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Effectiveness of Portfolio Diversification and the Dynamic Relationship between Stock and Currency Markets in the Emerging Eastern European and Russian Markets

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Abstract

This study investigates volatility spillovers and the dynamic relationship between the stock and currency markets in the Czech Republic, Poland, Hungary and Russia using four multivariate GARCH models. We analyze the optimal weights and the effectiveness of diversification for stock-currency portfolio holdings with respect to the following points. First, the empirical results show that the dynamic conditional correlation model with spillovers (DCC-S) generally yields the most effective diversification model, which implies that DCC-S can significantly improve the effectiveness of diversification. Second, we also provide the results of a Value at Risk analysis to determine the amount of capital reserves that investors should set aside to cover potential extreme losses when investing in a currency-stock portfolio. Third, our consideration of the time-varying weighting trend finds that weighting generally increases when economic events occur, except for in Russia, whose economic policies are considered to be unique. We find significant dynamic correlation in all of the countries considered in our analysis. Finally, we apply the unit root test for both time-varying correlations and weightings and find that the variables are stationary at their levels.

1. Introduction

Studies related to linkages between stock and currency markets mostly focus on developed markets (Yang and Doong, 2004; Francis et al., 2006). Although there is some literature that discusses such linkages regarding emerging markets (Tai, 2007; Morales, 2008; and Yang and Chang, 2008), there remains a gap in the research with respect to this field. In particular, the emerging Eastern European and Russian markets have gradually received increased attention from foreign investors in the past decade. However, there are only a limited number of studies investigating the linkages between the emerging stock and currency markets in Eastern Europe and Russia (Ulku and Demirci, 2012). We are aware of only four papers that empirically demonstrate the relationship between emerging stock and currency markets in Eastern Europe and Russia, i.e., Grambovas (2003), Stavarek (2005), Fedorova and Saleem (2010) and Tudor (2012).[1] According to the World Investment Report 2012, foreign direct investment (FDI) in the Eastern European and Russian markets has risen sharply in the last decade. The summary statistics of FDI in these countries are shown in *Table 1A* of the *Appendix*. The rapid increases in FDI and the relatively few studies on this issue indicate that further research on the Eastern European and Russian markets is required. Thus, this study examines the currency and stock markets in Russia and Eastern Europe (as represented by such markets in Poland, Hungary and the Czech Republic) in a setting of regional influences.

Investors allocate funds between currency and stock to diversify portfolio asset risk. Thus, the optimum weights of a portfolio are an important issue; the correlation between stock and currency is also important because the optimum weights are estimated by this correlation. With respect to the portfolio, correlation is thus an important factor in portfolio optimization and asset allocation. In general, correlation in this context has been widely discussed in the literature (Ghosh et al., 1996; Conover et al., 2002; Cotter and Stevenson, 2006; Huang and Zhong, 2006; and Case et al., 2012). However, none of these studies analyzed the correlations between stocks and currencies. A review of the literature indicates that more studies are needed because there has been insufficient focus on the correlation between the stock and currency markets. This study will examine the correlations between the stock and currency markets of Eastern Europe and Russia with a focus on their dynamic relationship, portfolio diversification and their optimum weights.

In our investigation of the portfolio, we first note that a more flexible portfolio can be more effectively diversified. Previous studies have used various methods to investigate the dynamic relationship between the stock and exchange markets. Grambovas (2003), Stavarek (2005) and Tudor (2012) used the Granger causality test to examine the relationship between the exchange rate and stock markets in emerging markets in Europe and Russia. Fedorova and Saleem (2010) used a bivariate GARCH model to find a significant linkage between the stock and currency markets in Hungary, the Czech Republic and Russia, but not in Poland. However, we focus on analyzing the conditional volatility and covariance across the markets dynamically over time. The dynamic conditional correlation (DCC) GARCH model, which provides a time-varying correlation in volatility among the markets, is a more appropriate model to capture the dynamic relationship and to construct a portfolio. In addition, compared to the constant conditional correlation (CCC) GARCH model, the DCC GARCH model enables the conditional correlation in volatility between the markets to vary over time. The DCC model developed by Engle (2002) provides a strong framework for analyzing dynamic conditional correlation and has been used in recently published papers (e.g., Huang and Zhong, 2006; Hassan and Malik, 2007; Agnolucci, 2009; Kang et al., 2009; Chang et al., 2011; and Arouri et al., 2011). For example, Hassan and Malik (2007), Agnolucci (2009), and Kang et al. (2009) have each shown that the model satisfactorily captures the conditional volatility and the dynamics of volatility interaction. Furthermore, Chang et al. (2011) used a multivariate DCC model to analyze the conditional correlations in the volatilities of Asian rubber spot and

[1] Using the Granger causality test, Grambovas (2003) empirically finds that there is a strong linkage between foreign exchange and stock markets in Greece and Hungary but not in the Czech Republic. Stavarek (2005) uses the Granger causality test based on a vector autoregressive (VAR) system to find that the stock market is not efficiently affected with respect to exchange rate forecasting in the EU-member countries and vice versa. Fedorova and Saleem (2010) use a bivariate GARCH model by Engle and Kroner (1995) to demonstrate that there is a direct linkage between stock markets and currency markets in Hungary, the Czech Republic and Russia, but not in Poland. Tudor (2012) uses the Granger causality test to find that changes in the exchange rate have a significant effect on stock markets in Brazil and Russia.

futures prices, and Arouri et al. (2011) applied the DCC model to analyze spillovers between oil prices and stock sector returns. Because the DCC model has been used in many dynamic conditional correlation studies, we apply this model to analyze the dynamic relationship between the stock and currency markets in Eastern Europe and Russia.

Shocks in a market may affect the volatility not only in that market but also in related markets. Accordingly, volatility spillovers among different assets receive considerable attention when portfolio managers are constructing portfolios and assigning optimum portfolio weights. In recent studies, the GARCH specification has been the most popular approach for evaluating volatility spillovers across related markets. Lin and Tamvakis (2001) and Milunovich and Thorp (2006) found that volatility spillovers were widely prominent across energy and financial markets. Fedorova and Saleem (2010) applied the GARCH model to analyze volatility spillovers between the stock and currency markets and found a direct link between these markets. Arouri et al. (2011) found evidence of significant volatility spillovers between oil and stock sector returns. Sadorsky (2012) analyzed volatility spillovers between oil prices and the stock prices of clean energy companies and technology companies and constructed optimal portfolios of these two market assets. Because the above-mentioned literature has rarely addressed volatility spillovers when investigating the correlation between stock and currency markets, we analyze such volatility spillovers in this study and construct stock-currency portfolios in accordance with such analysis.

The literature on Value at Risk (VaR) includes many studies aimed at calculating VaR for stock indices, currencies and commodity assets (Brooks and Persand, 2002; Giot and Laurent, 2003; Huang and Lin, 2004; Chan et al., 2007; Fan et al., 2008; and Hung et al., 2008). Similarly, this study also provides the results of VaR analyses to determine the amount of capital reserves that investors should set aside to cover potential extreme losses when investing in currency-stock portfolios. Moreover, we apply the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests for both time-varying correlations and weightings, and we find that both variables are stationary at their levels.

Our empirical study significantly contributes to this field of research and fills a gap in the literature on the dynamic relationship between stocks and currencies in Eastern Europe and Russia. We find that the DCC model with spillovers (DCC-S) provides the best diversification effectiveness for all pairs of stock-currency portfolios. Moreover, we provide the VaR results using DCC-S for the Eastern European and Russian markets. We also find that the time-varying weightings generally increase when economic events occur, except in Russia because of its unique economic policies. This case is more noticeable during the period of the European debt crisis. We further find that the weightings decline during the economic boom in 2009 that followed the subprime crisis. Finally, we find that both time-varying correlations and weightings are stationary at their levels for both the ADF and PP unit root tests. Our empirical results have important policy implications for the four countries considered.

2. Methodology

This study applies CCC and DCC models with spillovers to estimate the portfolio diversification and optimum weights between stock and currency in emerging

Eastern European and Russian markets. For each pair of stock and currency returns, the conditional means are given by:

$$R_t^S = \theta_{S,0} + \sum_{n=1}^{v} \theta_{S,n} R_{t\text{-}n}^C + \sum_{m=1}^{v} \alpha_{S,m} R_{t\text{-}m}^S + e_t^S \quad (1)$$

$$R_t^C = \theta_{C,0} + \sum_{n=1}^{v} \theta_{C,n} R_{t-n}^S + \sum_{m=1}^{v} \alpha_{C,m} R_{t\text{-}m}^C + \varepsilon_t^C \quad (2)$$

$$\boldsymbol{\varepsilon}_\mathbf{t} = \mathbf{H}_\mathbf{t}^{1/2} \boldsymbol{\eta}_\mathbf{t} \quad (3)$$

where R_t^S and R_t^C are the returns on stocks and the currency exchange rates, respectively. The formula for the return is $R_t = \ln\left(\frac{p_t}{p_{t-1}}\right)$. p_t is the daily closing price, and $\boldsymbol{\varepsilon}_\mathbf{t} = \left(\varepsilon_t^S, \varepsilon_t^C\right)$ We derive conditional means of the stock and currency returns from a VaR system to produce the terms in the set of equations (1) and (2). In other words, the second term in equation (2) denotes the impact of the lag stock returns on the current currency returns, and that in equation (1) denotes the impact of the lag currency returns on the current stock returns. The third term in equation (2) denotes the impact of the lag currency returns on the current currency returns, and that in the equation (1) means the impact of lag stock returns on the current stock returns. This study used the Bayesian information criterion (BIC) to determine the optimal lag length of the AR term in equations (1) and (2). $\mathbf{H}_\mathbf{t}^{1/2}$ is a (2×2) symmetric positive definite matrix and $\boldsymbol{\eta}_\mathbf{t} = \left(\eta_t^S, \eta_t^C\right)'$ is the vector of i.i.d. random errors with $E\left(\boldsymbol{\eta}_\mathbf{t}\right) = 0$ and $\mathrm{Var}\left(\boldsymbol{\eta}_\mathbf{t}\right) = \mathbf{I}_\mathbf{N}$. The most well-known and commonly used specifications are the CCC model by Bollerslev (1990) and the DCC model by Engle (2002). The CCC model with volatility spillovers and asymmetry (hereinafter referred to as CCC-S) is defined as

$$\mathbf{H}_\mathbf{t} = \mathbf{D}_\mathbf{t} \mathbf{P} \mathbf{D}_\mathbf{t} \quad (4)$$

where $\mathbf{D}_\mathbf{t} = \mathrm{diag}\left(\sqrt{h_t^S}, \sqrt{h_t^C}\right)$ and $\mathbf{P} = \left(\boldsymbol{\rho}_\mathbf{ij}\right)$ is the (2×2) matrix containing the constant conditional correlations, $\boldsymbol{\rho}_\mathbf{ij}$ with $\rho_{ii} = 1, \left(i = S, C\right)$.[2]

The conditional variances and covariance are given by

$$h_t^S = C_S + \sum_{i=1}^{p} \alpha_{S,i} \left(\varepsilon_{t-i}^S\right)^2 + \sum_{j=1}^{q} \beta_{S,j} h_{t-j}^S + \sum_{k=1}^{p} \alpha_{S,k} \left(\varepsilon_{t-k}^C\right)^2 \quad (5)$$

$$h_t^C = C_C + \sum_{i=1}^{p} \alpha_{C,i} \left(\varepsilon_{t\text{-}i}^C\right)^2 + \sum_{j=1}^{q} \beta_{C,j} h_{t\text{-}j}^C + \sum_{k=1}^{p} \alpha_{C,k} \left(\varepsilon_{t\text{-}k}^S\right)^2 \quad (6)$$

[2] Bollerslev (1990) shows that a positive sign is not necessary for the ARCH and GARCH coefficients to obtain a positive definite matrix **P**.

$$h_t^{SC} = \rho_{SC}\sqrt{h_t^S h_t^C} \tag{7}$$

where h_t^C, h_t^S, and h_t^{SC} are the conditional volatility of the currency market, the conditional volatility of the stock market, and the conditional covariance between currency and stock returns at time t, respectively.

The DCC model remedies the restrictive assumption of the constant conditional correlation by allowing the conditional correlation matrix to vary over time. In other words,

$$\mathbf{P_t} = \left(\mathrm{diag}\left(\mathbf{Q_t}\right)\right)^{-1/2}\mathbf{Q_t}\left(\mathrm{diag}\left(\mathbf{Q_t}\right)\right)^{-1/2} \tag{8}$$

where the (2×2) symmetric positive definite matrix $\mathbf{Q_t} = \left(\mathbf{q_t^{ij}}\right)$ is given by

$$\mathbf{Q_t} = \left(1-\alpha+\beta\right)\bar{\mathbf{Q}} + \alpha\boldsymbol{\eta}_{\mathbf{t}-1}\boldsymbol{\eta}'_{\mathbf{t}-1} + \beta\mathbf{Q}_{\mathbf{t}-1} \tag{9}$$

In equation (9), α and β are non-negative scalars such that $\alpha+\beta<1$, $\bar{\mathbf{Q}}$ is the (2×2) matrix of unconditional correlations of the standardized errors $\boldsymbol{\eta}_\mathbf{t}$. The conditional variances are specified as being similar to those of the CCC model.[3]

The conditional volatilities from CCC-S and DCC-S are used to construct optimal portfolio weights according to Kroner and Ng (1998). The optimal holding weight is given by

$$w_t = \frac{h_t^S - h_t^{SC}}{h_t^C - 2h_t^{SC} + h_t^S} \tag{10}$$

under the condition

$$w_t = \begin{cases} 0, & \text{if} \quad w_t < 0 \\ w_t, & \text{if} \quad 0 \le w_t \le 1 \\ 1, & \text{if} \quad w_t > 1 \end{cases} \tag{11}$$

In constructing portfolio weights between two assets, w_t is the weight of the stock index asset in a one-dollar stock-currency portfolio at time t, h_t^{SC} is the conditional covariance between stock and currency assets, and h_t^S is the conditional variance of the stock asset. The weight of the stock asset is $1-w_t$. Moreover, by estimating the time-varying weight of DCC-S for the four countries in our sample period, including economic events, we can identify whether the weighting increases when economic events occur.

The effectiveness of diversification (DE) across constructed portfolios can be evaluated by examining the realized hedging errors, which are determined as

$$\mathrm{DE} = \frac{Var_{undiversified} - Var_{diversified}}{Var_{undiversified}} \tag{12}$$

[3] DCC-S reduces to a DCC model when setting $\alpha_{S,k} = \alpha_{O,k} = 0$. The DCC model reduces to a CCC model when setting $\alpha = \beta = 0$.

where the variances of the diversification portfolio $\left(Var_{diversified}\right)$ are obtained from the variance of the return on the stock-currency portfolios, whereas the variance of the undiversified portfolio $\left(Var_{undiversified}\right)$ is the variance of the return on the portfolio of stocks. A higher DE ratio denotes greater diversification effectiveness in terms of the portfolio's variance reduction, which thus implies that the associated investment method can be considered a better diversification strategy.

This study uses *VaR* to compare the effectiveness of the portfolios while taking into consideration the correlation and portfolios without considering the correlation to predict risk. The portfolio VaR is defined as

$$\begin{aligned} VaR_p &= -Z^* \sigma_p W \\ &= -Z^* \left(\left(1 - w_t\right)^2 h_t^S + w_t^2 h_t^C + 2\left(1 - w_t\right) w_t h_t^{SC} \right)^{\frac{1}{2}} W \end{aligned} \qquad (13)$$

where VaR_p, Z^*, σ_p and W are the portfolio VaR, normal distribution, asset volatility and the amount invested, respectively.

3. Empirical Results

3.1 Data

This study employs daily currency exchange rates and stock index prices for the three emerging Eastern European and Russian markets: the Czech Republic, Hungary, Poland and Russia. All currency exchange rate data are obtained from the Datastream database. The sample period extends from January 2001 to December 2011 and consists of 3,130 observations. In addition, this study defines "economic events" as the 9/11 terrorist attacks in September 2001, the dollar crisis in the final quarter of 2004, the subprime crisis from the middle of 2007 to the end of 2008, and the European debt crisis during 2010 and 2011. We also collect the corresponding prices from the following stock indices from the Datastream database: the PX 50 index for the Czech Republic, the BUX index for Hungary, the WIG20 index for Poland and the RTS index for Russia.[4]

This study provides information on trading hours in the respective stock and currency markets for the four countries in Panel A of *Table 2A* in the *Appendix*. The opening and closing hours of stock and currency markets for these countries are shown in Panel B of *Table 2A*. Although there are non-overlapping opening and closing hours for the stock and currency markets in Panel B, we find that the ratio of non-overlapping hours is low except in Russia. However, because the economy in Russia is dominated by domestic demand, the higher non-overlapping ratio between the stock and currency markets has less impact on the investing weight of the stock-currency portfolio than it would in other countries.

[4] The PX 50 index, traded on the Prague Stock Exchange, is an index of major stocks on the Czech market. The BUX index is a capitalization-weighted index adjusted for free float and is the main index of the Budapest Stock Exchange. The WIG20 index is a stock market index of the twenty largest companies on the Warsaw Stock Exchange in Poland. The RTS (Russian Trading System) index, traded on the Moscow Exchange, is the benchmark index used to measure the Russian equities market.

Table 1 Summary Statistics (Annualizing Returns)

Items	Czech Republic	Hungary	Poland	Russia
Panel A: Stock index returns				
Mean	8.471%	8.204%	15.838%	21.024%
Std. Dev.	33.358	35.164	50.247	57.417
Maximum	46.624%	55.043%	82.804%	82.688%
Minimum	−74.906%	−76.227%	−84.279%	−128.781%
Skewness	−1.419*	−1.062	-0.599	−1.678**
Kurtosis	4.636*	4.197	2.540	5.335**
Jarque-Bera	4.916*	2.724	0.755	7.665**
Panel B: Currency returns				
Mean	−5.865%	−1.682%	−2.964%	1.063%
Std. Dev.	10.348	12.077	11.550	8.049
Maximum	8.827%	16.145%	19.585%	18.003%
Minimum	−18.480%	−21.451%	−21.652%	−8.928%
Skewness	0.185	-0.039	0.190	0.533
Kurtosis	1.428	1.781	2.789	2.786
Jarque-Bera	1.195	0.684	0.086	0.541

Note: ** and *** denote significance at the 5% and 1% levels, respectively.

3.2 Empirical Results

Table 1 shows descriptive statistics for the annualizing return series. In terms of stock markets (Panel A), Russia has the highest returns (21.024) and Hungary has the lowest (8.204). Russia exhibits the highest volatility (57.417) in the stock markets and the Czech Republic exhibits the lowest volatility (33.358). In the currency markets (Panel B), Russia has the highest returns (1.063). The worst performance regarding currency is that of the Czech Republic (−5.865). Hungary exhibits the highest volatility (12.077) in the currency market and Russia has the lowest volatility (8.049). This study finds that the return series of stock markets in the Czech Republic and Russia exhibit significant levels of skewness and kurtosis. The skewness is negative for stock returns, indicating that the stock returns are flatter to the left. The stock returns in these countries all exhibit leptokurtic situations, which shows that the probability of extreme stock prices in these countries is high. As a result, the Jarque-Bera test statistics only reject the null hypothesis of normality for the return series of stock markets in the Czech Republic and Russia.

We use the ADF unit root test to examine the null of a unit root in stock indices and corresponding exchange rates for the four sampled countries. The results of the ADF unit root test in *Table 2* show that stock indices and the corresponding exchange rates are all unit roots and that the first-order differences of those are stationary. These results suggest that stock indices and exchange rates are I (1) sequences in these countries.

Table 3 shows the results of the Ljung-Box Q tests for the standardized residuals and standardized residuals squared; there is no evidence of serial correlation

Table 2 Unit Root Test for Stock Indices and Exchange Rates for ADF

Items	Level			1st difference		
	C	C&T	Non	C	C&T	Non
Panel A: Stock index						
Czech Republic	−2.662*	−2.799	−0.795	−23.984***	−23.981***	−23.992***
Hungary	−2.506	−2.771	−0.724	−18.404***	−18.399***	−18.409***
Poland	−2.335	−2.406	−0.634	−19.904***	−19.901***	−19.901***
Russia	−2.257	−2.337	−0.745	−23.504***	−23.494***	−23.514***
Panel B: Exchange rate						
Czech Republic	−2.662*	−2.799	−0.795	−23.984***	−23.981***	−23.992***
Hungary	−2.506	−2.771	−0.724	−18.404***	−18.399***	−18.409***
Poland	−2.335	−2.406	−0.634	−19.904***	−19.901***	−19.901***
Russia	−2.257	−2.337	−0.745	−23.504***	−23.494***	-23.514***

Notes: ** and *** denote significance at the 5% and 1% levels, respectively.
C, C&T and Non indicate that the models have constant, constant and trend, and non-constant and no trend, respectively.

Table 3 Ljung-Box Q Tests

Country	*Q*(8) for stock		*Q*(8) for currency		Q^2(8) for stock		Q^2 (8) for currency	
	Statistic	*p*-value	Statistic	*p* -value	Statistic	*p* -value	Statistic	*p* -value
Panel A: Q test for DCC-S model								
Czech Republic	14.751	0.0642	4.070	0.8508	4.059	0.8518	18.353	0.0187
Hungary	9.207	0.3251	5.714	0.6792	5.256	0.7299	13.545	0.0944
Poland	16.071	0.0414	10.561	0.2278	1.615	0.9906	16.296	0.0383
Russia	11.101	0.1961	10.881	0.2085	10.530	0.2298	11.325	0.1839
Panel B: Q test for DCC model								
Czech Republic	14.780	0.0636	3.765	0.8777	4.104	0.8476	18.511	0.0177
Hungary	9.077	0.3359	6.636	0.5764	4.631	0.7961	12.301	0.1383
Poland	16.140	0.0404	10.305	0.2442	1.637	0.9902	17.030	0.0298
Russia	6.993	0.5374	10.835	0.2112	10.972	0.2033	7.881	0.4452
Panel C: Q test for CCC-S model								
Czech Republic	14.652	0.0663	3.841	0.8712	3.566	0.8940	18.942	0.0152
Hungary	6.520	0.5892	5.537	0.6989	4.574	0.8020	13.103	0.1084
Poland	14.479	0.0701	10.006	0.2646	1.381	0.9945	17.435	0.0259
Russia	9.309	0.3169	10.823	0.2119	10.370	0.2400	11.316	0.1844
Panel D: Q test for CCC model								
Czech Republic	14.650	0.0663	3.646	0.8876	3.612	0.8903	19.153	0.0141
Hungary	6.494	0.5919	5.804	0.6692	4.387	0.8206	12.753	0.1207
Poland	14.412	0.0716	9.702	0.2865	1.406	0.9942	19.267	0.0139
Russia	5.641	0.6873	10.794	0.2137	10.817	0.2123	7.880	0.4453

Table 4 LM Statistics for the Constant Correlations Test

Country	DCC-S	DCC-E	DCC
Czech Republic	29.6401***	29.1842***	29.6400***
Hungary	42.6066***	42.1991***	42.6204***
Poland	73.9114***	71.9732***	72.8407***
Russia	24.8932***	24.0005***	23.0514***

Note: : *** denotes significance at the 1% level.

Table 5 The Appropriate Model and the Lag Lengths of the Spillover Effects

Panel A: The appropriate model				
Country	DCC		DCC-S	DCC-EGARCH
Czech Republic	5.6072		5.5719#	5.5754
Hungary	6.2714		6.2377#	6.2529
Poland	5.4683		5.4579#	5.4683
Russia	4.5573		4.5358#	4.5607
Panel B: The lag lengths of the spillover effects on DCC-S				
Country	P = 1,Q = 1	P = 1,Q = 2	P = 2,Q = 1	P = 2,Q = 2
Czech Republic	5.5730#	5.5766	5.5756	5.5810
Hungary	6.2374#	6.2470	6.2424	6.2528
Poland	5.4463#	5.4498	5.4554	5.4656
Russia	4.5244#	4.5279	4.5249	4.5290

Note: # denotes the appropriate model for the return volatility.

at the 1% level for the DCC-S, DCC, CCC-S and CCC models. These results indicate that the DCC-S, DCC, CCC-S and CCC models are all suitable when estimating the optimal weights for currency-stock portfolios.[5]

We provide Tse's (2000) LM statistics for the constant correlations in *Table 4*. All statistics from the DCC-S and DCC model significantly reject the null hypothesis of constant correlation. The results indicate that the DCC-S and DCC models each demonstrate time-varying correlation. However, the results also indicate that the time-varying correlation is more suitable for the financial markets.

This study used the BIC to determine the appropriate model for return volatilities. The appropriate model for return volatilities determined by BIC is the DCC-S model for all countries reported in Panel A of *Table 5.* In addition, we use BIC to determine the lag lengths of spillover effects in equations (5) and (6), and P = 1, Q = 1 is appropriate for all countries reported in Panel B of *Table 5*.

Table 6 provides further proof and shows the results of the tests of the effectiveness of portfolio diversification and the optimal portfolio weights during the entire period and during crisis periods. The results in Panels A and C in *Table 6* show that the portfolio strategies involving currency and stock assets make it possible to considerably reduce portfolio risk (variance). We find that the DCC model's diversi-

[5] Our results for the optimal lag length of the AR term are 1, 1, 3 and 2 in the Czech Republic, Hungary, Poland and Russia, respectively.

Table 6 Portfolio Diversification Effectiveness and Average Optimal Portfolio Weights during the Entire Period and the Crisis Periods

Country	DCC-S	DCC	CCC-S	CCC
Panel A: Portfolio diversification effectiveness (%) during the entire period				
Czech Republic	**35.6395**	35.5835	34.8262	35.0060
Hungary	**24.4388**	24.3265	23.5171	23.4347
Poland	**33.9503**	33.8967	33.4379	33.6757
Russia	**85.9415**	85.8750	85.8936	85.8401
Panel B: The average Optimal portfolio weights during the entire period				
Czech Republic	0.7020	0.7028	0.7016	0.7020
Hungary	0.6968	0.6960	0.6960	0.6957
Poland	0.5769	0.5777	0.5715	0.5722
Russia	0.9489	0.9480	0.9537	0.9528
Panel C: Portfolio diversification effectiveness (%) during the crisis period				
Czech Republic	**52.4888**	52.3123	51.9821	52.0552
Hungary	**23.8183**	23.7963	23.5147	23.4045
Poland	**50.9617**	50.9086	50.3032	50.4568
Russia	**87.2014**	87.0722	87.0635	86.9539
Panel D: The average optimal portfolio weights during the crisis periods				
Czech Republic	0.7490	0.7511	0.7427	0.7444
Hungary	0.6840	0.6837	0.6940	0.6940
Poland	0.4970	0.4958	0.4820	0.4816
Russia	0.9352	0.9334	0.9412	0.9394

Notes: Figures in bold denote the highest diversification effectiveness in Panels A and C.
The financial crisis period in Panels C and D denotes the subprime crisis period from the middle of 2007 to the end of 2008.

fication effectiveness is greater than that of the CCC model both across the entire period and during crisis periods. Furthermore, the DCC-S model provides the best overall diversification effectiveness. When only the model that provides the best diversification effectiveness is considered (DCC-S), the diversification effectiveness ranges from 24.44% (Hungary) to 85.94% (Russia) during the entire period and from 23.82% (Hungary) to 87.20% (Russia) during crisis periods. The diversification effectiveness differs significantly across countries but generally remains relatively stable across the models and across the periods. This result is consistent for all cases and for all models considered.

We show the average values of the realized optimal portfolio weights in Panels B and D of *Table 6*.[6] The coefficients indicate that the average optimal weights for the stock assets in the portfolios vary substantially across markets but are only slightly different across the models used. The average optimal weights of the stock asset suggested by the DCC-S model for the Czech Republic, Hungary, Poland and Russia across the entire period are 70.20%, 69.68%, 57.69% and 94.89%, respec-

[6] The optimal holding weight is specified dynamically; therefore, this study provides an average optimal portfolio weight.

Figure 1 Czech Republic Weighting Tendency

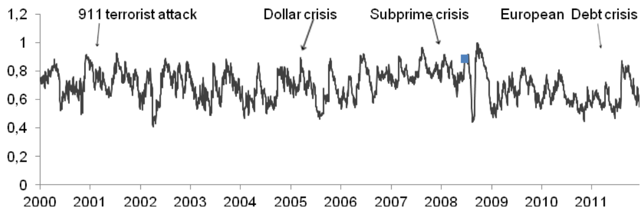


Figure 2 Hungary Weighting Tendency

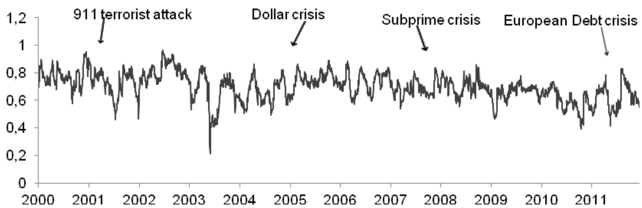


Figure 3 Poland Weighting Tendency

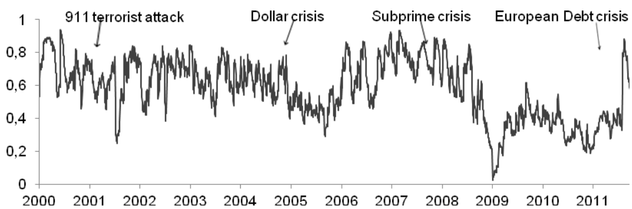
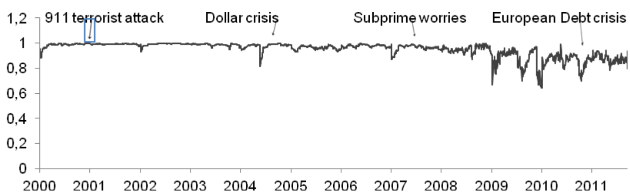


Figure 4 Russia Weighting Tendency



Note: In the figures, 911 terrorist attack occurs in September 11, 2001, dollar crisis occurs in the final quarter 2004, subprime worries occur form in the middle of 2007 and last to the end of 2008, and the European debt crisis occurs during 2010 and 2011.

tively. This result suggests that the average optimal allocations for the Czech (Hungarian, Polish and Russian) stock market in a one-dollar stock-currency portfolio in the entire period should be 70.2 (69.68, 57.69 and 94.89) cents, with the remaining 29.80 (30.32, 42.31 and 5.11) cents being invested in the Czech (Hungarian, Polish and Russian) currency market. Consequently, the time-varying weighted trends (estimated by the DCC-S model) for the four countries in *Figures 1* to *4* provide valuable information that would enable international investors to effectively

Table 7 Value at Risk Analysis

Country	DCC-S	DCC-S
	VaR (5%)	VaR (1%)
Czech Republic	9.2528	13.0864
Hungary	13.7842	19.4952
Poland	11.1620	15.7866
Russia	24.2040	34.2322

implement their optimal investment allocation between the stock and currency markets. To confirm the robustness of our results, this study computes them during the financial crisis period that is shown in Panels C and D of *Table 6*.[7] We find that the tendency of portfolio diversification effectiveness and average optimal portfolio weights during the crisis period is similar with that during the entire period.

Table 7 shows the mean 5% and 1% VaRs for the DCC-S currency-stock portfolios. The mean 5% VaRs in the different markets are 9.2528 (the Czech Republic), 13.7842 (Hungary), 11.1620 (Poland) and 24.2040 (Russia). The mean 1% VaRs in the markets are 13.0864 (the Czech Republic), 19.4952 (Hungary), 15.7866 (Poland) and 34.2322 (Russia). Using the 5% VaRs as an example, these figures indicate that investing in a ten-million-dollar currency-stock portfolio in these markets will result in a loss of 92,528 dollars (the Czech Republic), 137,832 dollars (Hungary), 111,620 dollars (Poland) and 242,040 dollars (Russia). Similarly, the results from the 1% VaRs indicate that investing in a ten-million-dollar currency-stock portfolio in these markets will result in a loss of 130,864 dollars (the Czech Republic), 194,952 dollars (Hungary), 157,866 dollars (Poland) and 342,322 dollars (Russia). The above findings suggest that investors should set aside an adequate amount of capital reserves to cover potential extreme losses when investing in currency-stock portfolios.

We display the time-varying weighted trends (estimated by DCC-S) for the four countries in *Figures 1* to *4*. We find that weighting generally rises when economic events occur, except for Russia, whose economic policies are considered to be unique. This trend is particularly apparent during the European debt crisis period. We also find that weighting declines during the economic boom in 2009 following the subprime crisis, which indicates that foreign investors prefer to hold local currency instead of investing in stocks when an economic crisis occurs and prefer to invest in stocks when the economy is booming.

Compared to the other three countries in Eastern Europe, we see from *Figures 1* to *4* that the average level of stock-currency weight in Russia is higher and the variance is lower, possibly because Russia tends to be more influenced by domestic demand than the other three countries. Domestic demand affects the volatility of a stock index more than it affects the volatility of the currency rate. Hence, the weight of stock assets that are owned by international investors is significantly higher than the weight of currency assets. Furthermore, the stability of stock-currency weight in Russia is higher than that in the other three countries.

[7] The financial crisis period in Panels C and D of *Table 6* denotes the subprime crisis period from the middle of 2007 to the end of 2008.

Table 8 Unit Root Tests for Correlation and Weighting

Country	Level	
	ADF	PP
Panel A: correlation		
Czech Republic	−3.5807**	−3.3614*
Hungary	−5.5377***	−5.7164***
Poland	−6.8626***	−6.9094***
Russia	−41.2198***	−40.8454***
Panel B: weighting		
Czech Republic	−7.4535***	−7.5803***
Hungary	−7.8538***	−7.7961***
Poland	−5.8987***	−6.0717***
Russia	−8.1316***	−8.6040***

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The results of the unit root tests in *Table 8* show the four countries' correlation series and weighted series estimated by the DCC-S model. All of the variables are stationary at their levels for both the ADF and PP unit root tests. Therefore, all the variables are integrated on order zero I(0). Conversely, the time-varying correlations and weightings are not displayed in the random-walk state, which indicates that the time-varying correlations and weightings are predictable and can be estimated.

4. Conclusions

The main objective of this study is to discuss the extent of volatility spillovers, portfolio diversification and dynamic relationships between the stock and currency markets in Eastern Europe (the Czech Republic, Hungary and Poland) and in Russia using DCC and CCC models.

The empirical results show that the DCC-S model is preferred over the other models, although the DCC model is a close second in model choice. The conditional volatilities from the DCC model can be used to estimate the effectiveness of diversification. Our results pertaining to diversification effectiveness show that the DCC-S model generally provides the best diversification effectiveness in all pairs of stock-currency markets. Moreover, the coefficients show that the optimal weights for the stock index assets in the diversification portfolios vary substantially across markets, but they are only slightly different across the models used.

This study also provides VaR results for the DCC-S model at the 5% and 1% levels to determine the amount of capital reserves that investors should set aside to cover potential extreme losses when investing in currency-stock portfolios. Furthermore, this study also presents the relevant time-varying weighted trends and finds that weightings generally rise when economic events occur, except in Russia because of its unique economic policies. This trend is particularly noticeable during the European debt crisis period. We also perform Tse's (2000) LM test and find significant dynamic correlation in all of the countries we consider. Finally, we apply the ADF and

PP unit root tests for both the time-varying correlations and weightings and find that both variables are stationary at their levels.

In conclusion, the relationship between the stock and currency assets in these markets should be considered dynamic, and the time-varying weight of the two assets is valuable information that helps improve the performance of a portfolio that is well diversified between stock and currency assets. This information also allows international investors to diversify the stock market's risk more effectively.

APPENDIX

Table 1A FDI in Eastern European and Russian Countries

Items	Czech Republic	Hungary	Poland	Russia
Panel A				
Increasing rate of FDI (from 2000 to 2011)	478%	269%	477%	1300%
Panel B				
FDI stocks in 2000 (million US dollars)	21,644	22,870	34,227	32,204
FDI stocks in 2011 (million US dollars)	125,245	84,447	197,538	457,474

Notes: The percentage in Panel A denotes the increasing rate of the amount of FDI from 2000 to 2011 in these countries.

The FDI stocks in Panel B is according to the world Investment Report 2012 of the United Nations Conference on Trade and Development (UNCTAD).

Table 2A Trading Hours

	Stock market	Currency market
Panel A: Trading hours		
Czech Republic	6.5	8.5
Hungary	8.61	8.0
Poland	7.58	8.0
Russia	7.5	8.0
Panel B: Opening and closing hours		
Czech Republic	9:30–16:00	09:30–18:00
Hungary	8:00–16:37	09:00–17:00
Poland	9:00–16:35	09:00–17:00
Russia	10:30–18:00	07:00–15:00

Note: In the figures, 911 terrorist attack occurs in September 11, 2001, dollar crisis occurs in the final quarter 2004, subprime worries occur form in the middle of 2007 and last to the end of 2008, and the European debt crisis occurs during 2010 and 2011.

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