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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.

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

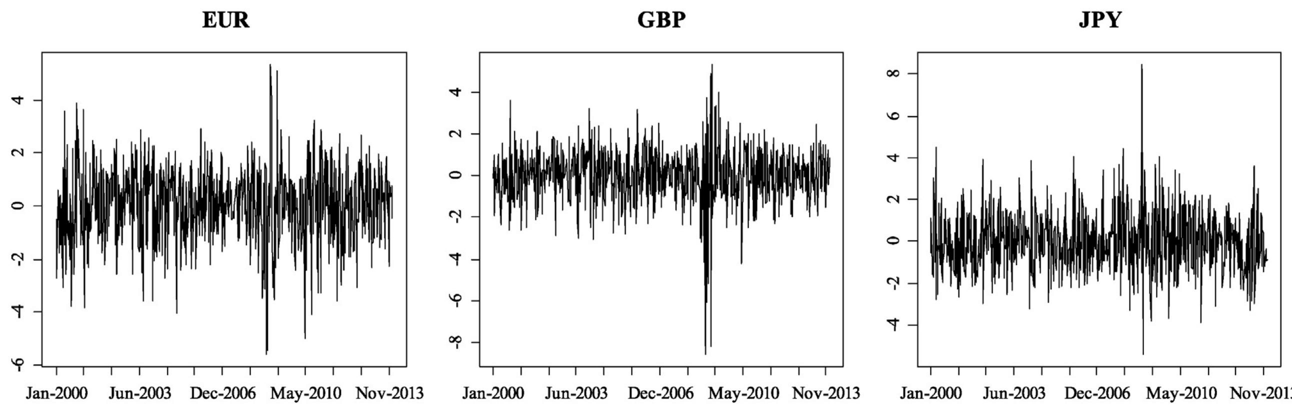

Fig. 1. Weekly log return series of the spot currency rates over the period 14 January 2000 to 27 December 2013.

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 $\alpha + \beta < 1$.

[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.

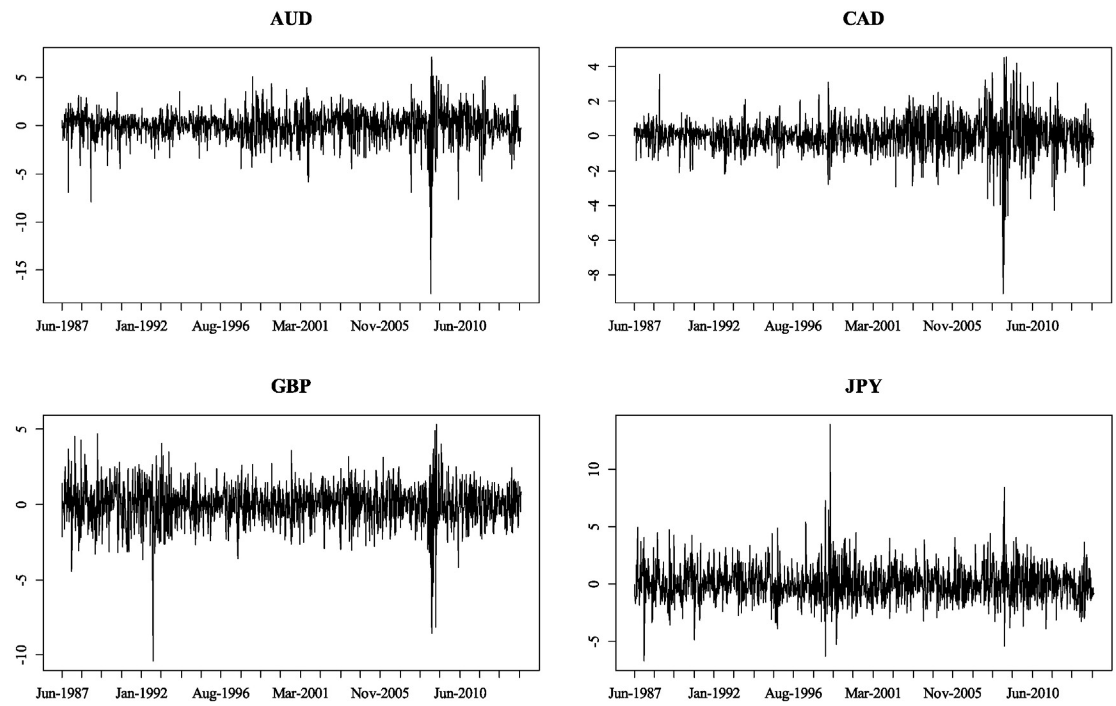

Fig. 2. Weekly log return series of the spot currency rates over the period 12 June 1987 to 27 December 2013.

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 $R\in\mathbb{R}^{2\times2}$ 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.

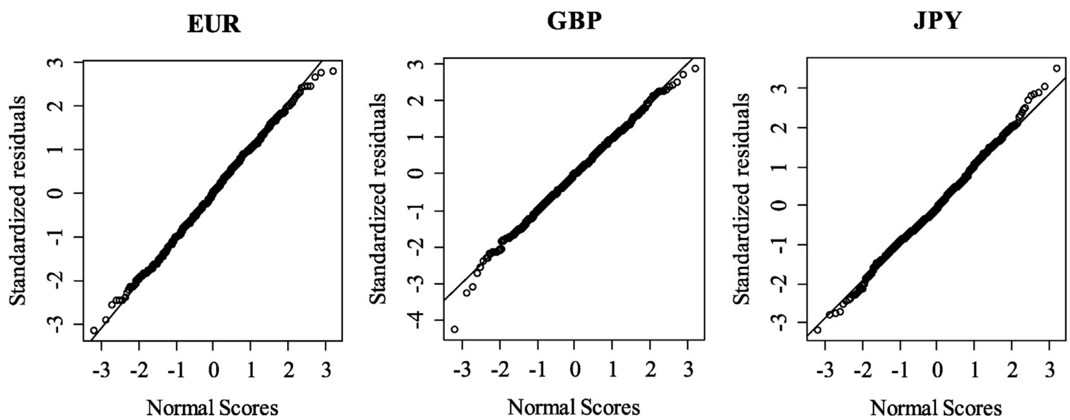

Fig. 3. The Normal Probability Plots (QQ plot) of the standardized returns fitted to the spot market returns of the Euro (EUR), British Pound (GBP) and Japanese Yen (JPY). For the standardized returns the copula DCC-EGARCH_RV model is estimated over the period from 14 January 2000 to 27 December 2013.

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

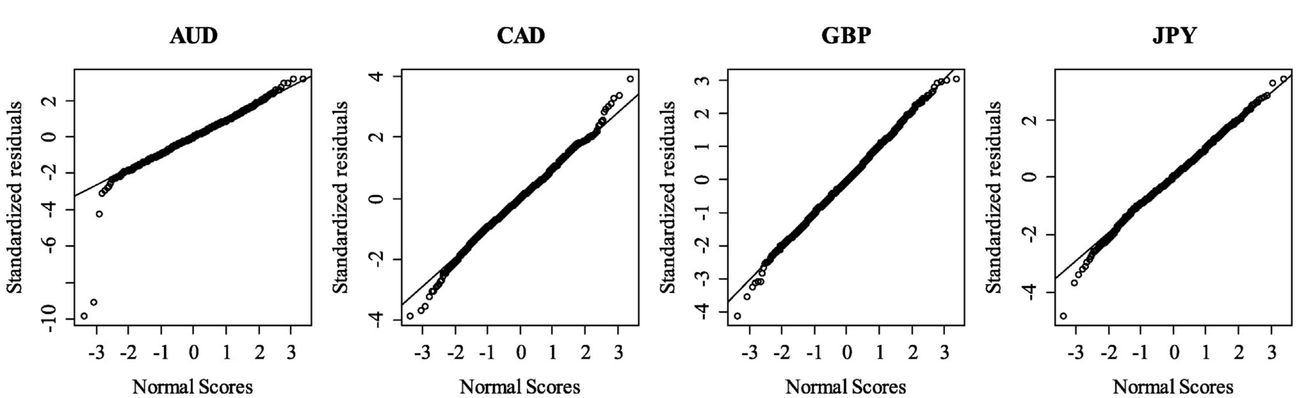

Fig. 4. The Normal Probability Plots (QQ plot) of the standardized returns fitted to the spot market returns of the Australian dollar (AUD), Canadian dollar (CAD), British Pound (GBP). For the standardized returns the copula DCC-EGARCH_RV model is estimated over the period from 12 June 1987 to 27 December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