International Journal of Economics and Finance; Vol. 6, No. 5; 2014
ISSN 1916-971X E-ISSN 1916-9728
Published by Canadian Center of Science and Education

The Persistency of Correlation between Currency Futures: A Macro Perspective

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Received: February 1, 2014 Accepted: February 19, 2014 Online Published: April 25, 2014

doi:10.5539/ijef.v6n5p17 URL: http://dx.doi.org/10.5539/ijef.v6n5p17

Abstract

This paper examines the dynamic correlation between currency futures prices. Using the Dynamic Conditional Correlation model (Engle, 2002) this study utilizes time-varying correlations, focusing on the persistency of correlation of currency prices. The sample includes eight currency futures traded on the Chicago Mercantile Exchange from 1999 to 2008 and the U.S. dollar index future. The study finds that the Canadian dollar and the Australian dollar have the highest persistency while the Swiss franc and the Russian ruble have the lowest persistency. In addition, the study finds that the time-varying conditional correlation between currency futures and the U.S. dollar futures is influenced by a country's macroeconomic conditions.

Keywords: DCC model, conditional correlation, currency futures, macroeconomic, GARCH

1. Introduction

According to the Triennial Central Bank Survey, conducted by the Bank of International Settlements, the forex market averages about $5.3 trillion per day (as of April 2013) (Note 1). Due to the important role this market plays in the world economy, the literature for the forex market has been growing rapidly. In this particular study we examine the dynamic correlation across currency futures prices to U.S. dollar index futures (Note 2), with a focus on the persistency of correlation between eight currency futures prices traded on the Chicago Mercantile Exchange: British pound, Brazilian real, Australian dollar, Canadian dollar, Japanese yen, Euro currency, Swiss franc, and Russian ruble. Using the Dynamic Conditional Correlation (DCC) model developed by Engle (2002), we incorporate time-varying correlations into our analysis. This study differentiates from previous studies in that it is the first to analyze the persistency of relation between currencies future prices.

This paper is most related to Lien and Yang (2006), which investigates the effects of spot-futures spread on the risk and return structure in currency markets. Using a bivariate GARCH framework, the authors find evidence that spreads on the risk and return structure of spot and futures markets produce asymmetric effects. The implications of these asymmetric effects are examined, with special consideration given to the performance of futures hedging strategies. This study differentiates from Lien and Yang (2006), however, in that our focus is on the persistency of correlation between currency futures prices and that we instead use a DCC framework. The DCC model is similar to a bivariate GARCH in spirit, but the DCC places several restrictions on how the correlation can change (in essence it is a special case of a bivariate GARCH).

In addition, this paper is also motivated by Harvey and Huang (1991) and Han, Kling and Sell (1999). Both of these papers explore how macroeconomic variables impact the currency futures market. In Harvey and Huang (1991), the authors examine volatility patterns in the forex market. They surmise that increases in volatility are more often attributed to macroeconomic news than private information through trading. In contrast, Han, Kling and Sell (1999) look at day-of-the-week effects in the currency futures market. Evidence in this paper suggests that the day-of-the-week effect is impacted by private information from trading or market microstructures, not macroeconomics news. Our paper tries to build upon these two studies by examining how different macroeconomic conditions affect the currency futures market. More specifically, we examine how four specific macroeconomic variables impact the correlation between US dollar futures and currency futures.

The sample spans from 1999 to 2008. The study finds that the persistency of currency futures interactions varies substantially across different currencies with the Canadian dollar and the Australian dollar having the greatest persistency while the Russian ruble and Swiss franc have the weakest. Further, the study finds that the time-varying conditional correlation between currency futures and the U.S. dollar futures is influenced by a country's macroeconomic conditions.

The rest of the paper is organized as follows: Section 2 describes the data, Section 3 presents the methodology, Section 4 examines the empirical results, and Section 5 gives the conclusion.

2. Data

The initial futures data consists of daily future prices for currency futures over the period January 1999 to December 2008. This data is collected from RC Research (www.Price-Data.com) and includes open, high, low, and close prices; as well as, volume and open interest. All daily future prices are in U.S. dollars. The currency futures included in this study are listed as follows: British pound, Brazilian real, Australian dollar, Canadian dollar, Japanese yen, Euro currency, Swiss franc, and Russian ruble. All eight currency futures are traded on the Chicago Mercantile Exchange (CME) and all currencies prices are coded the same way—the US$ price of per unit of currency. Table 1 provides a summary of the contract size, approximate margin, and minimal fluctuation of the 8 currency futures.

Table 1. Sample periods for currency futures traded in U.S.

Symbol	Futures Contract	Contract Size	Approximate Margin	Minimum Fluctuation	Observation
AD	Australian Dollar	A$100,000	$1,688.00	0.01 c/A$ = $10	5378
BP	British Pound	62,500 pound	$1,890.00	0.01 c/pound = $6.25	8384
BR	Brazilian Real	BR100,000	$3,500.00	0.005 c/BR = $5	3122
CD	Canadian Dollar	C$100,000	$1,215.00	0.01 c/C$ = $10	7898
EC	Euro Currency	EUR $125,000	$2,700.00	0.01 c/EUR = $12.50	2355
JY	Japanese Yen	Yen 12,500,000	$2,430.00	0.0001 c/JY = $12.50	8014
RU	Russian Ruble	MRR 2,500,000	$3,000.00	0.001 c/RR = $25	3858
SF	Swiss Franc	SF 125,000	$1,958.00	0.01 c/SF = $12.50	8383

Note. This table provides a summary of the listing exchange, the contract size, approximate margin, and minimal fluctuation of the eight currency futures (British pound, Brazilian real, Australian dollar, Canadian dollar, Japanese yen, Euro currency, Swiss franc, and Russian ruble). The data is daily frequency and spans from January 1999 to December 2008.

The weighted U.S. dollar futures are used as a basis for comparison. The U.S. dollar index (USDX) (Note 3) is an index (or measure) of the value of the United States dollar relative to a basket of foreign currencies. The USDX futures contract has two features that influence its pricing and its use. First, the USDX index is a geometric average, rather than an arithmetic average, of the constituent currencies. Second, the foreign exchange (FX) rates in the USDX index (in U.S. dollars per foreign exchange rate) are in the denominator of the index, implying that a dollar appreciation leads to a higher index level. Both the geometric averaging and the use of quoting convention have implication for the use of the USDX futures contract in hedging a foreign exchange exposure. Eytan, Harpaz, and Krull (1988) point out, the divergence between the geometric and arithmetic averages depend on both the volatilities of the individual currencies and their co-movements (sometimes referred to as their "correlations").

The USDX futures contract began trading on November 20, 1985 on the Financial Instruments Exchange, a division of the New York Cotton Exchange, which is now part of the New York Board of Trade (NYBOT). The USDX index was originally a geometrically weighted average of ten different currencies, with each currency representing a country that was a major trading partner with the United States. With the introduction of the Euro, the USDX index became a geometrically weighted average of six currencies, which represent five major U.S. trading partners and the Euro.

2.1 Index Formula

The formula for the index level on date t is the product of the six currencies spot rates, each raised a power related to a currency-specific weight. The general formula for the index can be written as:

$$USDX_t = K\prod_{i=1}^{N}\left(FX_{i,t}\right)^{-w_i} \quad (1)$$

where $USDX_t$ is the calculated level of the USDX index on date t, $FX_{i,t}$ is the foreign exchange rate (U.S. dollars per foreign currency unit) for currency i on date t, w_i is the weight associated with currency i (the weights are determined by the contract specs and sum to one (i.e., $\sum_{i=1}^{N} w_i = 1$), N is the number of currencies in the index for the USDX index, (N is currently six and was formerly ten), and K is a constant. Under the current USDX futures contract specs, the USDX index is equal to (Note 4).

$$USDX_t = 50.14348112\times\left(Euro_t\right)^{-0.576}\times\left(Yen_t\right)^{-0.136}\times\left(Sterling_t\right)^{-0.119} \times\left(Canadian\,Dollar_t\right)^{-0.091}\times\left(SwedishKroner_t\right)^{-0.042}\times\left(SwissFranc_t\right)^{-0.036} \quad (2)$$

We first begin by checking for stationarity of the price series data and find that the price series are non-stationary, while their first differences are stationary. This implies that the use of a return series is appropriate, with the return being computed as the log of the current price over the previous price. Table 2 provides the summary statistics of the daily currency futures returns.

Table 2. Summary statistics on daily currency futures returns

	Australian Dollar	British Pound	Brazilian Real	Canadian Dollar	Euro Currency	Japanese Yen	Russian Ruble	Swiss Franc
Mean	0.0318	-0.0085	-0.0734	0.0011	0.0497	0.0562	0.0907	0.0044
Median	0.1576	0.0000	0.0000	0.0000	0.0687	0.0000	0.4308	0.0000
Maximum	0.2245	0.1977	2.7795	0.0930	0.1145	0.3593	1.5433	2.1572
Minimum	-0.1967	-0.2287	-3.2046	-0.1141	-0.1156	-0.1827	-1.5546	-3.3271
Variance	0.0009	0.0009	0.0324	0.0002	0.0007	0.0010	0.0456	0.0011
Std. Dev.	0.2968	0.3037	1.7987	0.1573	0.2666	0.3122	2.1349	0.3377
Skewness	-0.3835	-0.0774	-1.3288	-0.0988	-0.0303	0.5644	0.0156	0.0932
Kurtosis	5.8860	7.1492	172.7144	6.3508	3.8294	8.3769	34.1887	5.9103
Jarque-Bera	1997.82	6021.84	3746507.82	3707.21	67.83	10078.15	156326.66	2970.23

Note. This table reports summary statistics on British pound, Brazilian real, Australian dollar, Canadian dollar, Japanese yen, Euro currency, Swiss franc, and Russian ruble returns. Daily currency returns are calculated as the difference in daily natural logarithmic of futures prices. Means and variances are multiplied by 100. The Jarque-Bera statistic is distributed as chi-square and tests for normality; the null hypothesis is that the data is distributed as a normal distribution. The data spans from January 1999 to December 2008.

The distribution of the daily futures returns is not normal, according to the Jarque-Bera test, and characterized by high kurtosis; especially, for the Brazilian real and Russian ruble. In addition, the Australian dollar, British pound, Brazilian real, Canadian dollar, and Euro currency futures returns are all negatively skewed. In contrast, the Japanese yen, Russian ruble, and Swiss franc are positively skewed.

Table 3. Correlation matrix of eight currency futures and USDX futures

	Australian Dollar	British Pound	Brazilian Real	Canadian Dollar	Euro Currency	Japanese Yen	Russian Ruble	Swiss Franc	USDX Futures
Australian Dollar	1								
British Pound	0.4191	1							
Brazilian Real	0.0282	-0.0167	1						
Canadian Dollar	0.4600	0.2780	0.0187	1					
Euro Currency	0.4621	0.6614	0.0066	0.2986	1				
Japanese Yen	0.1951	0.2816	0.0129	0.1033	0.3193	1			
Russian Ruble	0.0809	-0.0576	0.0464	0.0949	-0.0985	-0.0860	1		
Swiss Franc	0.3884	0.6283	-0.0052	0.2419	0.9165	0.4025	-0.1596	1	
USDX Futures	-0.4766	-0.7051	0.0039	-0.3767	-0.9351	-0.4559	0.0983	-0.8860	1

Note. This table provides the Spearman Correlations of British pound, Brazilian real, Australian dollar, Canadian dollar, Japanese yen, Euro currency, Swiss franc, and Russian ruble futures with USDX futures from January 1999 to December 2008.

Table 3 shows the Spearman correlation matrix for the eight currency futures. From the table one can see that the Brazilian real and the Russian ruble have the lowest correlation for the eight currency futures (all correlations are below 16%). The highest correlations that exist are between the Euro currency and the British pound (66%), the Euro currency and the Swiss franc (92%), Euro currency and USDX (-94%), Swiss franc and the British pound (63%), Swiss franc and USDX (-89%), and the British pound and USDX (-71%).

3. Methodology

In this paper we use both a GARCH (1,1) model (with a constant term in the mean equation) and the Dynamic Conditional Correlation (DCC) model. The GARCH (1,1) model can be defined as follows:

$$y_t = \mu + \varepsilon_t,\ \varepsilon_t|I_{t-1} \sim N(0, h_t) \tag{3}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{4}$$

where y_t is a stochastic process with conditional mean μ and ε_t as the error term. Given some past information set (I_{t-1}) ε_t is distributed normally with mean zero and variance h_t. More specifically h_t is the conditional variance, which is modeled as an ARMA process with constantω, ε_{t-1}^2 is the lagged squared innovations, and h_{t-1} is the lagged conditional variance. α and β are coefficients.

The DCC model, on the other hand, is merely an extension of the Constant Conditional Correlation (CCC) model. The main difference between the two models is that the DCC model allows the correlation matrix to be time varying. The DCC model, therefore, is unique in that it preserves the essence of a univariate GARCH model while incorporating a GARCH-like, dynamic correlation. Accordingly, the DCC can be written as:

$$H_t = D_t R_t D_t \tag{5}$$

$$R_t = diag\{Q_t\}^{-1/2} Q_t diag\{Q_t\}^{-1/2} \tag{6}$$

$$Q_t = S(1-\alpha-\beta) + \alpha\varepsilon_{t-1}\varepsilon'_{t-1} + \beta Q_{t-1} \tag{7}$$

where H_t is the conditional covariance matrix for a vector of k asset returns, R_t is the time-varying correlation matrix, D_t is the $k\times k$ diagonal matrix of time-varying standard deviations from a univariate GARCH model with $\sqrt{h_{i,t}}$ on the i^{th} diagonal, and Q_t denotes the conditional covariance matrix of the standardized residuals. α and β are parameter matrices. In addition S denotes the unconditional covariance matrix of the standardized residuals, while ε_t is the standardized, but correlated, residual vector.

The DCC model is constructed to permit a two-stage estimation of H_t. During the first step, a univariate GARCH model is fitted for each of the assets and the estimates of $h_{i,t}$ are obtained. In the second step, the asset returns are transformed by their estimated standard deviations and used to calculate the parameters of the conditional correlation. The log-likelihood function for the DCC model can be written as follows:

$$\begin{aligned} L &= -\frac{1}{2}\sum_t \left(k\log(2\pi) + \log|H_t| + r_t' H_t^{-1} r_t\right) \\ &= -\frac{1}{2}\sum_t \left(k\log(2\pi) + \log|D_t R_t D_t| + r_t' D_t^{-1} R_t^{-1} D_t^{-1} r\right) \\ &= -\frac{1}{2}\sum_t \left(k\log(2\pi) + 2\log|D_t| + \log|R_t| + \varepsilon_t' H_t^{-1}\varepsilon_t\right) \end{aligned} \tag{8}$$

In order to yield consistent parameter estimates a quasi-maximum likelihood estimation (QMLE) is used. The log-likelihood function, which can be expressed as:

$$L(\theta_1, \theta_2) = L_{Vol}(\theta_1) + L_{Corr}(\theta_1, \theta_2) \tag{9}$$

can be divided into two parts.

The volatility part:

$$L_{Vol}(\theta_1) = -\frac{1}{2}\sum_t \left(k\log(2\pi) + \log|D_t|^2 + r_t' D_t^{-2} r_t\right) \tag{10}$$

And the correlation component:

$$L_{Corr}(\theta_1, \theta_2) = -\frac{1}{2}\sum_t \left(\log|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t - \varepsilon_t'\varepsilon_t\right) \tag{11}$$

4. Empirical Results

4.1 Estimation of DCC Model

The estimate results for the GARCH model and the DCC model (Equation (5) to Equation (11)) are given in Table 4. Because the DCC beta parameter measures persistency of correlation it is therefore able to capture relative stability.

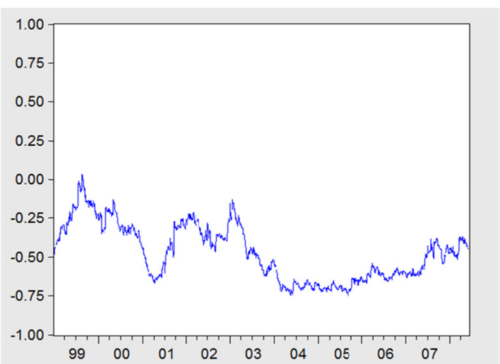
Table 4. DCC model results for eight currency futures

	Mean	Equation	Variance	Equation		DCC	Estimation	
Futures Contract	Intercept	USDX	Intercept	RESID(-1)^2	GARCH(-1)	DCC α	DCC β	Log likelihood
Australian Dollar	0.0000	-0.6928***	0.0000	0.0397***	0.9508***	0.0153***	0.9832***	-6279
British Pound	0.0000	-0.7315***	0.0000	0.0692***	0.8757***	0.0331***	0.9581***	-5806
Brazilian Real	0.0000	-0.1693***	0.0000	0.0421***	0.9703***	0.0069***	0.9079***	-6648
Canadian Dollar	0.0001	-0.2920***	0.0000	0.0313***	0.9615***	0.0138***	0.9837***	-6433
Euro Currency	0.0000	-1.1081***	0.0000	0.2537***	0.4107***	0.0728***	0.6073***	-4083
Japanese Yen	0.0000	-0.6507***	0.0000	0.0763***	0.8719***	0.0253***	0.9715***	-6299
Russian Ruble	0.0002	0.2280***	0.0000	0.1334***	0.7876***	0.0304***	0.5178***	-6638
Swiss Franc	0.0000	-1.1663***	0.0000	0.2038***	0.3603	0.0982***	0.3075***	-4791

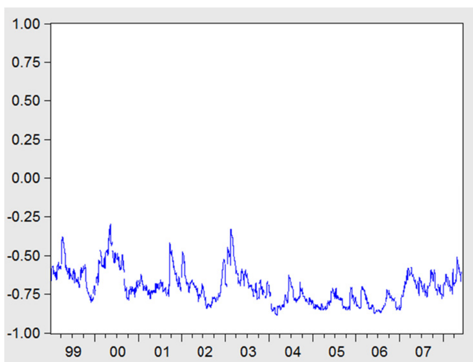
Note. The table reports the parameter estimates of the DCC model. The table shows the estimates of the mean return and variance equations, the DCC parameters, and the log likelihood statistics for British pound, Brazilian real, Australian dollar, Canadian dollar, Japanese yen, Euro currency, Swiss franc, and Russian ruble futures. *, **, *** denotes significance at the 10% level, 5% level, and 1% level respectively.

For example, the DCC beta parameter for the Euro is 0.6073. Recall that the Euro carries a 57.6% weight in the U.S. dollar index, which implies that the Euro will naturally be more closely related to the index. Therefore, the fact that the Euro has such a low persistency provides clearer evidence that its stability is low. On the other hand, the weight for the Japanese yen, British pound, and Canadian dollar are 13.6%, 11.9%, and 9.1% respectively; but the corresponding persistency of the correlation (the DCC beta parameter) is 0.9715, 0.9581, and 0.9837. This implies that the stability of the Japanese yen, British pound, and Canadian dollar are relatively high. Overall, the study finds that the Canadian dollar and the Australian dollar have the highest persistency while the Swiss franc and the Russian ruble have the lowest persistency.

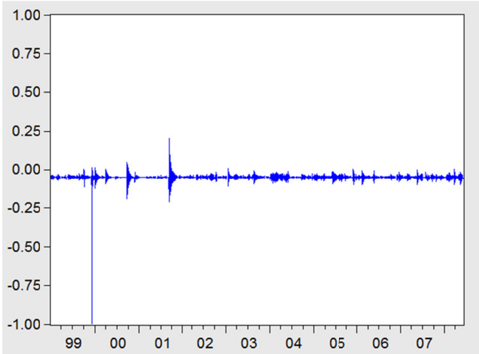
Figure 1 shows the dynamic conditional correlation between each of the eight currencies with the U.S. dollar futures. One striking feature is that the conditional correlation (noted as rho) between the Brazilian real and the U.S. dollar and the Russian ruble and the U.S. dollar have a tendency to be near zero and often change signs. Also, similar to the results of Table 4, the Australian dollar, British pound, Canadian dollar, and Japanese yen are the most persistently correlated with U.S. dollar futures. However, one does observe that these relationships can vary dramatically over the sample period.



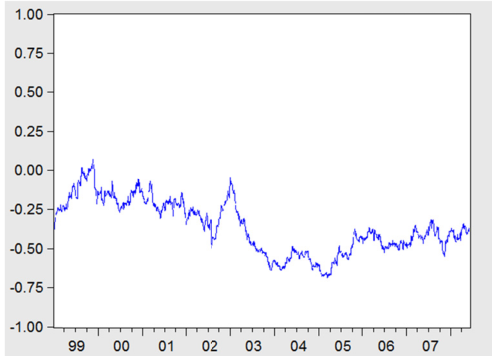
Panel A. Correlation between Australian Dollar and USDX Futures



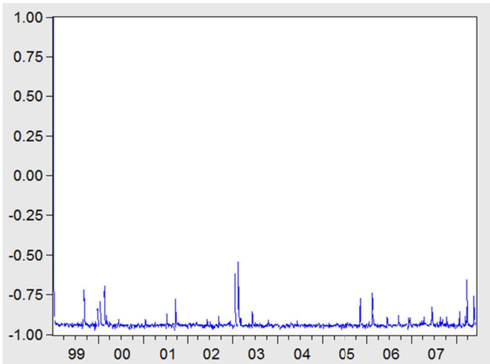
Panel B. Correlation between British Pound and USDX Futures



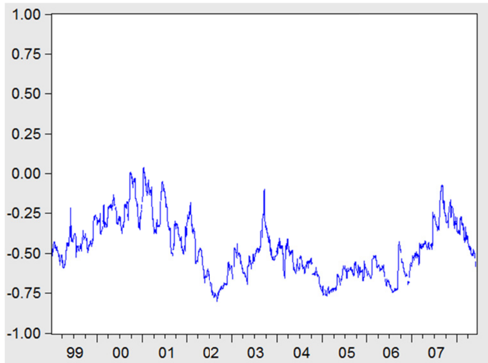
Panel C. Correlation between Brazilian Real and USDX Futures



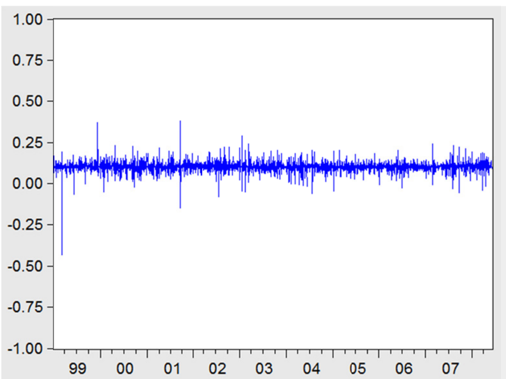
Panel D. Correlation between Canadian Dollar and USDX Futures



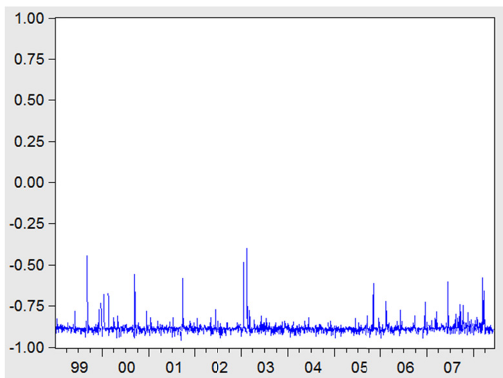
Panel E. Correlation between Euro Currency and USDX Futures



Panel F. Correlation between Japanese Yen and USDX Futures



Panel G. Correlation between Russia Ruble and USDX Futures



Panel H. Correlation between Swiss Franc and USDX Futures

Figure 1. Dynamic conditional correlation

Note. Figure 1 depicts the correlation estimates from the DCC model for the British pound, Brazilian real, Australian dollar, Canadian dollar, Japanese yen, Euro currency, Swiss franc, and Russian ruble futures from January 1999 to December 2008.

4.2 The Role Macroeconomic Variables

In this section we analysis the contributing factors to the time-varying correlations. In particular, we are interested in a set of macro variable that representing a country's economic growth.

$$rho = a + b_1 \times Industry\ Poduction + b_2 \times Inflation + b_3 \times Risk\ Free\ Rate + b_4 \times Money\ Grown \quad (12)$$

Table 5 shows how a country's macroeconomic growth impacts the varying correlations between currency futures and U.S. dollar futures. The dependent variable is the correlation (i.e. rho), which is estimated from the DCC model, while the independent variables are the logarithm of industry production, rate of inflation, risk-free rate, and growth of monetary base.

Table 5. Time-varying correlations and country characteristics

Futures Contract	a	b1	b2	b3	b4	t-stat(a)	t-stat(b1)	t-stat(b2)	t-stat(b3)	t-stat(b4)	R-Square
Australian Dollar	6.5355	4.9618	-7.5949	-0.0162	-0.4779	8.07	3.28	-6.05	-0.59	-1.34	0.46
	(0.8099)	(1.5139)	(1.2554)	(0.0273)	(0.3555)						
British Pound	10.8987	-3.4962	-2.4196	0.0495	-0.0032	2.04	-1.54	-4.31	1.89	-0.01	0.19
	(5.3537)	(2.2761)	(0.5610)	(0.0262)	(0.2223)						
Brazilian Real	-0.0896	0.0121	0.0096	0.0001	-0.0040	-1.26	0.24	0.47	0.69	-0.65	0.02
	(0.0710)	(0.0511)	(0.0206)	(0.0002)	(0.0060)						
Canadian Dollar	9.4786	-2.7364	-2.1924	0.0713	-0.0787	5.59	-3.14	-2.43	4.86	-0.39	0.65
	(1.6946)	(0.8712)	(0.9011)	(0.0146)	(0.2045)						
Euro Currency	-0.3188	-0.0096	-0.3177	-0.0121	0.0245	-1.18	-0.13	-2.12	-1.97	0.79	0.57
	(0.2693)	(0.0734)	(0.1497)	(0.0061)	(0.0312)						
Japanese Yen	-20.0789	-2.5421	11.8469	0.4173	0.2088	-2.02	-2.61	2.61	4.48	1.08	0.38
	(9.9588)	(0.9730)	(4.5341)	(0.0931)	(0.1934)						
Russian Ruble	0.0242	0.1103	-0.0619	-0.0006	-0.0045	0.18	0.82	-0.84	-0.23	-0.22	0.04
	(0.1373)	(0.1347)	(0.0738)	(0.0028)	(0.0209)						
Swiss Franc	0.5455	0.4356	-1.0009	-0.0033	-0.0775	1.13	4.04	-3.26	-1.20	-3.12	0.15
	(0.4814)	(0.1077)	(0.3066)	(0.0027)	(0.0248)						

Note. This table reports parameter estimates of $rho = a + b_1 \times Industry\ Poduction + b_2 \times Inflation + b_3 \times Risk\ Free\ Rate + b_4 \times Money\ Grown$ for British pound, Brazilian real, Australian dollar, Canadian dollar, Japanese yen, Euro currency, Swiss franc, and Russian ruble futures for the period from January 1999 to December 2008. Standard errors are reported in the parenthesis.

For both the Australian dollar and the Swiss franc industry production is statistically significant and positively related with the dependent variable. The Canadian dollar, on the other hand, is statistically significant and negatively related with rho in regards to industry production. As for inflation, with the exception of the Brazilian real and the Japanese yen, all currency futures are negatively related and statistically significant to rho. Only the Japanese yen is positively statistically significant for inflation. Lastly, in regards to the risk free rate and money growth, only the Canadian dollar and the Japanese yen are positively statistically significant for the risk free rate and only the Swiss franc is negatively statistically significant for money growth.

5. Conclusion

This study investigates the time-varying correlation between currency futures prices utilizing the DCC model, focusing on the persistency of correlation. The study finds that the Russian ruble and the Swiss franc have the weakest persistency while the Australian dollar and the Canadian dollar have the greater persistency. However, the relationships do vary somewhat over the sample period. In addition, the study finds that the time-varying conditional correlation between currency futures and the U.S. dollar futures is influenced by a country's macroeconomic conditions; specifically, industry production, inflation, the risk free rate and money growth.

In summary, this paper provides evidence on the persistency between different currency futures (British pound, Brazilian real, Australian dollar, Canadian dollar, Japanese yen, Euro currency, Swiss franc, and Russian ruble) and USDX futures and how macroeconomic growth variables impact that persistency.

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Notes

Note1. http://www.bis.org/publ/rpfx13fx.pdf

Note 2. U.S. dollar index futures are listed on the Financial Instruments Exchange (FINEX).

Note 3. The short-coming of using the U.S. Currency Futures Index is that it is an unequally weighted index, so the currency that is weighted more heavily, such as Euro, will inherently move more closely with the index.

Note 4. In other words, it is a weighted geometric mean of the following: Euro (EUR), 57.6% weight, Japanese yen (JPY) 13.6% weight, Pound sterling (GBP) 11.9% weight, Canadian dollar (CAD) 9.1% weight, Swedish krona (SEK) 4.2% weight, and Swiss franc (CHF) 3.6% weight.