European Research Studies
Vol. II, Iss. (1-4), 1999, pp. 3-14

The Japan Yen Foreign Exchange Volatility Redux; A Dual Relationship

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Abstract

This paper investigates the relationship between real volume data and volatility of the JY/USD exchange rate. We decompose the real volume data in expected and unexpected volume in order to investigate the time series properties and the unexpected/ volume-volatility relationship. There are a number of interesting implications arising from the empirical finding of this work. It seems that the real volume data have different behaviour and the time series properties compared with the wide used proxy of future volume data.

1. Introduction

The unavailability of spot turnover data has, until recently, been an important handicap for research into the microstructure of the foreign exchange market. Instead of 'real' trading volume data, a common used substitute is future's volume data from the Chicago International Monetary Market. Recently, a number of researchers have addressed the empirical aspects of the relation between volume and volatility. In the foreign exchange literature markets this relationship have been examined by Frankel and Froot (1990), Bessembinder and Seguin (1993), Jorion (1994), Chionis and MacDonald (1997). In all previous works, to obtain a representative aggregate measure of volume, the volume of future has been used. However, Dumas (1994) points out that the choice of future's volume from an organized market to measure total volumes of a market, working mostly over the counter, may also induce an omitted-variable problem in the estimation. Another implication arising from the unavailability of the real data is related to the inability of making inferences about the nature and the time series properties of the data generation process of volume.

In this paper a seven-year long time series of daily yen/dollar spot volume is used for the first time to examine the volume-volatility relationship. The work extends previous research along a number of dimensions. Firstly, this analysis investigates the statistical properties of this trading volume series. Secondly, we examine the relationship between volume and volatility. The empirical effects of volume /(un)predictable volume on volatility and the informative content of

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them, is the third component of this work. We find that employing the actual volume data, and decomposing it into expected and unexpected volume, produces a number of interesting issues related to the information content of the two volume components.

2. Previous Theoretical Research

Although in the stock market the volume-volatility issue is an extensively investigated subject, in the foreign exchange literature is still relative new. As a result, the empirical and theoretical research in the foreign exchange market is motivated by the theoretical work implemented in the stock market. Three main categories comprise the basic framework for the volume volatility relationship.

The first category includes the 'mixture of distributions hypothesis' or MDH

[Clark (1973) Epps and Epps (1976) Tauchen and Pitts(1983)]. According to this hypothesis the variance per transaction is monotonically related to the volume of that transaction. Consequently, price changes are sampled from a mixture of normal distributions with either volume per transaction or number of information arrivals acting as a mixing variable. Across to this framework Epps and Epps assume that there is a positive relationship between the extent to which traders disagree when they revise their reservation prices and the absolute value of the change in the market price. In another version, Tauchen and Pitts, by deriving the joint probability distribution of the price changes and trading volume, suggest that the variance of the price changes decreases with the number of traders. The empirical validity of the MDH in the foreign exchange market has been tested by a number of authors. For example, Bessembinder and Seguin (1993) used daily data over the interval May 1982 to March 1990; they partioned the volume into an expected and unexpected component and found that there is a strong positive relation between contemporaneous volume (predictable and unpredictable) and volatility. They also found that the impact of an unanticipated volume shock has a large effect on volatility. The other interesting implications of this line of research is that it suggests an asymmetric relationship between volume and volatility. Jorion (1994) seeks to test the correlation between the trading volume and volatility. The author confirms the positive relationship between unexpected volatility and unexpected volume as predicted by MDH. He also confirms the positive relationship between unexpected risk and expected volume.

The asymmetry information models of Admati and Pfeiderer (1988) and Subrahmanyam (1991)) are included in the second category. These models rely on the three different categories of traders. The informed traders, the discretionary liquidity traders and the non-discretionary traders. Using these models the authors explain the high concentration of trading volume on open and close time of the market. Bollerslev and Domowitz (1993) make an evaluation of the asymetric information model by looking at the behavior of quote arrivals of continuously recorded DM/USD over the period 9/4/90 to 30/06/90. The empirical evidence seems to support the asymmetric information models. However, Hsieh and Kleidon (1994) examined how well the asymmetric models can explain the behaviour of the volatility in the DM/USD market using the data set constructed by Bollerslev and Domowitz. They conclude that their findings are not consistent with the basic theoretical framework.

An additional branch of this literature that we address, concerns the 'noisy trading hypothesis'. This hypothesis stimulates the research of Frankel and Froot (1990). They consider the relationship between heterogeneity (defined as the percentage standard deviation of forecasts across respondents in a weekly survey conducted by Money Market Services (MMS) international), volatility (which is defined as the squared percentage of the 15-minute changes in the future price, averaged over the week) and trading volume (which is measured by the weekly number of future contacts traded on the International Monetary Market exchange (IMM)). Prior to this Grammatikos and Saunders (1986) analyzed foreign currency futures contracts and found that detrended volume is positively related to volatility. They also find evidence of bidirectional causality: volume appears to Granger-cause volatility and vice-versa.

Chionis and MacDonald (1997) examine a number of hypotheses stemming from the market microstructure literature. In particular, they use a disaggregate survey data base, consisting of the foreign exchange expectations of over 150 forecasters, to construct both aggregate and disaggregate measures of dispersion. These measures are then used to examine the relationship between volatility, volume and heterogeneity. They found strong evidence of Granger causality among volume, volatility and hetrogeneity. GARCH modelling techniques are also employed to test a set of hypotheses relating to the conditional volatility of exchange rate returns.

The real volume data for the JY have been previously used by Hartmann (1996). The author, in an attempt to estimate the determinants of USD/JY bid-ask spreads, has shown that unpredictable foreign exchange turnover (a measure of the rate of information arrival) increases spreads, while predictable turnover decreases them. Another important piece of evidence which arises from this research is the conditional heteroskedasticity documented into unpredictable spot volume data.

3. Description of the data and tests of market microstructure hypotheses.

The trading volume data set is provided by Nihon Keizai Shimbun Europe Ltd. The period covered is from 1 September 1988 to 1 March 1998 on a daily basis. These data reflects the sum of all transactions conducted by all foreign exchange brokers in Tokyo during the opening time. This sum can be expected to cover a considerable part of global dollar/yen spot foreign exchange turnover.

Before any hypothesis and tests, we must examine the stationarity properties of the volume (v) data series. To do so, we use the ADF test statistics since they are considered the most appropriate to deal with the autoregressive structure. In table 1 we present the appropriate values of the DF and ADF tests. According to these results we can reject the null hypothesis of a unit root . So we may apply time series models based on the assumption of stationarity. In addition, however, for the volume data the time trend seems statistically significant. Table 2a,b presents the autocorrelation coefficients and summary statistics of the series. Our volume data are highly serially correlated and this has been frequently documented, indicating that volume is highly forecastable (see Jorion (1994))

The main aim of this work is to examine whether the 'real' volume data have different time series properties compared to the future proxy used by the others and whether the trading volume components convey any information. The existing theoretical analyses of volume and volatility does not distinguish between anticipated and unanticipated components of volume. To this end, in addition to the volume series (v), we test the information content of the two components of volume using a range of tests and statistics. We decompose the volume series in two components one expected (exv) and one unexpected (unv). To measure expected volume the trend model is estimated simultaneously with an ARMA process:

$$\log(V_t) = \alpha + \beta t + \varepsilon_t\,,\ \varepsilon_t = \phi_1\, \varepsilon_{t-1} + \phi_2\, \varepsilon_{t-2} + \theta_1\, u_{t-1} + u_t \qquad (1)$$

An ARMA (2, 1) process appears to provide a parsimonious fit since upper order terms are not significant. The time series model allows us to to decompose the volume into an expected component E_t [log (V_{t+1})] and an error process ε_t. Estimates of the ARMA process are presented in Table 3. The ARMA coefficients are highly statistically significant, as is the time trend coefficient.

Initially, we test for cross correlation between unv/ exv, v and volatility. More specifically, we test for the positive correlation, as predicted by the MDH, between unexpected volume and volatility. Surprisingly, the results (see table 4) do not suggest highly positive cross correlation between any volume series and volatility. This is in contrast with the results derived by previous researcher for the foreign exchange market.

Further illumination of the relationship between the v, and the volume components, and volatility can be obtained by implementing Granger-causality tests. The Granger procedure is chosen because it has the *advantage* of offering a powerful, yet simple, way of testing causality. We start by estimating bivariate relationships of the following:

$$svol_t = \sum_{i=1}^{p} \alpha_i svol_{t-i} + \sum_{i=1}^{p} \beta_i volu_{t-i} + \varepsilon_t\,, \qquad (2)$$

and

$$volu_t = \sum_{i=1}^{p} \alpha_i volu_{t-i} + \sum_{i=1}^{p} \beta_i vol_{t-i} + \varepsilon_t, \qquad (3)$$

where svolt denotes exchange rate volatility, volut denotes volume and εt denotes a random error term. volt is deemed to Granger-cause volut if the sum of the svol lags are jointly significant in (3) and the sum of the svol lags are jointly zero in (2). Bi-directional causality occurs when the sum of the lags on svolt or volut are jointly significant in (2) and (3). In testing the joint significance of the lagged terms it is standard practice to use a conventional F-statistic. Here, because of the evident heteroscedastic nature of the disturbances in (2) and (3) we use linear Wald test statistics which incorporate a White-Hansen correction for heteroscedasticity. That is, the coefficient variance-covariance matrix has the following form:

$$(\mathbf{X'X})^{-1}\mathrm{mcov}(\mathbf{X},\mathbf{u})(\mathbf{X'X})^{-1}$$

where mcov(**X**,**u**) refers to the following matrix

$$\sum_{K=-L}^{L} \sum_{T} \mathbf{u}_t \mathbf{X'}_t \mathbf{X}_{t\text{-}K} \mathbf{u}_{t\text{-}K}$$

and the methods of Newey and West (1987) have been used to ensure that the matrix is positive-definite.

Our Granger-causality results for testing the relationship between the two components of volume and volatility are presented in Table 5. The lag length ensures residual whitness. We also experimented with parsimonious versions of these general VAR systems and the results were qualitatively very similar to those with the general lag structure and are therefore not reported here. Table 5 should be read in the following way. The information contained in the column labeled causality indicates the direction of causality tested. The numbers not in brackets in the column headed Chi-squ. is a linear Wald test, robust to conditional heteroscedasticity, which tests the joint significance of the causal variable indicated in the Causality column; marginal significance levels are contained in parenthesis under the statistics. The numbers not in parenthesis in the Q column are Ljung-Box portmanteau statistics for residual correlation and have a marginal significance level noted in brackets. The results are quite striking in the sense that volume and the volume components do not Granger-cause volatility at any level of significance. Interestingly, there is very clear evidence of reverse causality from volatility to unexpected volume and volume. This finding support our previous results that apart from heterogeneity, volatility is the driving force in the foreign exchange market .

Our findings that there is no causality running either from the volume series or from any of the two volume components, to volatility are quite striking. Frankel and Froot and Grammatikos and Saunders found evidence of bidirectional Granger-causality between volume and volatility while Chionis and MacDonald examined the volume-volatility relationship for JY DM and BP and detected in only one instance Granger-causality. Consequently, the existing findings contrast markedly with previous research, providing new information about the volume-volatility relationship.

4. Testing the Informative contents of Volume

In this section we examine the information properties of the volume series. This part emanates from the work of Lamoureux and Lastrapes (1990) who implemented the test using stock market data. The authors used volume as a proxy for information arrival and they showed that this proxy has significant explanatory power regarding the conditional variance of daily returns. In particular, for a sample of 20 US common stock returns, they find that ARCH effects vanish when volume is included as an explanatory variable in the conditional variance equation. Across to the same line of research, Gannon (1994), and Lamoureux and Lastrapes (1994) (in the stock market) find that the ARCH effects disappear when volume is also employed as a proxy for information, and consequently the conditional variance can be used as a proxy instead of volume. Conversely, Bessembinder and Seguin (1992, 1993) and Lamoureux and Lastrapes (1994) show that volume is not sufficient to remove the ARCH effects in variance. Consequently, whether volume adequately explains the information found in volatility, or whether conditional variance effects can be partly or fully explained by an ARCH model, is not completely settled. Across to the same line Chionis and MacDonald enter the future volume's contracts into the conditional volatility equation. In contrast to the Lamoureux and Lastrapes the coefficients of the lagged variance and errors remain statistically significant and has the same values while the coefficient of volume does not. The results are highly suggestive that the lagged variance and residuals are the key contributory factors to the estimation of the conditional variance, even when the additional information about the volume of the foreign exchange market is included. The incorporation of the synthetic-volume data in the equation of the conditional variance of the GARCH(1,1) process does not affect the significance of the GARCH coefficients.

In the following, we fit an ARCH(1) and a GARCH (1,1) in which the conditional mean is first formulated as an ARIMA process and then the conditional variance of exchange rate changes is estimated as an ARCH /GARCH process. Relying on our previous work, we retain the assumption that the conditional mean is modelled as a random walk process. We approximate the percentage nominal return on JY, obtained from dates t-1 to t as

$$A_t = 100[\log s_{it} - \log s_{it-1}].$$

The conditional mean equation has the form[1]:

$$A_t = \mu + \varepsilon_t \,, \tag{4a}$$

and the conditional variance takes the form for GARCH (1,1)

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \sigma_{t-1}^2 \,, \tag{4b}$$

or for ARCH (1)

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + a_3 (un)\exp.volume$$

and

$$\varepsilon_t / \Psi_{t-1} \sim N(0, \sigma_t^2), \quad t = 1, \qquad 2 \ldots T \,. \tag{4c}$$

where Ψ_{t-1}, denotes the time t-1 information set and μ, a_0 , a_1 , and a_2 and a_3 are parameters to be estimated.

Table 6,7 reports Full Information Maximum Likelihood estimates using the Berndt, Hall, Hall, and Hausman (1974) (BHHH) algorithm. Engle (1982) shows that the efficiency of Maximum-Likelihood estimation relative to least-

1 For test checking the adequacy of the model see Chionis and MacDonald (1997).

squares is positive and may be very large, so we apply the former, using the latter only to provide starting values for the estimated parameters. Given the severe kurtosis and heteroskedasticity present in the data, conventional standard errors will have questionable value (Bollerslev and Wooldrige 1992). However, Baillie and Bollerslev (1990) have shown that in the present model with heteroskedastic errors suitable robust standard errors may be obtained using the correction of White(1982),[2] and these are used in the present application. According to the robust standard errors, we find a positive and significant coefficient for ARCH (1) and GARCH(1,1), suggesting a strong conditional heteroskedastic effects. The positive and significant conditional heteroskedastic terms indicates also the well documented property of many financial series that 'news' clusters in time.

A measure of the persistence of variance as measured by GARCH is the sum of (a_1+a_2). for the variable to be stationarity the restrictions $(a_1+a_2)<1$ must hold. If the parameters in the conditional variance are positive and also $(a_1+a_2)>1$, then the shocks to volatility persist over time. The degree of persistence is determined by the magnitude of these parameters. As can be seen from Tables 5, 6 the degree of persistence is positive and less than one and this finding is consistent with the other research on the foreign exchange market (see, Baillie and Bollerslev (1990), Bollerslev and Domowitz (1993), Bollerslev and Melvin (1994), Jorion (1995)).

The informative power predicted and unpredicted volume may also be tested by entering the volume data into the conditional variance equation. If volume conveys information and the news comes in clusters then the conditional variance of returns will be an increasing function of the number of information arrivals (unexpected volume). We re-estimate the (G)ARCH models with lagged v, exv, or unv included. The (G)ARCH coefficients remain significant and the volume components are all statistically significant, indicating that in the JY market the participants use both volume and volatility to extrapolate information. The most interesting finding arises from the different signs associated with the expected and unexpected volume. The expected volume seems to influence negatively the conditional variance. On the contrary the unexpected volume enters with a positive sign into the conditional variance equation. This finding is in accordance with the findings of Bessembinder and Senguin (1992) and Jorion (1994) who suggest a positive relationship between unexpected volume and conditional variance. One explanation is that the higher unexpected trading volume reveals higher heterogeneity and this is associated with greater variance in price volatility. As regards the sign of the expected volume, this is predicted by the model of Tauchen and Pitts. This model predicts that the variance of the price volatility decreases with the number of traders. Without loss of generality, we can assume that there is a fixed number of participants in the foreign exchange market ; then the number of traders is associated with the expected volume. In this case the expected volume seems to wash-out the interagent differences.

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[2] Following White, asymptotic standard errors for the parameters in the conditional mean and variance functions that are robust to departures from normality have also been derived by Weiss (1984,1985).

In our previous work we argued that an explanation of the effect that volume effects do not appear to be statistically strong could be due to the use of futures volume from Chicago IMM as a proxy for global spot volumes in the currencies considered. Although the cross correlation between the real and proxy data is very high (see table 5), the findings of the present work confirm our concern about the use of the futures volume as proxy for the real volume data. In sum , the evidence indicates that the real volume data have significant effects upon the conditional variance.

5. Conclusions

Despite the impressive role of volume in financial research, its use in the foreign exchange literature the research is limited. In Japan the availability of JY volume data allowed us to investigate both the time series properties of the particular series and to shed more light on the volume- volatility relationship. There are a number of interesting implications arising from the empirical finding of this work.

Considering the results derived in the first part we can say that the real volume data, unlike the future's volume proxy, is a mean reverting process with significant trend and highly serially correlated. Granger-causality tests cannot detect any significant causation running from volume to volatility (although there is strong evidence supporting the causation from volatility to volume). If volatility is strictly exogeneous with respect to volume, then this can be interpreted as evidence on the structural modelling between two variables, formulating functions who explain volume in terms of volatility changes.

However, we noted a striking finding for the relationship between volume and conditional volatility. In particular, it is provided empirical support for the hypothesis that the conditional heteroskecastic model is dependent on the daily time dependence in the rate of information arrival to the market of the JY. The question of whether or not market activity affects volatility is of particular interest given the theoretical results of MDH. In contrast to the results for the stock market, we find that the conditional variance coefficients do not disappear when volume is included in the variance equation. This suggests that price volatility and volume share the variation in the information flow variable. In the present study apart from the expected volume, the unexpected volume seem to be used by the participants in the JY market as a proxy for information arrival. But the informative contents of unexpected volume, differently affects the conditional variance. This study also contains a worrisome finding for those who consider that the future volume adequately proxies real volume data.

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Table 1: *Volume Unit Root Test*

ADF(12)	-4.45
ADF(10),trend	-5.150

Into parentheses the lag length for white noise residuals

Table 2a: *Autocorrelation coefficients (significance level)*

Number of lags	Q
5	1677 (0.000)
10	2527 (0.000)
20	3784 (0.000)
50	5793 (0.000)
100	8501 (0.000)
401	10897 (0.000)

Table 2b: *Statistics*

mean	1.794
variance	0.0400
Skewness	-0.342
Sig.Level (Sk=0)	0
Kurtosis	0.412
Sig.Level (k=0)	0.0007

Table 3: *Modelling Volume*

$V=a+bt+u_t \; u_t=\phi_1 u_{t-1}+\phi_2 u_{t-2}+\theta_1 \varepsilon_{t-1}+\varepsilon_t$

con	time	ϕ_1	ϕ_2	θ_1	R^2
1.89* (0.009)	-0.0001* (0.00001)				0.98
	0.83	1.126* (0.04)	-0.168 (0.036)	-0.782* (0.034)	

Table 4: *Cross Correlation*

	v/vol	unv/vol	exv/vol	proxy/real
Q (1-50)	56.582	65.225	72.806	78.9670
	(0.242)	(0.0727)	(0.0192)	(0.000)
Q (1-100)	102.6918	107.4707	105.6668	3322.5478
	(0.406)	(0.286)	(0.329)	(0.000)
Q(1-150)	142.9260	149.1233	139.5661	4421.5515
	(0.646)	(0.504)	(0.718)	(0.000)
Q(1-250)	278.3263	278.1765	259.4325	4729.1707
	(0.105)	(0.106)	(0.327)	(0.000)
Q(1-401)	520.898	430.505	461.6986	4947.976
	(0.000)	(0.141)	(0.0193)	(0.000)

Table 5: *Volume and Volatility*
Table: Granger-causality results

Causality	Chi-squ.	Q
Vol /→Volatility	27.79	19.00
	(0.317)	(0.991)
Volatility →Vol	39.28	20.57
	(0.034)	(0.98)
Exp.Vol /→ Volatility	27.32	20.49
	(0.339)	(0.98)
Unex Vol /→ Volatility	30.06	19.3
	(0.221)	(0.983)
Volatility → Exp.Vol	38.03	17.96
	(0.008)	(0.99)
Volatility→Unex Vol	37.78	19.5
	(0.009)	(0.99)

Notes. For variable definitions see Table 1. The figures not in brackets in the column Chi-square are linear Wald statistics testing the direction of Granger causality noted in the columns labeled ‘Causality’, while the numbers in brackets are the corresponding marginal significance levels The figures not in brackets in the columns labeled ‘Q’ are Ljung-Box statistics for no serial correlation in the VAR while the numbers in parenthesis are the corresponding marginal significance levels.

Table 6 : *ARCH (1)* Models*

	ARCH(1,)	ARCH(1),expV	ARCH(1)uneV	ARCH(1)V
μ	- 0.007*	-0.0096	-0.0075	-0.007
	(0.003)	(0.007)	(0.007)	(0.007)
a_0	0.741*	0.073*	0.074*	-0.038*
	(0.002)	(0.004)	(0.002)	(0.0138)
a_1	0.111*	0.121	0.115*	0.0997
	(0.015)	(0.017)	(0.015)	(0.0586)
a_2		-0.027*	0.024*	0.0628*
		(0.0088)	(0.01)	(0.009)
F. Value	1203	1605	1605	1221
$(a_1 + a_2)$		0.094	0.091	0.159

Table 7 : *GARCH (1,1)* Models*

	GARCH(1,1)	GARCH(1,1), expV	GARCH(1,1), unex.V	GARCH(1,1), Volume
μ	- 0.007	-0.0111	-0.008	-0.008
	(0.007)	(0.006)	(0.008)	(0.006)
a_0	0.004*	0.004*	0.0038*	-0.0153*
	(0.0032)	(0.0009)	(0.001)	(0.004)
a_1	0.105*	0.108*	0.0738*	0.07*
	(0.046)	(0.012)	(0.03)	(0.012)
a_2	0.841*	0.837*	0.879*	0.847*
	(0.075)	(0.017)	(0.03)	(0.0162)
a_3		-0.013*	0.0173*	0.016*
		(0.001)	(0.008)	(0.004)
F. Value	1605	1605	1250	1605
$(a_1 + a_2 + a_3)$		0.932	0.973	0.933

Notes. t-statistics are in parentheses. * The parameters remain unchanged by using MA(1)-GARCH(1.1), or MA(1)-I-GARCH(1.1)