs. RV_V		1.113*			−1.365	
		(0.442)			(1.448)	
RV_{II} vs. RV_{VI}		0.945**				−0.630
		(0.296)				(0.566)
RV_{III} vs. RV_{IV}			1.311	−0.191		
			(1.590)	(1.485)		
RV_{III} vs. RV_V			1.364		−0.332	
			(1.500)		(2.023)	
RV_{III} vs. RV_{VI}			6.030			−3.924
			(4.769)			(3.782)
RV_{IV} vs. RV_V				0.835	−0.030	
				(1.599)	(2.419)	
RV_{IV} vs. RV_{VI}				−0.106		0.945
				(1.629)		(1.393)
RV_V vs. RV_{VI}					−0.259	1.018
					(2.204)	(1.310)

Notes: In the table is presented the parameter estimates, and inside the parenthesis the standard errors of the estimated GMM regression. The signs ***, ** and * of the two-tailed *t*-test indicate statistical significance at 0.1%, 1% and 5%, respectively.

models in the *ARMA* structure indicate that the realized variance series from high frequency index data, $RV_{III} - RV_{VI}$, are better fitted to the data.

The estimation results show that the *MSE* values are lower for the models where skewed conditional distribution density is employed for the innovations and the model is fitted to the futures observations, RV_I and RV_{II}.[10] For all the other estimated models, which are fitted to the estimated realized variance series $RV_{III} - RV_{VI}$, the *MSE* values in the observed forecast horizons do not indicate better forecast performance.[11] It is also notable that in Table 3 (*Panel E*), the high value of *MSE* at 24.37 for the 22-day ahead forecasts, where the model is fitted to the realized variance series, RV_I, indicates an overestimation bias in the forecasts.

6.1. Encompassing test

A test to evaluate single forecasts' out-of-sample performance against the others was conducted to check the robustness of the results based on the loss function values of the *MSE* and the *HRMSE*. The forecast test used in this paper follows the methodology applied in earlier studies (see Chong & Hendry, 1986; Pong et al., 2004; Clements, Michael, & Harvey, 2010) to assess the information content of forecasts. The test is implemented in a regression,

$$R_t^2 = \alpha + \beta_j \widehat{RV}_{j,t}^f + \beta_i \widehat{RV}_{i,t}^f + \varepsilon_t, \tag{19}$$

[8] The daily volatility measure implied by the VIX quote is equivalent to a measure of daily volatility approximation, $(VIX/(100\sqrt{252}))^2$ (see Chicago Board Options Exchange, 2003).

[9] The optimal model is considered in fixed forms of the *AR(FI)MA(p,d,q)* model with and without parameter for skewed distribution and the long memory, *d*, specification.

[10] The estimation results of the models where skewed conditional distribution density is employed in the estimation procedure, are not reported. However, the results are available from the author upon request.

[11] It was observed that the performance of the forecasts are not improved as a result of the fixed form structures.

where the R_t^2 is the squared daily logarithm return as a proxy for the true volatility, $\widehat{RV}_{j,t}^{f}$ is the forecast j, $\widehat{RV}_{i,t}^{f}$ is the forecast i, and ε_t is a random error. For the regression the generalized method of moments (GMM) proposed by Hansen (1982) is applied based on the Newey and West's (1994) heteroskedasticity- and autocorrelation-consistent (HAC) covariances. In the model specification, the instruments are restricted to the estimators used in the regression. In the estimation of the regression, a significant value of the coefficient implies the incremental predictive information content of the forecasts. Furthermore, multicollinearity of the variables can make both the estimated β coefficients appear insignificant, and conversely both the coefficients can be significant due to nonoverlapping information.

Table 4 presents the results of the encompassing test that evaluates the best performing forecasts over the 22-day forecast horizon.[12] The regression parameter estimates and the standard errors of the coefficient values are reported in the table. By viewing the encompassing analyses between the blocks 1–2 and 3–5 of Panel A, it can be seen that the forecasts based on the futures observations contain incremental information beyond that of the index based observations. This finding is similar to that observed according to the values of the loss functions *HRMSE* and *MSE*. A pair-wise comparison of the coefficients between the variables of the forecasts based on the futures observations, RV_I and RV_{II}, suggests they are not significant, suggesting multicollinearity of the variables. Similarly, it is assumed that the insignificance of the coefficient values of the variables based on the forecasts on the index observations, $RV_{III} - RV_{IV}$, is a result of multicollinearity.

7. Conclusion

This study utilized the distributional properties of the logarithm-transformed high frequency realized volatility series to forecast the volatility of S&P 500 index daily returns. For the forecasts the logarithm-transformed realized variances are modeled directly in the *AR(FI)MA* model specification. In the previous literature the volatility and forecast of assets returns are estimated from lower frequency observations, such as daily, weekly and monthly observations (*e.g.* Roh, 2007; Bildirici & Ersin, 2009). At present, the availability of high frequency financial observations enable to use the observations as a more informative source that improves efficiency of forecasts of the volatility. Hence, as a contribution to the previous literature, in this paper 10 min frequency of the S&P 500 index and futures observations is utilized to improve efficiency of the volatility forecasts.

The efficiency of volatility forecast is based on assumption that the estimate of volatility forecast incorporates all relevant information in the forecast produced. Theoretically, the forecasts based on the futures 23.25 h intraday observations should be superior compared to the index based forecasts or any forecast estimated from lower frequency observations. In particular, the empirical findings of this paper show that the measured realized variance series from the deseasonalized filtered returns of the futures observations enable to produce the best performing forecasts. This suggests the importance to consider the effect of seasonality as well as effect of autocorrelation in the applied methods to measure the realized volatility.

In this paper the AICc criterion is applied to acquire the most functional structure for the estimated AR(FI)MA model. The iterative selection process applied shows also the importance to consider the symmetric and skewed conditional distribution densities for the optimal model structure. It is evident that in the AR(FI)MA model specification the structure of the distribution characteristics considered improves efficiency of the forecasts. In addition to select the optimal structure for the model, it is essential to consider the issue of trade-off between greater statistical power from higher frequency of intraday observations obtained at the cost of serial autocorrelation. Andersen and Bollerslev (1998) show that the unbiased and consistent estimator of realized variance depends on the assumption that continuous price process follows semi-martingale process. The assumption presupposes also that the intraday returns are not serially correlated. In this study, as the 10 min frequency observations is utilized, the autocorrelation and the effect of seasonality in returns are mitigated within the applied methods to measure the realized variances.

In the *AR(FI)MA* model framework, it is evident that applied deseasonalized filtered returns for the estimated realized variances series improve the forecasts accuracy. This is observable for both the futures and index based forecasts produced at 1-, 10-, and 22 min horizons. In addition, the results of the encompassing test indicate that the forecasts based on the futures observations contain incremental information over that of the forecasts based on the index observations. However, it is observed that the fractionally integrated long memory process of the *ARFIMA* model structure is not an optimal fit to the S&P 500 realized volatility series. The optimal fit structure and the model for best performing out-of-sample forecasts is reduced to a structure of short memory process, *i.e.*, the structure of the *ARMA* model.

Areal and Taylor (2002) examined the properties of realized volatility series based on a high frequency returns series of the FTSE-100 stock index on futures contracts. The study concluded that the distribution of the logarithm of volatility is not exactly normal. Similarly in this study, the empirical findings show that the realized volatility series are not normally distributed, hence this property is utilized to produce more accurate forecasts. It is evident that the realized variance series from the deseasonalized filtered returns of the futures observations in the optimal *AR(FI)MA* model estimation structure produce the best performing forecasts. This superiority over the other forecasts accounts for the advantage of the estimated *ARMA* model where the distributional property of skewness is employed for innovations. Furthermore, by taking into account the skewness in the model estimation process, establishes that the out-of-sample forecasts produced are unbiased estimates of the true volatility.

An interesting subject for future research is the degree of autocorrelation in returns of the high frequency observations. The issue of autocorrelation gives rise to the insight of an optimal frequency interval over which the high frequency returns are calculated. Achieved knowledge of autocorrelation, in addition to the effect of seasonality inherent in returns of the high frequency observations, enable to enhance use of various volatility models in volatility estimation and forecasting. This implies that the model-free realized volatility is considerable to extend into various fields of studies which cover correlation relationship of predicted and measured values of variables in interest. In assumed correlation studies, it would be advantageous to consider calculated realized volatility measures in context of multivariate models. This field of studies is formidable, covering research of correlation, spillover effects and comparisons of available multivariate volatility models to estimate and forecast volatility.

[12] The models and the best performing forecast results based on the loss functions of the *HRMSE* and *MSE* are presented in Table 2. The encompassing test performed for the forecasts produced over the 1-day and 10-day horizons show that the results of the test are not sensitive to the choice of horizon.

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Dynamic conditional copula correlation and optimal hedge ratios with currency futures

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ABSTRACT

This study investigates efficiency of the futures hedge implemented through the currency markets. The copula DCC-EGARCH model is estimated with the bivariate error correction term to minimize variance of the currency portfolios. The estimation results for the currencies of the Australian dollar, Canadian dollar, euro, British pound and Japanese yen show that the inclusion of the external realized variance estimators into the variance equation of the estimated model improves the model's ability to account for the clustered data variance. In hedging portfolios, the information content of the realized variance estimator effectively reduces the variance of the portfolios.

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1. Introduction

Foreign exchange rate interdependence between the underlying futures contract is widely utilized to reduce currency risk (Chan, 2010; Gagnon, Lypny, & McCurdy, 1998; Ku, Chen, & Chen, 2007; Lien & Yang, 2006; Lien & Yang, 2010; Lioui & Poncet, 2002). For effective risk hedging strategy with the futures, it is calculated the hedge ratio that specifies the number of futures contracts required to reduce the variance of portfolio returns. The method of ordinary last square (OLS) regression is conventionally used to derive the optimal hedge ratio. The main issue related to the method is the second moment of the time series that is assumed to be constant over time. In the existing literature this assumption is commonly utilized to form static optimal hedge ratios through the futures contracts to minimize variance of the hedged portfolios (see e.g. Figlewski, 1985; Ederington, 1979; Malliaris & Urrutia, 1991; Benet, 1992: Geppert, 1995). However, disadvantage of the method is that it does not take into account the time varying characteristic of the spot and futures price changes.

Engle (2002) proposed the dynamic conditional correlation (DCC) model that is generally used in dynamic hedging strategies. The advantage of the model is its property to capture dynamics of the covariance between variables (see e.g. Bauwens, Laurent, & Rombouts, 2006; Christoffersen, Errunza, Jacobs, & Jin, 2014; Pelletier, 2006). Ku et al. (2007) investigate properties of the DCC model on the optimal hedge ratios of British and Japanese currencies in both futures markets. In their research the error correction term is also incorporated to the DCC model to capture the long-run stochastic trend that is commonly referred to the spot and futures markets' cointegration. In terms of hedging performance the empirical results show that the model performs the best. Recently, the copula-based GARCH model has shown its efficiency to capture time varying characteristic of the variables in interest. The copula method applied with the GARCH models emerged interest in several studies (Patton, 2006; Jondeau & Rockinger, 2006; Lee & Long, 2009; Ning, 2010; Garcia & Tsafack, 2011). The theory of the copula, first introduced by Sklar (1959), considers copula as a function that links marginal distributions into a multivariate joint distribution function to capture dependence structure between the variables.

In this study changes in spot and futures prices for the currencies of the Australian dollar (AUD), Canadian dollar (CAD), British pound (GBP), Euro (EUR) and Japanese yen (JPY) are used to analyze hedging effectiveness of the estimated models. It extends the existing literature by demonstrating applicability of the copula DCC-EGARCH model to capture dynamics of the covariance between variables to form efficient hedges in currency markets. The bivariate error correction model is applied with the specified DCC model augmented with the realized variance estimator in the variance equation of the model. The estimation results show that the model is able to form consistent estimate of the conditional covariance matrix and finally improve efficiency of the dynamic hedges. For comparison purposes, also the OLS, error correction model (ECM) and constant conditional correlation (CCC) model are estimated. The method of hedging effectiveness (HE), proposed by Ederington (1979), is calculated to verify adequacy of the applied method to the model characteristics of the time series and to compare efficiency of the hedges.

This paper contributes to the previous literature related to portfolio hedging strategies (e.g. Baillie & Myers, 1991; Lien, Tse, & Tsui, 2002;

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Park & Jei, 2010; Su & Wu, 2014) by demonstrating increased efficiency of the hedges based on the strategy implemented by the copula DCC-EGARCH model. The superiority of the efficiency is attributed to the information content of the realized volatility estimator that is included into the variance equation of the model. The results of the study suggest that the realized volatility estimator adds information in explaining the exchange rates return variance.

The research is implemented in two phases to test robustness of hedging effectiveness of the models estimated. First, the currency spot and futures returns of the euro (EUR), British pound (GBP) and Japanese yen (JPY) are used. The estimation period covers the return series from 14 January 2000 to 27 December 2013. Also, for an artificial data the bootstrap method for data simulation is utilized. It is applied the method that Politis and Romano (1994) suggest for stationary and weekly dependent data. The advantage of the method for simulated returns generation is its property to preserve time series returns cross-sectional dependences. In the data simulation procedure for each of the currencies and futures of Euro, British Pound and Japanese Yen, a one thousand artificial data is generated. All the models are fitted to the currency spot and futures simulated returns i.e. each of the model is one thousand times estimated. Finally, from the estimation results the confidence levels of the performance measures is calculated.

Secondly, in this study to test robustness of the hedges based on the models applied the return series that cover a longer time period is utilized from 12 June 1987 to 27 December 2013. For the models estimation the longer time period of the currency spot and futures returns of the Australian dollar (AUD), Canadian dollar (CAD), British pound (GBP) and Japanese yen (JPY) is used.

This study is related to the earlier studies presented by Hsu, Tseng, and Wang (2008); Lai and Sheu (2010) and Sheu and Lai (2014) on examination of the GARCH model ability to estimate risk risk-minimizing hedge ratios. For the S&P 500 and FTSE 100 futures hedge, Hsu et al. (2008) compared the performance of the estimated dynamic hedging model between the other models. They show that the outperformance of the optimal dynamic hedge is based on the efficiency of the improved copula GARCH model. Lai and Sheu (2010) analyzed multivariate GARCH models with encompassed realized variance estimates in futures hedging and effect of hedge horizon on hedge ratio. Similarly, Sheu and Lai (2014) investigate the effect of information content of realized variance range effect on futures hedging.

In previous research Conlon and Cotter (2012) consider the moving-window OLS hedging and the distributional characteristics of the hedging portfolio returns. The optimal hedge ratio applied in futures hedging shows that the hedge is inadequate to account for excess kurtosis of the hedge portfolio returns distribution. In this current research the optimal hedge ratio is applied in context of multivariate GARCH models. In the currency portfolio hedging it is recognized generally known character of the GARCH models' inability to capture all excess kurtosis in financial returns. Bollerslev (1987) considers this issue by used *t*-distribution and Nelson (1991) by a generalized error distribution. Recently Malmsten and Teräsvirta (2010) show that excess kurtosis is not accounted by applied standard GARCH models. This character of the GARCH models applied is observable in particularly in high volatility periods. Hence, the external realized variance estimators are included into the variance equations of the model to improve the model ability to fit into the estimated currency spot and futures returns in high volatility periods.

Fernandez (2008) shows that in terms of hedging effectiveness the commodity portfolio hedge based on the method of the copula correlation outperforms the multivariate GARCH model. In this paper the copula DCC-EGARCH model is utilized to model returns dependency. In the model estimation the joint distribution of the Gaussian copula links the marginal distributions of the spot and futures returns together, hence it is assumed the method more effectively captures dynamics of the spot and futures correlation. Particularly, similar to Fernandez (2008) the outperformance of the DCC-EGARCH with the external realized volatility estimator included into the variance equation of the model is possible partly to account for the outcome of the utilized copula based method.

Several studies consider multivariate GARCH models to form the optimal hedge strategy. Chang, González-Serrano, and Jiménez-Martín (2013) analyze hedge ratios and performance of near-month and next-to-near-month futures contracts on spot exchange rates of Euro, British pound and Japanese yen. The estimated conditional covariance from the applied multivariate GARCH models showed their importance in daily hedge for the currencies. Caporin, Jimenez-Martin, and Gonzalez-Serrano (2014) in their study compare hedging performance of several multivariate GARCH models, including strategies based on linear regression and variance smoothing. In their study, they focused on the impact of currency hedge and improved risk-return trade-off within the financial turmoil originated from the subprime and the Euro sovereign bonds. The results of their study suggest that for the applied dynamic covariance models the measures of hedging effectiveness and Sharpe ratio show improved performance.

Kroner and Sultan (1993) demonstrate the performance differences between strategies based on dynamic and static hedge in a framework of bivariate GARCH and ordinary least square OLS regression, respectively. Similar empirical studies of Chakraborty and Barkoulas (1999) support the findings that the dynamic hedging strategy encompasses the strategies based on the estimated static covariance. Lien et al. (2002) examines differences of hedging performances between least square OLS regression and constant correlation vector generalized autoregressive conditional heteroscedasticity (VGARCH) model. Their findings indicate that the OLS hedging encompasses the VGARCH model in efficiency.

As proposed in earlier studies (see e.g. Engle, 1982; Engle & Granger, 1987), time varying variance-covariance structure of the data series is not accounted for by the utilized OLS regression. Thus, to capture heteroscedasticity of conditional variances and correlations of asset returns Engle (2002) proposed the DCC model, which is also frequently utilized in subsequent literature. Campbell, Serfaty-De Medeiros, and Viceira (2010) analyze mean-variance of portfolios of several currencies to manage risk of the international bond and equity investments. The results of the study show hedging benefits for the portfolios of bond investments and benefits for equity are related to the correlation of specific pairs of currency and equity that states a long or short position investments in the specified currency. The findings of their research indicate that dynamic hedges outperform static hedge of portfolios constructed. With similar studies De Roon, Nijman, and Werker (2003) conclude that dynamic hedges conditional on the interest rate spread improve efficiency of the hedges.

The remaining sections of this study are organized as follows. Section 2 introduces the data employed in this paper. Section 3 introduces the employed methodologies. Section 4 presents the empirical results and the final section concludes.

2. Data

In this study the Chicago Mercantile Exchange (CME) spot and futures contract settlement observations for the Australian dollar (AUD), Canadian dollar (CAD), euro (EUR), British pound (BP), and Japanese yen (JPY) in US dollars are used. The futures non-adjusted settlement data observations are based on the spo*t*-month continuous contract calculations. All the observations are weekly closing prices collected from the Datastream database. For the euro (EUR), Britain pound (GBP) and Japanese yen (JPY) the data incorporates 730 observations from 7 January 2000 to 27 December 2013. To obtain log returns (see Fig. 1) the time series observation i at time t and $t-1$ are calculated for the spot (S) and futures (F) closing prices as $s_{i,t} = \log(S_{i,t}/S_{i,t-1})$ and $f_{i,t} = \log(F_{i,t}/F_{i,t-1})$, respectively.

Similarly, the Chicago Mercantile Exchange (CME) spot and futures contract settlement observations for the Australian dollar (AUD), Canadian dollar (CAD), British pound (BP), and Japanese yen (JPY) in US

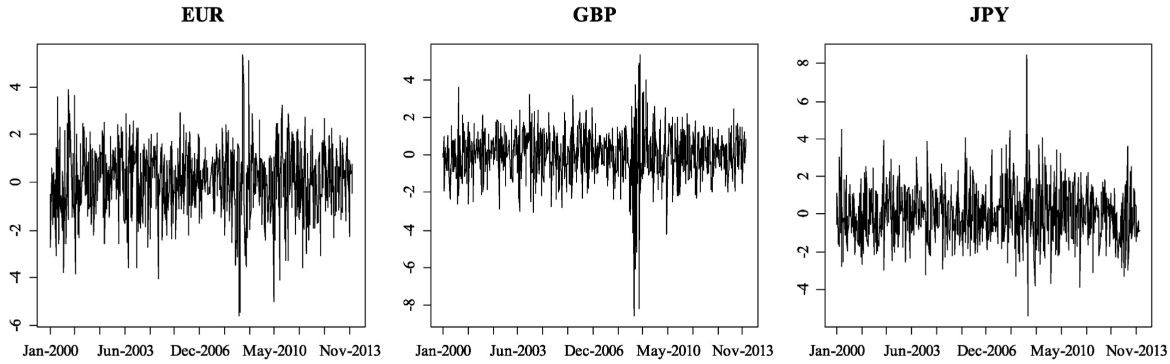

Fig. 1. Weekly log return series of the spot currency rates over the period 14 January 2000 to 27 December 2013.

dollars are collected. In this study the weekly closing prices of a longer time period that incorporates 1387 observations is utilized from 5 June 1987 to 27 December 2013. For the models estimation the currency spot and futures returns of the Australian dollar (AUD), Canadian dollar (CAD), British pound (GBP) and Japanese yen (JPY) is used. In Fig. 2 the log returns of the spot returns are presented.

3. Methodology

Andersen and Bollerslev (1998) introduced a method to estimate actual daily volatility of foreign exchange market by summing squared intraday returns.[1] In addition, Barndorff-Nielsen and Shephard (2002) outlined the semi-martingale process to the methodology of actual daily variability defined as a realized volatility. They show that discrete daily sum of squared returns constitute and unbiased and consistent approximation of the actual volatility. In this study, returns series of the currency spot prices are used to form the realized volatility as follows,

$$RV_t = \sum_d^D s_{d,t}^2 \tag{1}$$

where sum of squared daily returns $s_{d,t}^2$ in week t constitutes an approximation of the realized volatility RV_t for weekly returns (see e.g. French, Schwert, & Stambaugh, 1987; Schwert, 1989). In purpose to utilize information content of the currency squared returns on volatility estimation the series of realized variance is utilized in a structure of a variance equation of the DCC-EGARCH model (see Eqs. (5) and (6)).

3.1. DCC GARCH model estimation

Engle (2002) proposed the time-varying dynamic conditional correlation (DCC) model where correlations between assets are estimated in two-step procedure.[2] In the first-step, univariate GARCH models are estimated for each asset and in the second-step, standardized innovations is used to produce estimates of the dynamic correlations. In this study the univariate exponential GARCH (EGARCH) model, introduced by Nelson (1991) is used in the model estimation.[3]

For the first step of the DCC model estimation the test results of the cointegration (see Table 2) support inclusion of the error correction term $S_{t-1}-\gamma F_{t-1}$ with the structure of the EGARCH(1,1) model as follows,

$$s_t = c_s + \theta_s(S_{t-1}-\gamma F_{t-1}) + \epsilon_{st} \tag{2}$$

$$f_t = c_f + \theta_f(S_{t-1}-\gamma F_{t-1}) + \epsilon_{ft} \tag{3}$$

$$\begin{pmatrix} \epsilon_{st} \\ \epsilon_{ft} \end{pmatrix} \Big| \Psi_{t-1} \sim N(0, H_t) \tag{4}$$

$$\log(\sigma_{st}^2) = \omega_s + \alpha_s(|\epsilon_{t-1}| - E|\epsilon_{t-1}|) + \gamma_s\epsilon_{t-1} + \beta_s \log(\sigma_{t-1}^2) + RV_{st-1} \tag{5}$$

$$\log\left(\sigma_{ft}^2\right) = \omega_f + \alpha_f(|\epsilon_{t-1}| - E|\epsilon_{t-1}|) + \gamma_f\epsilon_{t-1} + \beta_f \log(\sigma_{t-1}^2) + RV_{ft-1} \tag{6}$$

where Ψ_{t-1} is the information set an time $t-1$ and H_t is the conditional variance-covariance matrix estimated at time t.

In this paper it is followed the Engle and Granger (1987) two-step procedure to capture spot and futures long-run relationship. Hence, for the mean equation of the DCC model the term $S_{t-1}-\gamma F_{t-1}$ is estimated in the cointegrating regression $S_t = c + \gamma F_t + \epsilon_t$, where the residuals of the regression represent an error correction term in the model. Furthermore, in order to capture information content of weekly returns on the estimated correlations it is included the lagged value of the realized volatility $RV_{(\cdot)}$ estimator into the variance equation of the model.

In the model estimation procedure the time varying covariance is obtained such that,

$$H_t = D_t R_t D_t, \tag{7}$$

where $D_t = diag(\sqrt{h_{1,t}}, \cdots, \sqrt{h_{N,t}})$ is a diagonal matrix of time varying variances $h_{i,t}$ from the first step univariate EGARCH process and R_t is positive definite conditional correlation matrix of the standardized residuals $\varepsilon_t = D_t^{-1}\epsilon_t \sim N(0, R_t)$. The conditional correlation matrix R_t is obtained as follows,

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{8}$$

$$Q_t = (1-\alpha-\beta)\hat{Q} + \alpha\varepsilon_{t-1}\varepsilon_{t-1}^{'} + \beta Q_{t-1}, \tag{9}$$

where $\hat{Q}$ is the $N \times N$ matrix constructed of unconditional covariance of standardized residuals ε_t.[4] For stationary and positive definiteness of the matrix $\hat{Q}$ scalars parameters α and β are non-negative and satisfies constraint $\alpha + \beta < 1$.

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[1] Andersen and Bollerslev (1998) intraday returns based on 5-min data observations.

[2] For the models estimated in this study the R statistic package rmgarch (Ghalanos, 2014) is utilized.

[3] The EGARCH model with different structures of lagged log variances and standardized innovations is considered. For hedging performance the EGARCH(1,1) model showed superiority over any other structures of the model.

[4] Bollerslev (1990) introduced the constant conditional correlation (CCC) model, where the correlation of the matrix R_t is constant unconditional correlation between the estimated variables.

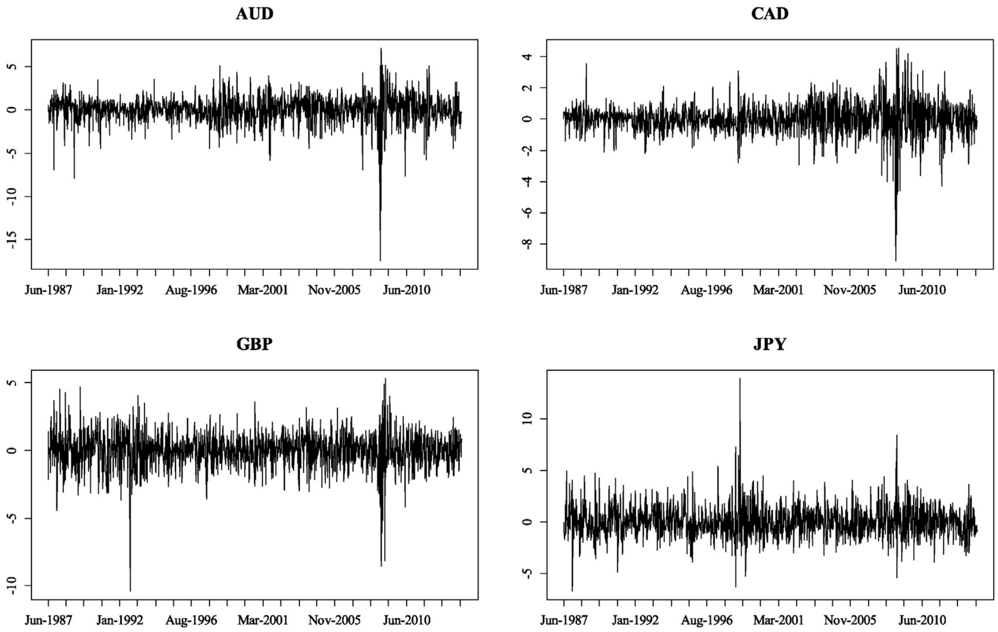

Fig. 2. Weekly log return series of the spot currency rates over the period 12 June 1987 to 27 December 2013.

3.2. Copula DCC GARCH

However, for the model estimation the assumption of linear dependence and multivariate normality of distribution of standardized innovations is not necessarily satisfied. It is possible that anticipated linear dependence and empirical distribution differ from the multivariate normal function. In this study it is applied the copula EGARCH-DCC model to obtain estimates of the bivariate dynamic correlations between the returns of the spot and futures observations. In the model estimation the joint distribution of the Gaussian copula links the marginal distributions of the spot and futures returns together to solve problems related to multivariate normality and linear dependence.

Sklar (1959) introduced the theory that there exists a unique n-dimensional copula as a function that links marginal distributions into a multivariate joint distribution function. The definition of an n-dimensional copula is a multivariate distribution function defined on the unit cube $[0,1]^n$, with uniform margins. The theory shows that a vector of standardized residuals $\varepsilon_t = \{\varepsilon_{1,t}, \varepsilon_{2,t}, \dots, \varepsilon_{k,t}\}$ of joint k-dimensional distribution function H with margins $F_1, F_2, \dots, F_k$ are need to be transformed to the uniform distribution (see Eqs. (2)–(6)) by the probability integral transformation method as follows,

$$u_{i,t} = F(\varepsilon_{i,t}) \text{ with } u_{i,t} \sim U[0,1]. \tag{10}$$

The joint distribution function of the standardized residuals can be presented as,

$$H(\varepsilon_{1,t}, \varepsilon_{2,t}, \dots, \varepsilon_{k,t}) = C(F_1(\varepsilon_{1,t}), F_2(\varepsilon_{2,t}), \dots, F_k(\varepsilon_{k,t})), \tag{11}$$

where a k-variate copula C links marginal distributions into a joint distribution function. The copula C as follows,

$$(u_{1,t}, u_{2,t}, \dots, u_{k,t}) = H\left(F_1^{-1}(\varepsilon_{1,t}), F_2^{-1}(\varepsilon_{2,t}), \dots, F_k^{-1}(\varepsilon_{k,t})\right), \tag{12}$$

is determined for any absolutely continuous marginal distributions, where the dependence relationship is completely determined by the copula and shape by the marginal distributions.

The Gaussian copula is the copula adapted in the standard multivariate normal distribution. In this study the Gaussian bivariate copula is used to link the marginal distributions of the spot u_1 and futures u_2 returns into the joint distribution. The bivariate Gaussian copula is of the following form,

$$C(u_{1,t}, u_{2,t}) = \Phi_R\left(\Phi^{-1}(\varepsilon_{1,t}), \Phi^{-1}(\varepsilon_{2,t})\right), \tag{13}$$

where a given correlation matrix $R \in \mathbb{R}^{2\times 2}$ is the joint cumulative distribution function of a multivariate standard normal distribution and Φ^{-1} is inverse of the univariate cumulative distribution function of a standard normal distribution. The Gaussian bivariate copula density function can be stated as

$$C(u_1, u_2) = \frac{1}{\sqrt{detR}} exp\left(-\frac{1}{2}\begin{pmatrix}\Phi^{-1}(u_1)\\ \Phi^{-1}(u_2)\end{pmatrix}^T \left(R^{-1} - \mathrm{I}\right)\begin{pmatrix}\Phi^{-1}(u_1)\\ \Phi^{-1}(u_2)\end{pmatrix}\right), \tag{14}$$

where I is the identity matrix.

3.3. Hedging

To reduce the risk exposure of foreign exchange cash position an opposite position on futures contracts is chosen such that the variance of hedged position is minimized. For dynamic hedging purposes the method of maximum likelihood estimation is applied for the copula DCC-EGARCH model to obtain estimates of conditional standard deviations $\sqrt{h_{s,t}}, \sqrt{h_{f,t}}$ and correlations $\rho_{sf,t}$. Then, the optimal hedge ratio $b_t = h_{sf,t}/h_{f,t} = \rho_{sf,t}\sqrt{h_{s,t}}/\sqrt{h_{f,t}}$ captures time-varying correlations of the hedges, conversely to the estimated constant correlation model where the optimal hedge ratio $b_t = h_{sf,t}/h_{f,t} = \hat{\rho}_{sf}\sqrt{h_{s,t}}/\sqrt{h_{f,t}}$ is presumed not to outperform the hedge constituted by the dynamic correlation model.

Following Ederington (1979) it is calculated the hedge with futures $s_t - b_t f_t$ and following measure for variance decrease of hedged portfolio as a hedging effective index as follows,

$$HE = \left(\sigma^2_{unhedged} - \sigma^2_{hedged}\right) / \sigma^2_{unhedged} \quad (15)$$

where the index is a measure of percentage change of unhedged portfolio variance as a result of hedge with futures.

4. Estimation results

Panel A in Table 1 presents distributional properties of the spot and futures data. It is notable that all the test statistics of spot and futures log returns for skewness, kurtosis and Jarque-Bera values show high significance, indicating non-normality distribution of the series. For the data series the augmented unit root test (ADF) of Dickey and Fuller (1979) is used to test the series stationary, where the test statistics and probability values are based on the calculated MacKinnon's (1996) response surface coefficients. Panel B in Table 1 presents the statistic values of the ADF test which indicate rejection of the null hypothesis of existence of a unit root for log differences of the spot and futures prices. However, the null cannot be rejected for log levels of the data. Furthermore, the Box-Ljung test for the standardized squared residuals show correlation between the series of spot and futures returns. The test results suggest time varying variance structure for the return series, hence supporting applicability of a GARCH model for variance estimation.

According to the ADF test that indicates stationary of log difference of the futures and spot prices a following cointegration test is used to check possible long-term relationship of the log values of the spot and futures prices.[5] Engle and Granger (1987) introduced the concept of cointegration and the two-step procedure for estimating long-run relationship between two integrated variables. In the first-step of the procedure the proposed error correction term is simply estimated by the ordinary least squared (OLS) regression, where the residuals of the regression are the errors from the long-run equilibrium related to the two integrated variables. Applying the proposed method in this study, it is noticed that the ADF test statistics of the regressions (see Table 2) indicate rejection of the null, hence confirming that the futures and spot time series are cointegrated with the cointegrating parameters γ close to or equal to unity. This implies applicability of the error correction term inclusion into the mean equations (see Eqs. (2) and (3)).

A common character of time series is the volatility clustering that refers to tendency of large (small) changes in prices to be followed by large (small) changes, of either sign. In this study, for the clustered nature of the data the exponential GARCH model is utilized to fit the model into the time series of the AUD, CAD, EUR, GBP and JPY currency spot and futures markets returns. In addition to the hedging effectiveness it is of interest to evaluate impact of the specification differences of the model to fit to the data, hence the variance equation based on the univariate EGARCH model with and without the external realized variance estimators RV_s and RV_f is estimated.

In Table 3 (Panel A) are presented the estimation results of the copula-EGARCH-DCC models. Considering the model fit to the data, it can be seen that the Ljung-Box test statistic values (Table 3, Panel B) of the squared standardized residuals of the EGARCH models estimated to the EUR and GBP market data do not show autocorrelation. As opposed to the EUR and GBP markets the high significant test statistic values indicate that the model estimated to the futures of the JPY market cannot fit to the data. In addition, it is notable that for all the estimated models the value of the realized variance parameter RV_s and RV_f is statistically highly significant. Also, it follows that the parameter RV_s has stronger impact on the estimated volatility, as the realized volatility estimates are formed from the squared currency spot returns.

The EGARCH model is commonly utilized to account for the asymmetric effect of residuals on the conditional variance estimates.

[5] The null for the test hypothesis is that relationship of the series is not cointegrated.

Table 1
Descriptive statistics for weekly log returns for the Euro (EUR), British pound (GBP) and Japanese yen (JPY) that incorporate 729 observations over the period 14 January 2000 to 29 December 2013 and for the Australian dollar (AUD), Canadian dollar (CAD), British pound (GBP) and Japanese yen (JPY) that incorporate 1386 observations over the period from 12 June 1987 to 27 December 2013.

	EUR		GBP		JPY		AUD		CAD		GBP		JPY	
	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Panel A:														
N	729	729	729	729	729	729	1386	1386	1386	1386	1386	1386	1386	1386
Mean	0.04	0.039	0.001	0.001	0.001	−0.001	0.016	0.017	0.016	0.016	0.001	0.001	0.023	0.022
Max	5.338	5.145	5.319	4.895	8.465	7.26	7.099	7.113	4.548	5.773	5.319	4.95	13.904	15.09
Min	−5.609	−6.273	−8.595	−8.716	−5.421	−4.889	−17.371	−17.007	−9.075	−9.323	−10.389	−9.887	−6.673	−6.214
Std.	1.417	1.43	1.344	1.325	1.433	1.458	1.651	1.685	1.046	1.057	1.366	1.392	1.565	1.603
Skew	−0.247**	−0.268**	−0.798***	−0.534***	0.488***	0.296**	−1.473***	−1.223***	−0.841***	−0.857***	−0.678***	−0.517***	0.88***	0.884***
Kurt	0.831***	0.929***	4.814***	3.591**	1.974***	1.105***	12.089***	10.201***	8.216***	8.739***	4.8***	3.627***	5.875***	6.398***
J–B	28.9***	35.6***	787.9***	430.4***	149***	48.6***	8972.6***	6377.8***	4077.1***	4597.7***	1443.6***	825.5***	2180.9***	2554.9***
$Q^2(8)$	47.2***	63.4***	276.1***	280.7***	48***	39.2***	308.8***	354.5***	808***	610.5***	184.3***	163***	46.4***	54.9***
$Q^2(16)$	106.2***	103.7***	491***	479.8***	49.5***	42.4***	339.4***	416.7***	980.5***	755.7***	306.6***	267***	99.1***	77.9***
$Q^2(24)$	131.3***	132.9***	513***	518.1***	55.1***	57.5***	350.9***	435.6***	1025.2***	812.7***	327.2***	294.9***	118.6***	103.5***
Panel B:														
Log p	−0.267	−0.279	−0.317	−0.324	−0.068	−1.223	−1.103	−1.148	−1.131	−1.137	−0.503	−0.509	−0.64	−2.038
Log r	−18.4***	−18.7***	−20.4***	−20.1***	−18.8***	−18.9***	−25.9***	−25.7***	−27.9***	−27.3***	−26.5***	−26.8***	−26.0***	−26.2***

Notes: In Panel A, the critical test statistic values of skewness $\pm\sqrt{6/N}$ *t-stat and excess kurtosis $\pm\sqrt{24/N}$*t-stat are set to assess normality of the series, where N is a number of observations and the *t*-statistics are based on the critical values of two-tailed test. The Jarque–Bera test statistic value is a goodness-of-fit measure of departure from normality and the Box–Ljung portmanteau test statistics test values $Q^2(i)$ (where $i = 8, 16, 24$ indicate order of serial correlations) for autocorrelation standardized squared residuals. In Panel B, the *t*-test statistic values for the Augmented Dickey–Fuller unit root test are based on test statistic using MacKinnon's (1996) response surface approach. In table, the signs ***, ** and * of the two-tailed *t*-test indicate statistical significance at 0.1%, 1% and 5%, respectively.

Table 2
Cointegration test.

	Panel A: time period 01/07/2000–12/27/2013			Panel B: time period 06/05/1987–12/27/2013			
	EUR	GBP	JPY	AUD	CAD	GBP	JPY
c	-0.047^{*}	0.522	-0.003^{***}	0.672^{***}	0.207^{***}	0.375	-0.364^{***}
	(0.021)	(0.001)	(0.000)	(0.030)	(0.018)	(0.069)	(0.016)
γ	1^{***}	1.003^{***}	1.013^{***}	1.008^{***}	1.004^{***}	1.007^{***}	1.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ADF	-11.71^{***}	-12.154^{***}	-10.416^{***}	-15.182^{***}	-12.469^{***}	-14.036^{***}	-13.197^{***}

Notes: In Table, the long run relationships for the series are estimated by regression model $S_t = c + \gamma F_t + \epsilon_t$, where S_t and F_t are the log values of the daily spot and futures prices, respectively. An Augmented Dickey–Fuller unit root test is applied for the residuals, ϵ_t, assuming normal distribution with zero mean of the residuals. The parameter estimates of the regressions are presented and their standard errors inside the parenthesis. The *t*-test values are based on test statistic using MacKinnon's (1996) response surface approach, where the signs ***, ** and * of the two-tailed *t*-test indicate statistical significance at 0.1%, 1% and 5%, respectively.

However, noticing the two-sided nature of currency markets the asymmetric effect is not the expectation. The advantage of the EGARCH model utilized in this study is that the estimated parameters of the model are unrestricted. As a result, according to the model unrestricted specification, it is expected a better estimate of the conditional variance. It is notable that the parameters of the EGARCH models estimated to the

Table 3
Estimated copula EGARCH-DCC models.

	The copula-EGARCH_RV (DCC) model			The copula-EGARCH (DCC)		
	EUR	GBP	JPY	EUR	GBP	JPY
Panel A: parameter estimates						
Conditional mean:						
c_s	0.078	0.058	−0.041	0.048	0.014^{*}	0.003
	(0.046)	(0.040)	(0.046)	(0.049)	(0.006)	(0.051)
θ_s	-0.402^{**}	-0.319^{*}	0.01	-0.356^{*}	-0.478^{***}	−0.074
	(0.147)	(0.132)	(0.111)	(0.157)	(0.051)	(0.121)
c_f	0.083	0.056	−0.043	0.056	0.026	0.002
	(0.049)	(0.040)	(0.051)	(0.075)	(0.043)	(0.058)
θ_f	0.246	0.273^{*}	0.44^{***}	0.23	0.144	0.303^{***}
	(0.151)	(0.116)	(0.117)	(0.174)	(0.138)	(0.069)
Conditional variance:						
ω_s	−0.045	-0.284^{***}	0.028	0.013^{**}	0.017	0.148^{**}
	(0.096)	(0.081)	(0.112)	(0.005)	(0.014)	(0.056)
α_s	−0.018	−0.068	0.004	−0.021	−0.026	0.095
	(0.046)	(0.040)	(0.066)	(0.018)	(0.022)	(0.049)
β_s	−0.064	−0.033	0.086	0.977^{***}	0.958^{***}	0.787^{***}
	(0.072)	(0.067)	(0.267)	(0.001)	(0.031)	(0.075)
γ_s	−0.069	0.066	-0.315^{***}	0.131^{***}	0.214^{**}	0.109
	(0.083)	(0.074)	(0.089)	(0.010)	(0.079)	(0.083)
RV_s	0.293^{***}	0.31^{***}	0.222^{***}			
	(0.036)	(0.037)	(0.045)			
ω_f	−0.004	-0.241^{**}	0.054	0.015	0.019	0.163^{*}
	(0.102)	(0.079)	(0.097)	(0.023)	(0.012)	(0.066)
α_f	−0.02	-0.083^{*}	−4.92e-04	−0.028	−0.034	0.089
	(0.052)	(0.041)	(0.062)	(0.061)	(0.026)	(0.049)
β_f	−0.024	−1.55e-05	0.13	0.975^{***}	0.949^{***}	0.774^{***}
	(0.081)	(0.066)	(0.197)	(0.027)	(0.029)	(0.083)
γ_f	−0.049	0.14	-0.265^{*}	0.114	0.227^{**}	0.142^{*}
	(0.092)	(0.079)	(0.105)	(0.288)	(0.086)	(0.070)
RV_f	0.283^{***}	0.292^{***}	0.212^{***}			
	(0.039)	(0.037)	(0.038)			
Conditional correlation:						
α_{DCC}	0.033	0.016^{*}	0.014^{*}	0.045	0.025^{*}	0.008
	(0.021)	(0.007)	(0.006)	(0.025)	(0.011)	(0.008)
β_{DCC}	0.964^{***}	0.979^{***}	0.978^{***}	0.891^{***}	0.963^{***}	0.976^{***}
	(0.034)	(0.014)	(0.010)	(0.127)	(0.023)	(0.021)
Panel B: diagnostics						
Standardized residuals:						
JB_s	2.216	2.873	2.829	21.154^{***}	43.767^{***}	141.875^{***}
JB_f	13.28^{**}	8.243^{*}	173.995^{***}	18.644^{***}	6.1^{*}	118.944^{***}
Standardized squared residuals:						
$Q_S^2(8)$	8.2	5.2	6.5	6.9	3.7	11.9
$Q_S^2(16)$	18.8	18.8	15.3	18.6	17.4	15.1
$Q_S^2(24)$	33.1	31	23.1	30.4	22.6	24
$Q_f^2(8)$	11.8	14	4.4	3.7	9.5	3.6
$Q_f^2(16)$	23.2	30	54.5^{***}	10.4	14	51.1^{***}
$Q_f^2(24)$	30.4	38.7	62^{***}	21	24.7	53.8^{***}

Notes: In the table, Panel A, the parameters of conditional mean, variance and correlation are from Eqs. (2)–(6). The standard errors of the parameters are presented inside the parenthesis. In the Panel B are presented the Jarque Bera test statistics values $JB_{(\cdot)}$ for the standardized residuals and the Box-Ljung test statistic values $Q^2(i)$ (where $i = 8, 16, 24$ indicate order of serial correlations) of autocorrelation for the standardized squared residuals. In the table the subscript s = spot and f = futures. The signs ***, ** and * of the two-tailed *t*-test indicate statistical significance at 0.1%, 1% and 5%, respectively.

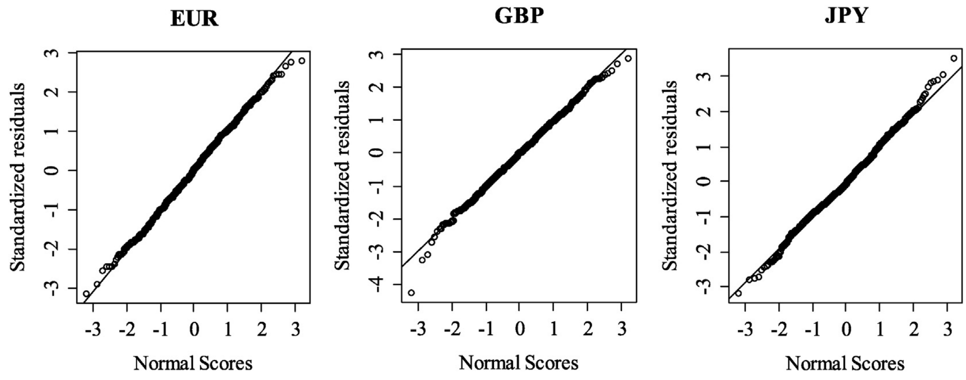

Fig. 3. The Normal Probability Plots (QQ plot) of the standardized returns fitted to the spot market returns of the Euro (EUR), British Pound (GBP) and Japanese Yen (JPY). For the standardized returns the copula DCC-EGARCH_RV model is estimated over the period from 14 January 2000 to 27 December 2013.

EUR and GBP market data with external estimators RV_s and RV_f do not show asymmetric impact on the estimated conditional variance. The estimation results for these markets indicate the models' ability to capture more efficiently dynamics of the variance.

In the second-step of the model estimation the standardized residuals are used to procedure estimates of the dynamic correlations. The theoretical assumption is that the standardized residuals are normally distributed. As a result, for the external estimators (Table 3, Panel B) the Jarque-Bera test statistics indicate normality of the distribution of the standardized residuals of the estimated models fitted to the spot market returns (see Fig. 3). In addition to capture dynamics of the variance, for normality, it is assumed that the models are also more efficient to capture dynamics of the conditional correlation.

According to the normality of the standardized returns fitted to the spot market return of the Australian dollar (AUD) it is observable that the estimated copula DCC-EGARCH model with included external realized variance estimators RV_s and RV_f cannot completely capture the market returns distributional characteristics (see Fig. 4). The normality plot indicates that the model is not perfectly fitted to the data of the Australian dollar (AUD), especially to very low values of the market returns. However, for all the other market returns the normality plots indicate the models ability to fit into the market data (see Figs. 3 and 4).

It is of interest to study the model's ability to explain volatility clustering of the data and the estimated models hedging performance. A preliminary assumption is that the conditional variance estimated outperforms the estimated unconditional variance in hedging performance. In Table 4 the measures of the hedging performance show that the estimated unconditional OLS model's ability to reduce variance of a portfolio is generally larger compared to the other models. The only exceptions are the dynamic conditional correlation models estimated with the external estimators $RV_{(\cdot)}$ for the EUR and GBP markets. For these models the test statistics show that the squared standardized residuals do not show autocorrelation, i.e. the volatility clustering is properly explained by the models. In addition to the conditional correlation models, it is observable that the hedging performance of the constant correlation models is weak, suggesting that the constant correlation is inadequate as used to minimize variance of a portfolio.

To examine robustness of the results based on the efficiency measures presented, a one thousand artificial data series for each of the currencies and futures of Euro, British Pound and Japanese Yen is generated (see Table 4). All the models are fitted to the currency spot and futures simulated returns i.e. each of the model is one thousand times estimated. Finally, from the estimation results the confidence levels of the performance measures is calculated. The confidence levels reinforce the findings of this study. According to the simulated data and the confidence levels produced it is possible to conclude that the external realized variance estimators included into the models do have positive effect on the currency portfolio hedging performance.

Also, for the models hedging performance comparison it is utilized the low, middle and high variance levels during the estimation period. This is implemented by dividing the time period to low, middle and high volatility levels (see Table 5). The level of volatility is calculated from the realized volatility measure of the currency returns. The first quartile (Q_1) of the realized variance series represents the low level, the second quartile (Q_2) the middle level and the third quartile (Q_3) the high level of volatility. Finally, each of the weekly currency returns observation is categorized based on the quartile of the realized volatility measure and the efficiency measures are calculated. The results of models hedging performance

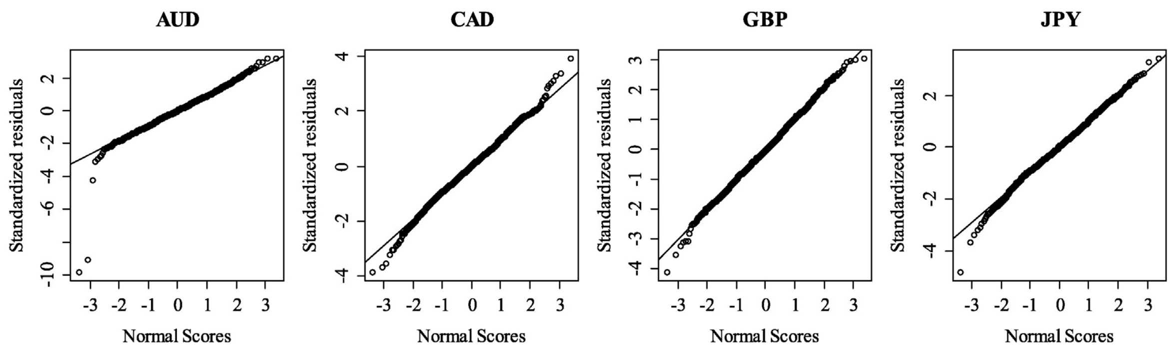

Fig. 4. The Normal Probability Plots (QQ plot) of the standardized returns fitted to the spot market returns of the Australian dollar (AUD), Canadian dollar (CAD), British Pound (GBP). For the standardized returns the copula DCC-EGARCH_RV model is estimated over the period from 12 June 1987 to 27 December 2013.

Table 4
The hedging performance measures with 90% confidence intervals (*CI*) presented. The models are fitted to the currency spot and futures returns series over the period from 14 January 2000 to 27 December 2013.

	EUR	90% CI	GBP	90% CI	JPY	90% CI
Portfolio variance						
OLS	0.1742	(0.1768, 0.2530)	0.1267	(0.1437, 0.2215)	0.14	(0.1768, 0.2855)
ECM	0.1748	(0.1770, 0.2527)	0.1267	(0.1771, 0.2873)	0.141	(0.1434, 0.2228)
CCC-EGARCH	0.3039	(0.2915, 0.3871)	0.2628	(0.2355, 0.3437)	0.2797	(0.2840, 0.3889)
CCC-EGARCH_RV	0.3041	(0.2874, 0.3779)	0.2488	(0.2264, 0.3407)	0.2735	(0.2765, 0.4090)
DCC-EGARCH	0.1755	(0.1793, 0.2603)	0.1314	(0.1454, 0.2308)	0.1421	(0.1770, 0.2794)
DCC-EGARCH_RV	0.1724	(0.1773, 0.2584)	0.123	(0.1441, 0.2579)	0.1402	(0.1773, 0.3394)
Unhedged	2.0081	(1.7746, 2.3896)	1.8056	(1.4081, 2.1688)	2.0538	(1.7145, 2.2527)
Hedge effectiveness (HE)						
OLS	0.9133	(0.8776, 0.9125)	0.9298	(0.8764, 0.9158)	0.9319	(0.8533, 0.9096)
ECM	0.913	(0.8777, 0.9124)	0.9298	(0.8525, 0.9095)	0.9313	(0.8764, 0.9155)
CCC-EGARCH	0.8487	(0.8213, 0.8492)	0.8545	(0.8210, 0.8523)	0.8638	(0.8068, 0.8475)
CCC-EGARCH_RV	0.8486	(0.8247, 0.8536)	0.8622	(0.8217, 0.8622)	0.8668	(0.7931, 0.8543)
DCC-EGARCH	0.9126	(0.8739, 0.9115)	0.9272	(0.8739, 0.9145)	0.9308	(0.8577, 0.9091)
DCC-EGARCH_RV	0.9142	(0.8755, 0.9133)	0.9319	(0.8509, 0.9172)	0.9317	(0.8241, 0.9075)
Hedge ratio (average)						
OLS	0.9557	(0.8776, 0.9125)	0.9644	(0.8764, 0.9158)	0.9655	(0.8533, 0.9096)
ECM	0.9661	(0.8777, 0.9124)	0.9646	(0.8525, 0.9095)	0.9766	(0.8764, 0.9155)
CCC-EGARCH	0.6949	(0.8213, 0.8492)	0.7061	(0.8210, 0.8523)	0.696	(0.8068, 0.8475)
CCC-EGARCH_RV	0.6893	(0.8247, 0.8536)	0.6971	(0.8217, 0.8622)	0.6911	(0.7931, 0.8543)
DCC-EGARCH	0.9594	(0.8739, 0.9115)	0.975	(0.8739, 0.9145)	0.9609	(0.8577, 0.9091)
DCC-EGARCH_RV	0.9478	(0.8755, 0.9133)	0.957	(0.8509, 0.9172)	0.9484	(0.8241, 0.9075)

Notes: In Table, the OLS is a model estimated by regression $S_t = c + \gamma F_t + \epsilon_t$, where S_t and F_t are the log values of the daily spot and futures prices, respectively and the error correction model (ECM) introduced by Engle and Granger (1987) is applied in a regression $s_t = c + \theta(S_{t-1} - \gamma F_{t-1}) + \epsilon_t$. The constant correlation model (CCC) of Bollerslev (1990) is modeled to assess properties of constant and dynamic correlation on hedging performance (see Eqs. (7)–(9)). The estimation result of the models DCC-EGARCH and DCC-EGARC_RV are presented in Table 3.

comparison show that the external realized variance estimator in the variance equation of the model improves hedging efficiency of the model in all levels of the exchange rates volatility.

The outperformance of the conditional hedge is in agreement with previous studies such as Baillie and Myers (1991); Kroner and Sultan (1993); Park and Switzer (1995); Choudhry (2004); Zanotti, Gabbi, and

Table 5
Effect of a level of currency spot returns variance on hedging performance. The models are fitted to the currency spot and futures returns series over the period from 14 January 2000 to 27 December 2013.

	Low level			Middle level			High level		
	EUR	GBP	JPY	EUR	GBP	JPY	EUR	GBP	JPY
Portfolio variance									
OLS	0.0820	0.0841	0.1052	0.1742	0.0977	0.1106	0.2676	0.2258	0.2343
ECM	0.0828	0.0841	0.1057	0.1742	0.0977	0.1116	0.2690	0.2257	0.2359
CCC-EGARCH	0.1539	0.1329	0.1874	0.2904	0.1888	0.2210	0.4817	0.5323	0.4920
CCC-EGARCH_RV	0.1528	0.1330	0.1858	0.2967	0.1873	0.2160	0.4713	0.4780	0.4789
DCC-EGARCH	0.0858	0.0861	0.1045	0.1746	0.1040	0.1116	0.2684	0.2312	0.2415
DCC-EGARCH_RV	0.0800	0.0830	0.1056	0.1731	0.0981	0.1079	0.2644	0.2107	0.2398
Unhedged	1.1770	1.2420	0.9041	1.7840	1.6750	1.3944	3.2920	3.6420	3.4639
Hedge effectiveness (HE)									
OLS	0.9304	0.9070	0.9153	0.9024	0.9299	0.9340	0.9187	0.9348	0.9357
ECM	0.9297	0.9070	0.9149	0.9023	0.9299	0.9333	0.9183	0.9348	0.9352
CCC-EGARCH	0.8693	0.8530	0.8491	0.8372	0.8646	0.8681	0.8537	0.8463	0.8649
CCC-EGARCH_RV	0.8702	0.8528	0.8504	0.8336	0.8656	0.8710	0.8568	0.8620	0.8685
DCC-EGARCH	0.9272	0.9048	0.9159	0.9021	0.9254	0.9333	0.9185	0.9332	0.9337
DCC-EGARCH_RV	0.9321	0.9082	0.9150	0.9030	0.9297	0.9356	0.9197	0.9392	0.9341
Hedge ratio (average)									
OLS	0.9557	0.9644	0.9655	0.9557	0.9644	0.9655	0.9557	0.9644	0.9655
ECM	0.9661	0.9646	0.9766	0.9661	0.9646	0.9766	0.9661	0.9646	0.9766
CCC-EGARCH	0.6911	0.7086	0.6984	0.6970	0.7060	0.6955	0.6945	0.7036	0.6946
CCC-EGARCH_RV	0.6904	0.6986	0.6910	0.6889	0.6962	0.6906	0.6891	0.6974	0.6923
DCC-EGARCH	0.9538	0.9774	0.9641	0.9622	0.9748	0.9600	0.9594	0.9730	0.9598
DCC-EGARCH_RV	0.9482	0.9589	0.9486	0.9471	0.9556	0.9473	0.9485	0.9579	0.9505

Notes: In Table, the OLS is a model estimated by regression $S_t = c + \gamma F_t + \epsilon_t$, where S_t and F_t are the log values of the daily spot and futures prices, respectively and the error correction model (ECM) introduced by Engle and Granger (1987) is applied in a regression $s_t = c + \theta(S_{t-1} - \gamma F_{t-1}) + \epsilon_t$. The constant correlation model (CCC) of Bollerslev (1990) is modeled to assess properties of constant and dynamic correlation on hedging performance (see Eqs. (7)–(9)). The estimation result of the models DCC-EGARCH and DCC-EGARC_RV are presented in Table 3.

Table 6
The hedging performance measures presented. The models are fitted to the currency spot and futures returns series over the period from 12 June 1987 to 27 December 2013.

	AUD	CAD	GBP	JPY
Portfolio variance				
OLS	0.3015	0.1122	0.1832	0.2012
ECM	0.3039	0.1126	0.1831	0.2025
CCC-EGARCH	0.4504	0.1743	0.3142	0.3594
CCC-EGARCH_RV	0.4526	0.1603	0.2849	0.3417
DCC-EGARCH	0.3080	0.1136	0.1936	0.2057
DCC-EGARCH_RV	0.2931	0.1305	0.1764	0.2610
Unhedged	2.7256	1.0934	1.8651	2.4497
Hedge effectiveness (HE)				
OLS	0.8894	0.8974	0.9018	0.9179
ECM	0.8885	0.8970	0.9018	0.9173
CCC-EGARCH	0.8347	0.8406	0.8315	0.8533
CCC-EGARCH_RV	0.8339	0.8533	0.8473	0.8605
DCC-EGARCH	0.8870	0.8961	0.8962	0.9160
DCC-EGARCH_RV	0.8925	0.8806	0.9054	0.8934
Hedge ratio (average)				
OLS	0.9433	0.9474	0.9498	0.9583
ECM	0.9589	0.9596	0.9486	0.9677
CCC-EGARCH	0.6897	0.6898	0.6872	0.6915
CCC-EGARCH_RV	0.6841	0.6860	0.6712	0.6829
DCC-EGARCH	0.9364	0.9266	0.9371	0.9463
DCC-EGARCH_RV	0.9152	0.9180	0.9106	0.9268

Notes: In Table, the OLS is a model estimated by regression $S_t = c + \gamma F_t + \epsilon_t$, where S_t and F_t are the log values of the daily spot and futures prices, respectively and the error correction model (ECM) introduced by Engle and Granger (1987) is applied in a regression $s_t = c + \theta(S_{t-1} - \gamma F_{t-1}) + \epsilon_t$. The constant correlation model (CCC) of Bollerslev (1990) is modeled to assess properties of constant correlation on hedging performance (see Eqs. (7)–(8)). The dynamic conditional correlation model (DCC) of Engle (2002) is estimated to compare hedging efficiency of the dynamic conditional correlations (see Eqs. (7)–(9)).

Geranio (2010). Common for these studies is that the constant conditional correlation model outperforms the traditional OLS hedge strategy. However, in this study the results show that the constant correlation model has the lowest hedging performance compared to the others. It can be seen that the advantage of the dynamic conditional correlation model is that the model takes into account the time-varying correlation between the spot and futures markets returns (see e.g. Ku et al., 2007; Su & Wu, 2014).

In Table 6 the spot and futures prices for the currencies of the Australian dollar (AUD), Canadian dollar (CAD), British pound (GBP), Euro (EUR) and Japanese yen (JPY) are used to analyze hedging effectiveness of the estimated models. The results of the hedging effectiveness are similar compared to the spot and futures prices for the currencies of the euro (EUR), Britain pound (GBP) and Japanese yen (JPY) presented (see Table 4).

Also, for the spot and futures prices for the currencies presented in Table 6 the hedging performance comparison it is utilized to the low, middle and high variance levels during the estimation period (see Table 7). It is observed that for the Australian dollar (AUD) the estimated copula DCC-EGARCH model underperforms in the portfolio hedging performance compared to the data of the other currencies. This is possible to account for the characteristic of currency returns distribution that exhibit high values of skewness and excess kurtosis (see Table 1). The outcome is that the copula DCC-EGARCH model with included external realized variance estimators RV_s and RV_f estimated cannot completely capture high values of skewness and excess kurtosis of the market data. For the other market returns the model is fitted into the market data and the hedging performance measures show outperformance of the model in variance reduction.

In this study it is observed that the conditional hedge is superior compared to the traditional unconditional hedging strategy. However, the outcome is a result from the estimated conditional correlation models assumed that the model can appropriately explain volatility

Table 7
Effect of a level of currency spot returns variance on hedging performance. The models are fitted to the currency spot and futures returns series over the period from 12 June 1987 to 27 December 2013.

	Low level				Middle level				High Level			
	AUD	CAD	GBP	JPY	AUD	CAD	GBP	JPY	AUD	CAD	GBP	JPY
Portfolio variance												
OLS	0.1773	0.0421	0.0987	0.1293	0.1657	0.0421	0.0987	0.1293	0.6976	0.2471	0.3458	0.3444
ECM	0.1794	0.0428	0.0986	0.1304	0.1667	0.0802	0.1446	0.1660	0.7028	0.2475	0.3458	0.3470
CCC-EGARCH	0.2176	0.0504	0.1465	0.1868	0.2869	0.1281	0.2237	0.2948	1.0072	0.3908	0.6620	0.6624
CCC-EGARCH_RV	0.2206	0.0511	0.1516	0.1918	0.2912	0.1243	0.2245	0.2893	1.0027	0.3421	0.5382	0.5968
DCC-EGARCH	0.1745	0.0412	0.1002	0.1305	0.1710	0.0807	0.1492	0.1688	0.7153	0.2523	0.3768	0.3547
DCC-EGARCH_RV	0.1755	0.0395	0.0967	0.1260	0.1684	0.0776	0.1385	0.1626	0.6605	0.3276	0.3331	0.5895
Unhedged	1.0220	0.2880	0.8476	1.1740	1.8990	0.7701	1.4651	1.9350	5.9850	2.5400	3.6637	4.7570
					Hedge effectiveness (HE)							
OLS	0.8266	0.8538	0.8836	0.8899	0.9127	0.8962	0.9012	0.9146	0.8834	0.9027	0.9056	0.9276
ECM	0.8245	0.8514	0.8836	0.8889	0.9122	0.8958	0.9013	0.9142	0.8826	0.9025	0.9056	0.9271
CCC-EGARCH	0.7872	0.8249	0.8271	0.8409	0.8489	0.8337	0.8473	0.8476	0.8317	0.8461	0.8193	0.8608
CCC-EGARCH_RV	0.7842	0.8225	0.8211	0.8366	0.8466	0.8386	0.8468	0.8504	0.8325	0.8653	0.8531	0.8745
DCC-EGARCH	0.8293	0.8570	0.8818	0.8888	0.9099	0.8953	0.8981	0.9128	0.8805	0.9007	0.8971	0.9254
DCC-EGARCH_RV	0.8284	0.8629	0.8860	0.8927	0.9113	0.8993	0.9055	0.9159	0.8896	0.8710	0.9091	0.8761
					Hedge ratio (average)							
OLS	0.9433	0.9474	0.9498	0.9583	0.9433	0.9474	0.9498	0.9583	0.9433	0.9474	0.9498	0.9583
ECM	0.9589	0.9596	0.9486	0.9677	0.9589	0.9596	0.9486	0.9677	0.9589	0.9596	0.9486	0.9677
CCC-EGARCH	0.6776	0.6760	0.6907	0.6962	0.6923	0.6919	0.6891	0.6918	0.6966	0.6993	0.6799	0.6861
CCC-EGARCH_RV	0.6814	0.6730	0.6715	0.6800	0.6833	0.6809	0.6702	0.6815	0.6885	0.7092	0.6729	0.6886
DCC-EGARCH	0.9183	0.9000	0.9429	0.9505	0.9409	0.9301	0.9400	0.9467	0.9455	0.9463	0.9252	0.9410
DCC-EGARCH_RV	0.9096	0.8964	0.9130	0.9226	0.9156	0.9116	0.9094	0.9254	0.9198	0.9524	0.9106	0.9335

Notes: In Table, the OLS is a model estimated by regression $S_t = c + \gamma F_t + \epsilon_t$, where S_t and F_t are the log values of the daily spot and futures prices, respectively and the error correction model (ECM) introduced by Engle and Granger (1987) is applied in a regression $s_t = c + \theta(S_{t-1} - \gamma F_{t-1}) + \epsilon_t$. The constant correlation model (CCC) of Bollerslev (1990) is modeled to assess properties of constant correlation on hedging performance (see Eqs. (7)–(8)). The dynamic conditional correlation model (DCC) of Engle (2002) is estimated to compare hedging efficiency of the dynamic conditional correlations (see Eqs. (7)–(9)).

clustering of the data. The estimated copula-EGARCH-DCC models with the external realized variance estimators are able to explain clustering of the data and show also superiority in portfolio variance reduction. The result indicates importance of the realized volatility estimator in explaining exchange rates returns variance.

5. Conclusions

This study shows effectiveness of the utilized copula-EGARCH-DCC model to reduce variance of portfolios of foreign currencies of the Australian dollar, Canadian dollar, euro, British pound and Japanese yen. For the portfolio hedging purposes, it is recognized efficiency of the estimated bivariate model to account for the evolution of the dynamic conditional correlation between the spot and futures markets. However, the measures of the hedging performance show that the estimated unconditional OLS model's ability to reduce variance of a portfolio is generally larger compared to the other models. The only exception is the dynamic conditional correlation model estimated for the currency markets, i.e. the copula-EGARCH-DCC model with the external realized volatility estimators included into the variance equation of the model. This can be seen as efficiency of the model to account for the clustered nature of the data variance.

The in-sample hedging effectiveness in this study examined, suggests that the conditional hedge outperforms the traditional unconditional hedging strategy. As the estimation results show, the conditional correlation model with included external realized variance estimators is superior in portfolio variance reduction. Also, the estimation results of the longer time period in this research applied confirm the findings. In effect, the external realized variance estimator included into the variance equations of the model improves the model ability to fit into the data of the currency market returns estimated. The outcome of the superiority is a result from the information content of the realized variance estimates that improves ability of the model to estimate the conditional variance of the market data in low and high volatility periods. In addition, it is observed that the constant correlation models hedging performance is weak, suggesting that the model is inadequate as used to minimize variance of a portfolio.

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