Nonlinear Dependencies And Chaos In The Bilateral Exchange Rate Of The Dollar

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ABSTRACT

Employing the daily bilateral exchange rate of the dollar against the Canadian dollar, the Swiss franc and the Japanese yen, we conduct a battery of tests for the presence of low-dimension chaos. The three stationary series are subjected to Correlation Dimension tests, BDS tests, and tests for entropy. While we find strong evidence of nonlinear dependence in the data, the evidence is not consistent with chaos. Our test results indicate that GARCH-type processes explain the nonlinearities in the data. We also show that employing seasonally adjusted index series enhances the robustness of results via the existing tests for chaotic structure.

Keywords: Bilateral exchange rate of the dollar, low-dimension chaos, GARCH type processes

INTRODUCTION

This paper is a continuation of research on the behavior of the daily exchange rate of the dollar. We investigate nonlinearities and chaos in the daily bilateral exchange rates of the US dollar against the Canadian dollar, the Swiss franc, and the Japanese yen.

The behavior of the bilateral exchange rate of the dollar may be significantly different from the broader effective exchange rate. This may be due to the weighting process that could smooth the effective rates series. Adrangi et al. (2008) investigate nonlinearities and the daily volatility in the effective exchange rate of the dollar. However, the aggregation and the trade-weighting of bilateral exchange rates to construct the effective exchange rate may also distort the actual behavior of the bilateral exchange rates.

Several factors motivate the paper. First, economists have long been interested in exchange rate fluctuations and forecasting them (see Kim and Karemera (2006), among others). . The volatility and movements of the dollar are of particular interest to money managers, securities authorities and world Central Banks because the dollar plays the role of international anchor currency, and international capital movements among nations has steadily increased in the last two decades. Furthermore, the dollar has experienced volatility in recent years and depreciated against major currencies, such as the Canadian dollar and the British pound.

Second, the volatility in financial markets has generated interest in applying chaos theory to these markets including movements in the exchange rate of the dollar. Technical analysis has been used in forecasting other financial time series and may be successful in forecasting short-term fluctuations in the dollar if the series is nonlinear and/or chaotic (see for example, Blume, Easley, and O'Hara (1994), Bohan (1981), Brock, Lakonishok, and LeBaron (1992), Brush (1986), Clyde and Osler (1997), LeBaron (1991), Pruitt and White (1988, 1989), Taylor (1994), among others).

Third, Nonlinear dynamics may be able to explain a richer array of time series behavior. For example, sudden movements and wide fluctuations in asset prices, exchange rates, and other financial and economic series may not be properly captured by linear models, while nonlinear models may explain these behaviors (for instance, see Baumol and Benhabib (1989).

In this paper, we first examine the daily percentage changes of the bilateral exchange rates of the dollar for nonlinearities. If nonlinearities are evident, we investigate whether chaos is the source of these nonlinearities. Finally, if nonlinearities are not stemming from chaotic behavior, we search for econometric models that may easily explain the nonlinear dynamics in the series.

Our findings show strong evidence that the exchange series exhibit nonlinear dependencies. However, we find evidence that the series behavior may be inconsistent with chaotic structure. We argue that employing a seasonally adjusted index series contributes to obtaining robust results via the existing tests for chaotic structure. We identify Asymmetric Component GARCH (1,1) process as the model that best explains the nonlinearities in the daily dollar rates. Our findings are particularly compelling because they confirm the power of a commonly known nonlinear model in explaining the behavior of the exchange rates.

TESTING FOR CHAOS

The common tests of chaos are discussed in Adrangi et al. (2001a), Adrangi et al. (2001b), and Adrangi et al. (2004). We repeat them in this paper to inform the reader. There are three tests that we employ here: (i) the Correlation Dimension of Grassberger and Procaccia (1983) and Takens (1984), (ii) the BDS statistic of Brock, Dechert, and Scheinkman (1987), and (iii) a measure of entropy termed Kolmogorov-Sinai invariant, also known as Kolmogorov entropy.

Correlation Dimensions

Consider the stationary time series x_t, t =1...T. One imbeds x_t in an m-dimensional space by forming M-histories starting at each date t: $x_t^2 = \{x_t, x_{t+1}\}$,.., $x_t^M = \{x_t, x_{t+1}, {}_{t+2},\dots\dots\dots\dots$

$x_{t+M-1}\}$. One employs the stack of these scalars to carry out the analysis. If the true system is n-dimensional, provided M ≥ 2n+1, the M-histories can help recreate the dynamics of the underlying system, if they exist (Takens (1984)). For a given embedding dimension M and a distance ε, the correlation integral is given by

$$C^M(\varepsilon) = \lim_{T\to\infty} \{\text{the number of (i,j) for which } \left\| x_i^M - x_j^M \right\| \le \varepsilon\} / T^2 \tag{1}$$

where $\| \;\|$ is the distance induced by the norm. For small values of ε, one has $C^M(\varepsilon) \sim \varepsilon^D$ where D is the dimension of the system (see Grassberger and Procaccia (1983)). The Correlation Dimension in embedding dimension M is given by

$$D^M = \lim_{\varepsilon\to 0} \lim_{T\to 0} \{\ln C^M(\varepsilon) / \ln \varepsilon\} \tag{2}$$

and the Correlation Dimension is itself given by

$$D = \lim_{M\to 0} \ln D^M \tag{3}$$

We estimate the statistic

$$SC^M = \frac{\{\ln C^M(\varepsilon_i) - \ln C^M(\varepsilon_{i-1})\}}{\{\ln(\varepsilon_i) - \ln(\varepsilon_{i-1})\}} \tag{4}$$

for various levels of M (e.g., Brock and Sayers (1988)). The SC^M statistic is a local estimate of the slope of the C^M versus e function. Following Franc and Stengos (1989), we take the average of the three highest values of SC^M for each embedding dimension.

BDS Statistics

Brock, Dechert and Scheinkman (1987) employ the correlation integral to obtain a statistical test that has been shown to have strong power in detecting various types of nonlinearity as well as deterministic chaos. BDS show that if x_t is (i.i.d) with a nondegenerate distribution,

$$C^M(\varepsilon) \to C^1(\varepsilon)^M \quad ,as \quad T \to infinity \tag{5}$$

for fixed M and ε. Employing this property, BDS show that the statistic

$$W^M(\varepsilon) = \sqrt{T}\{[C^M(\varepsilon) - C^1(\varepsilon)^M]/\sigma^M(\varepsilon)\} \tag{6}$$

where σ^M, the standard deviation of [·], has a limiting standard normal distribution under the null hypothesis of IID. W^M is termed the BDS statistic. Nonlinearity will be established if W^M is significant for a stationary series void of linear dependence. The absence of chaos will be suggested if it is demonstrated that the nonlinear structure arises from a known non-deterministic system.

Kolmogorov Entropy

Kolmogorov entropy quantifies the concept of sensitive dependence of a series on initial conditions. Kolmogorov entropy (K) measures the speed with which the trajectories of a time-series diverge so that they become distinguishable.

Grassberger and Procaccia (1983) devise a measure for K which is more computationally manageable than earlier measures of entropy. The measure is given by

$$K_2 = \lim_{\varepsilon \to 0} \lim_{m \to infinity} \lim_{N \to infinity} \ln\left(\frac{C^M(\varepsilon)}{C^{M+1}(\varepsilon)}\right). \tag{7}$$

If a time series is non-complex and completely predictable, $K_2 \to 0$. If the time series is completely random, $K_2 \to \infty$. That is, the lower the value of K_2, the more predictable the system. For chaotic systems, one would expect $0 < K_2 < \infty$, at least in principle.

DATA AND SUMMARY STATISTICS

We utilize the daily bilateral dollar exchange rate series from January 1974 through mid July 2009, thereby covering the time period when the value of the dollar has been determined in a free float foreign exchange market system. We focus our tests on daily percentage changes, which are obtained by taking the ratio of log of the exchange rates as in $R_t = (\ln(P_t/P_{t-1}))\cdot 100$, where P_t represents the closing value on day t.

Table 1 presents the diagnostics for the R_t series. The returns series are found to be stationary employing the Augmented Dickey Fuller (ADF) statistics. There are linear and nonlinear dependencies as indicated by the Q and Q^2 statistics, and Autoregressive Conditional Heteroskedasticity (ARCH) effects is suggested by the ARCH(6) chi-square statistic. The summary of findings of Table 1 is as follows: (i) there are clear indications that nonlinear dynamics are generating the daily dollar exchange values, (ii) these nonlinearities may be explained by ARCH effects, and (iii) whether these dynamics are chaotic in origin is the question that we turn to next.

To capture the linear structure and daily seasonalities we first estimate an autoregressive model for the dollar with controls for possible day-of-the-week effects, as in

$$R_t = \sum_{i=1}^{p} \beta_i R_{t-i} + \sum_{j=1}^{5} \gamma_j D_{jt} + \varepsilon_t, \qquad (8)$$

where D_{jt} represent day-of-the-week dummy variables. The lag length for each series is selected based on the Akaike (1974) criterion. The residual term (ε_t) represents the index movements that are purged of linear relationships and seasonal influences.

Table 2 presents the estimation results for equation (8). We see that the AR (1) or AR (4) models with the day-of-the-week dummies completely explain the linear dependencies in the R_t series. For instance, the Q (12), in all cases, is statistically insignificant at all usual significance levels. However, Q^2 (12) LM statistics are significant at the one percent level showing that the seasonal AR models in equation (8) are not capable of explaining nonlinearities present in the series. Thus, we turn our attention to testing for the source of these nonlinearities. The correlation dimension and BDS statistics are employed to see if the nonlinearities are consistent with chaos.

Correlation Dimension Estimates

Table 3 reports the Correlation Dimension (SC^M) estimates for various components of the dollar returns series alongside that for the Logistic series developed earlier. Results show that correlation dimension estimates do not settle with increasing dimension. For instance, SC^M estimates for the logistic map stay around one as the embedding dimension rises. Furthermore, the estimates for the logistic series are not sensitive to the AR transformation, consistent with chaotic behavior.

For the dollar series, on the other hand, SC^M estimates show inconsistent behavior with chaotic structures. For instance, the SC^M does not settle. The estimates for the AR transformation do not change results much, but are mostly larger and do not settle with increasing of the embedding dimension.

BDS Test Results

Table 4 reports the BDS statistics (Brock, Dechert and Scheinkman (1987)) for [AR(p),S] series and standardized residuals ($\varepsilon/\sqrt{h}$) from three GARCH- type models: GARCH (1,1), Exponential GARCH (1,1), and Asymmetric Component GARCH (1,1).

The BDS statistics are evaluated against critical values obtained by bootstrapping the null distribution for each of the GARCH models. The critical values for the BDS statistics are reported in Adrangi et al. (2001a), Adrangi et al. (2001b), and Adrangi et al. (2004).

The BDS statistics strongly reject the null of no nonlinearity in the [AR(p),S] errors for the dollar return series. However, BDS statistics for the standardized residuals from the GARCH-type models are mostly insignificant at the 1 and 5 percent levels. On the whole, the BDS test results provide compelling evidence that the nonlinear dependencies in the dollar exchange rate returns series arise from GARCH-type effects, rather than from a complex, chaotic structure.

From the BDS statistics presented in Table 4, it is apparent that the variations of the GARCH model may explain the nonlinearities in the dollar series. Table 5 reports the maximum likelihood estimation of a Asymmetric Component GARCH (1,1) model. It is clear that this model fits the dollar return series well. All coefficients in the [AR(p),S] and the variance equations are significant at the one or five percent significance levels.

Kolmogorov Entropy Estimates

We examined the Kolmogorov entropy estimates (embedding dimension 15 to 30) for the Logistic map ($w = 3.75$, $x_0 = .10$) and [AR(1),S] for the dollar return series. Kolmogorov entropy estimates are considered the most direct test of chaotic behavior. The estimates for the Logistic map provide the benchmarks for a known chaotic series. The entropy estimates for the dollar return series show little sign that the series is settling down as do those for the Logistic map, i.e., there is no clear evidence of low dimension chaos in the dollar returns. The standardized residuals from the GARCH (1,1) model and the returns series demonstrate a pattern that is not consistent with the chaotic pattern shown by the logistic function.

SUMMARY AND CONCLUSIONS

Financial researchers have become interested in chaotic time series in the past two decades because many economic and financial time series appear random. However, random-looking variables may, in fact, be chaotic and thus, may be predictable by technical tools, at least in the short-run.

Employing the daily bilateral exchange rates of the dollar, we conduct a battery of tests for the presence of low-dimension chaos. The stationary percentage change series are subjected to Correlation Dimension tests, BDS tests, and tests for entropy. While we find strong evidence of nonlinear dependence in the data, the evidence is not consistent with chaos. Our test results indicate that GARCH-type processes explain the nonlinearities in the data. We also show that employing seasonally adjusted return series enhances the robustness of results via the existing tests for chaotic structures. For the bilateral exchange rates, we show that an Asymmetric Component GARCH (1,1) model adequately explains the nonlinearities in the series. Thus, relatively common nonlinear econometric models may be employed to gather information and predict future movements and the volatility of these series. This information may be valuable for money mangers, global fund managers, country fund investors, as well as local monetary policy and exchange authorities and central banks. It also suggests that the "weak form" of the Efficient Market Hypothesis for the case of the bilateral dollar exchange rates may be violated. This is so because GARCH-type nonlinear models may be employed for possible predictive purposes. This point may be the topic of further research.

AUTHOR INFORMATION

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Table 1: Return Diagnostics

	Canadian dollar	Swiss franc	Japanese yen
Mean	0.0013	-0.013	-0.013
SD	0.385	0.739	0.663
SK	-0.243	-0.055	-0.557
K	17.73	6.107	7.700
JB	80880.37***	3600.51**	8691.59***
ADF	-42.111***	-42.403***	92.536***
ADF(T)	-42.150***	-42.411***	-92.532***
PP	-91.077***	-92.975***	-92.891***
PP(T)	-91.093***	-92.975***	-92.891***
Q(12)	35.49***	21.359***	26.750***
$Q^2(12)$	5917.5***	1058.8***	1007.5***
ARCH(6)	1302.08***	426.42***	474.37***

The Table presents the return diagnostics for the bilateral daily exchange rates of the US dollar against the Canadian dollar, Swiss franc, and the Japanese yen series over the interval, January 1974 through July 2009 (8927 observations). Returns are given by $R_t = \ln(P_t/P_{t-1})\cdot 100$, where P_t represents closing exchange rate on day t. ADF, ADF(T) represent the Augmented Dickey Fuller tests (Dickey and Fuller (1981)) for unit roots, with and without trend respectively. The Q(12) and $Q^2(12)$ statistics represent the Ljung-Box (Q) statistics for autocorrelation of the R_t and R_t^2 series respectively. The ARCH(6) statistic is the Engle (1982) test for ARCH (of order 6) and is χ^2 distributed with 6 degrees of freedom.
*** represents the significance level of .01.

Table 2: Linear Structure and Seasonality

	Canadian dollar		Swiss franc		Japanese yen	
Intercept	0.0225***	(2.506)	-0.005	(-0.221)	-0.0352**	(-2.145)
R_{t-1}	0.0347***	(3.278)	0.0164*	(1.653)	0.0209**	(1.975)
R_{t-2}	-0.0017	(-0.165)				
R_{t-3}	0.0177*	(1.670)				
R_{t-4}	0.0029	(0.278)				
Mon	-0.0276***	(-2.112)	-0.0505**	(-2.013)	0.0328	(0.266)
Tue	-0.0335***	(-2.625)	0.0069	(0.280)	0.0359*	(1.277)
Wed	-0.0300***	(-2.363)	0.0103	(0.425)	0.0162	(-0.105)
Thr	0.0158	(-1.239)	-0.0101**	(-0.448)	0.0181	(-0.642)
R^2	0.002		0.001			0.0008
LM(1)	343.33***		124.53***			282.11***
Q(12)	22.39**		19.20*			21.77**
$Q^2(12)$	5795.7***		1055.5***			1013..80***

The coefficients and residual diagnostics are from the OLS regressions of returns on prior returns and twelve monthly dummies. The lag-length was selected based on Akaike's (1974) criterion. The Lagrange Multiplier statistic of first order autocorrelation (LM(1), Chi-square) tests the null of no autocorrelation of order one in the regression residuals. The Q(12) and $Q^2(12)$ statistics represent the Ljung-Box (Q) statistics for autocorrelation in the residuals. *,**, and *** represent the significance levels of .10, .05, and .01, respectively.

Table 3: Correlation Dimension Estimates

Canadain Dollar

M=	5	10	15	20
Logistic	1.02	1.00	1.03	1.06
Logistic AR	0.96	1.06	1.09	1.07
Returns	3.795	5.110	6.237	6.831
AR(4)	3.210	5.108	6.236	6.840
AR(4),S	3.221	5.165	6.360	7.039
Shuffled	28.064	7.455	11.457	15.359

Swiss Franc

M=	5	10	15	20
Logistic	1.02	1.00	1.03	1.06
Logistic AR	0.96	1.06	1.09	1.07
Returns	3.816	7.169	9.997	12.266
AR(1)	3.813	7.162	10.075	12.249
AR(1),S	3.803	7.138	9.957	12.413
Shuffled	3.962	7.989	11.992	16.536

Japanse Yen

M=	5	10	15	20
Logistic	1.02	1.00	1.03	1.06
Logistic AR	0.96	1.06	1.09	1.07
Returns	3.564	6.339	8.618	10.811
AR(1)	3.571	6.354	8.669	10.698
AR(1),S	3.566	6.323	8.555	10.576
Shuffled	3.806	7.491	11.406	14.696

The Table reports SC^M statistics for the Logistic series (w = 3.750, n = 2250), daily bilateral exchange rates of the dollar (dollars/Canadian, francs and yen/US dollar) against the Canadian dollar, Swiss franc and the Japanese yen for the period of January1974 through July 2007 series and their various components over four embedding dimensions: 5, 10, 15, 20. AR (p) represents autoregressive (order p) residuals, AR(p),S represents residuals from autoregressive models that correct for day-of-the-week effects in the data.

Table 4: BDS statistics

Panel A: Canadian dollar

ε/σ	M 2	3	4	5
[AR(4),S] Residuals				
0.04563	18.263	23.645	30.473	39.366
0.09125	18.505	23.178	27.614	32.408
0.13688	18.085	22.412	25.883	28.990
0.18250	16.839	20.927	23.998	26.346
GARCH (1,1) Standard Errors				
0.03720	1.568	0.195	-0.049	-0.379
0.07440	1.710	0.478	0.209	-0.065
0.11160	1.908	0.737	0.312	-0.058
0.14880	2.233	1.292	0.831	0.366
Exponential GARCH Standard Errors				
0.037	0.768	-0.729	-1.023	-1.282
0.075	1.148	-0.207	-0.477	-0.757
0.113	1.670	0.383	-0.001	-0.320
0.150	2.328	1.336	0.914	0.508
Component GARCH Standard Errors				
0.03664	0.169	-1.340	-1.71	-1.960
0.07328	0.272	-1.241	-1.640	-1.930
0.10992	0.349	-1.076	-1.628	-1.984
0.14656	0.734	-0.392	-0.986	-1.461

Panel B: Swiss franc

ε/σ	**M** **2**	**3**	**4**	**5**
[AR(1),S] Residuals				
0.036	6.254	8.290	10.075	11.919
0.073	6.843	8.914	10.817	12.496
0.109	7.739	9.685	11.522	12.992
0.146	8.969	10.771	12.495	19.675
GARCH (1,1) Standard Errors				
0.044	-2.149	-2.380	-2.303	-2.168
0.089	-2.243	-2.612	-2.599	-2.658
0.134	-1.961	-2.501	-2.614	-2.727
0.176	-1.199	-1.874	-2.0733	-2.318
Exponential GARCH Standard Errors				
0.044	-2.368	-2.687	-2.728	-2.757
0.088	-2.374	-2.739	-2.777	-2.846
0.132	-1.787	-2.283	-2.414	-2.501
0.176	-0.823	-1.407	-1.569	-1.726
Asymmetric Component GARCH Standard Errors				
0.044	-2.308	-2.414	-2.377	-2.225
0.089	-2.443	-2.998	-2.664	-2.678
0.133	-2.171	-2.559	-2.694	-2.771
0.177	-1.402	-1.952	-2.171	-2.385

Panel C: Japanese yen	**M**			
ε/σ	**2**	**3**	**4**	**5**
[AR(1),S] Residuals				
0.03708	9.266	11.666	14.364	17.589
0.07415	9.046	10.978	13.068	15.013
0.11123	9.702	11.520	13.220	14.525
0.14830	10.235	12.257	13.820	14.825
GARCH (1,1) Standard Errors				
0.04209	1.627	1.227	1.631	2.266
0.08418	0.899	0.264	0.694	1.101
0.12627	0.897	0.344	0.744	0.945
0.16836	1.391	1.195	1.529	1.524
Exponential GARCH Standard Errors				
0.041	0.539	-0.101	0.061	0.455
0.082	0.201	-0.677	-0.443	-0.206
0.124	0.775	0.033	0.283	0.380
0.166	1.701	1.465	1.779	1.760
Asymmetric Component GARCH Standard Errors				
0.041	1.561	1.360	1.802	2.533
0.082	0.854	0.447	0.896	1.386
0.124	0.848	0.540	0.955	1.246
0.165	1.334	1.405	1.766	1.847

The figures are BDS statistics for [AR(p),S] residuals, and standardized residuals $\varepsilon/\sqrt{h}$ from three ARCH-type models. The BDS statistics are evaluated against critical values obtained from Monte Carlo simulation in Adrangi et al. (2001a), Adrangi et al. (2001b), and Adrangi et al. (2004) .

** represents the significance levels of .05.

Table 5: ARCH Dynamics in the Dollar Exchange Rates

	Canadian dollar [h_t]		Swiss franc [h_t]		Japanese yen [h_t]	
constant	1.087**	(3.515)	0.695***	(7.199)	-36.995***	(-25.241)
Perm : q(-1)-c1	0.999***	(11801.982)	0.992***	(592.815)	1.000***	(387587.404)
Perm: ARCH(-1)-GARCH(-1)	0.041***	(9.574)	0.063***	(19.214)	0.025***	(20.027)
Trans: (Arch(-1)-q(-1))	0.065***	(10.261)	-0.010	(-1.386)	0.066***	(13.907)
Trans: GARCH(-1)-q(-1)	0.870***	(57.611)	-0.434***	(49.781)	0.818***	(149.564)
LL(ACGARCH)	-1560.717		-9171.601		-7923.447	

The maximum likelihood estimates are from Asymmetric Component GARCH(1,1) models fitted to the exchange rates of the dollar against the Canadian dollar, Swiss franc, and the Japanese yen series, respectively. Statistics in ( ) are t-values. LL represents the log-likelihood function.
*** represents the significance level of .01.

NOTES