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RETURN, TRADING VOLUME, AND MARKET DEPTH IN CURRENCY FUTURES MARKETS

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HKIMR Working Paper No.20/2008

October 2008

Return, Trading Volume, and Market Depth in Currency Futures Markets

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October 2008

Abstract

We use a class of stochastic volatility models with multiple latent factors to investigate the joint dynamics of return, trading volume, and open interest (a proxy for market depth) in currency futures markets. In accordance with theory, the empirical evidence indicates that there is more than one latent factor affecting these three variables. However, the evidence is ambivalent on the choice between two- and three-latent-factor models. These three variables also display different patterns of information spillovers across currency futures.

Keywords: Stochastic Volatility Model, Multiple Latent Factors, Model Comparison, Volatility Spillovers
JEL Classification: C32, F31

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* Acknowledgments: Both Cheng and Cheung acknowledge the financial support of faculty research funds of the University of California at Santa Cruz.

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1. Introduction

In this study, we investigate the interactions between return, trading volume, and market depth in three currency futures markets. Theoretically, return, trading volume, and market depth are jointly determined by information flows to the market. An empirical model that considers just one or two of these three variables is at least inefficient, if not misspecified. Most of the existing empirical studies, however, consider only the return dynamics or the return and trading volume interactions.[1]

The theoretical models that illustrate the links between return, trading volume, and market depth include the sequential information arrival models (Copeland, 1976; Jennings, Starks and Fellingham, 1981), the mixture of distributions models (Clark, 1973; Epps and Epps, 1976; Tauchen and Pitts, 1983; Andersen, 1996), and the trading models developed by Kyle (1985) and Admati and Pfleiderer (1988).[2] A common theme of these models is that, depending on model structures, these variables can respond differently to information flows to the market.

It is conceivable that the currency futures market is affected by different types of information. For instance, there is private and public information about the exchange rate under consideration. In the context of exchange rates, Lyons (2001) lists three types of information that are relevant for trading. Information about payoffs of holding the foreign exchange is the first type. The second type is discount-rate information related to inventory effects, which can be viewed as short-run information. The third type is discount-rate information related to portfolio balance effects that have a more long-lasting impact than inventory effects. Return, trading volume, and market depth can be influenced by these types of information differently.

Against the backdrop of the possibility that there are different types of information, we would like to adopt an empirical specification that allows for several information variables in modeling the joint behavior of return, trading volume, and market depth. Another challenge is the paucity of data on the relevant information variables. Some variables including the number of traders and order flow convey useful market information (Tauchen and Pitts, 1983; Lyons, 2001). Unfortunately we do not have these data. In the current study, we adopt a stochastic volatility model specification that can be derived from the mixture of distributions framework.

One advantage of using a stochastic volatility model is that the observables are assumed to be subordinated to some latent variables, which can be interpreted as the unobservable information variables. The model can be easily set up to accommodate differential effects of different types of information. In

1 Karpoff (1987) reviews early empirical studies on return and trading volume. More recent studies include Andersen (1996) and Gallant, Rossi and Tauchen (1992). The performance of some bivariate (mixture) models is evaluated by, for example, Liesenfeld (2001) and Watanabe (2000). Bessembinder and Seguin (1993) and Fung and Patterson (2001), for example, consider the interactions between return, trading volume, and market depth. Other related studies include Elyasiani, Kocagil and Mansur (2007), Fung and Patterson (1999), Lien and Yang (2006), and Nikolaou and Sarno (2006).

2 See, also, for example, Shleifer, de Long, Summers and Waldmann (1990), Lakonishok and Smidt (1989), and Chen, Cuny and Haugen (1995).

general, the latent variable approach offers a flexible way to model unobservable market information. The approach has a well known limitation – we do not know the precise nature of information being captured by the latent variable. Nonetheless, we can infer, say, whether a latent variable tends to display a transitory or persistent effect.

Another advantage is that the stochastic volatility model is not subject to some problems affecting other estimation procedures. For instance, the generalized autoregressive conditional heteroskedasticity (GARCH) framework is not considered. It is because if return, trading volume, and open interest (a proxy for market depth) are jointly determined, then estimating a trading-volume-and-open-interest augmented GARCH model can lead to simultaneity bias and inappropriate inferences.[3] On the other hand, a properly specified stochastic volatility model does not have simultaneity bias.

Besides shedding some light on the information effects on return, trading volume, and market depth, the estimated latent variables offer an opportunity to examine the flows of different types of information and the pattern of volatility spillovers. Volatility spillover is traditionally examined using the GARCH framework. Since the stochastic volatility model is an appropriate specification in the present case, the resulting observed volatility spillover should offer some good insights on inter-market information flows. To be fair, we should point out the informational interpretation of latent variables is mainly an empirical one. That is, we should be cautious and should not over-interpret the results.

To anticipate the results, it is found that the model estimates are broadly supportive of the theory. The return, trading volume, and market depth are affected by more than one latent factor. However, the choice between two- and three-latent-factor models is not clear-cut. The three variables respond differently to the latent variables. The results on volatility spillovers suggest that the information affecting return and trading volume flows from a more active market to a less active one and there are feedback interactions between open interests in different markets.

2. Data

We consider daily data on returns, trading volumes, and open interests of the British pound, Canadian dollar, and Japanese yen currency futures contracts traded in the Chicago Mercantile Exchange. We consider currency futures mainly because of the prominent role of foreign exchanges in the global economy. The futures trading activity is relatively low before the 1990s. Thus, we work with the sample from January 1990 to December 2004.[4]

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3 Lamoureux and Lastrapes (1990) is a study that added trading volume to GARCH models. See Fleming Kirby and Ostdiek (2005, 2006) for an alternative view on the interactions between trading volume and volatility persistence.

4 The data were purchased directly from the Prophet Financial Systems, Inc.

In this exercise, we follow the literature and use open interest as a proxy for market depth. The variable also represents the amount of capital committed to investments in futures and, hence, is affected by information on the payoffs and on risk (Bessembinder and Seguin, 1993). It is noted that a high (low) level of trading volume does not necessarily lead to a high (low) open interest. Indeed, the open interest is related to the net buying/selling activity and trading volume is a measure of gross trading activity.

Excluding the euro futures, the British pound, Canadian dollar, and Japanese yen contracts are the most actively traded contracts in the Chicago Mercantile Exchange. The euro currency futures contract is not included because of its relatively short trading history. These data are expressed in logarithmic terms. The futures return series was compiled from individual contracts using the "roll on volume" approach. That is, the data on the *front* month (nearby) contract – the contract that is expiring next, is used to construct the series until its trading volume is overtaken by the next contract out. At that point of time, the data of the next contract are used – that is, the data roll to the next contract out. The rationale for the rollover scheme is to ensure that data are from the most actively traded contract.[5]

The returns on futures are considered because the prices were found to be I(1) series. For trading volume and open interest, they are characterized by an I(1) process with day-of-the-week effects. Thus, we removed both the stochastic trend and day-of-the-week effects from these two data series. Henceforth, trading volume and open interest refer to the transformed data rather than raw data themselves. The unit root test results are available upon request.

Table 1 presents some descriptive statistics. As expected, the means of these variables are quite close to zero. The standard errors show that data on returns and trading volumes have comparable levels of (unconditional) volatility. The volatility of the open interest, however, is much lower than the other two variables. While there are both positive and negative skewness coefficients, the kurtosis coefficients show that, compared with a normal variable, these three variables have a relatively high concentration around the mean and more extreme realizations – an empirical fact commonly reported in the literature.

The sample autocorrelation coefficients of the squared variables, which are the focus of the subsequent analyses, are presented in the lower panel of Table 1. Compared with the other two variables, the squared return data display a more persistent autocorrelation pattern. Both British pound and Canadian dollar futures have their autocorrelation estimates in the order of 0.1 while the Japanese yen futures see their autocorrelation decrease monotonically with the lag order. In contrast, the autocorrelation of squared trading volumes drops off quite quickly after the first lag. On the squared open interest, only the Canadian dollar futures have a large first order coefficient. The autocorrelation patterns are suggestive of different driving forces underlying these variables.

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5 Another popular method to compile a historical futures return series is to switch from the front month contract to the next contract out at the first trading day of the expiration month of the front month contract.

3. Models and Estimation Results

Since its introduction in the 1980s, the class of stochastic volatility models has gradually established its popularity in financial econometrics – see, for example, Shephard (2005) for a comprehensive introduction. The recent emergence of computing-intensive simulation-based and numerical methods amid the drastic increase in computing power spurs considerable interest in estimating stochastic volatility models.

In this exercise, we use the simulation-based Monte Carlo Markov Chain (MCMC) method to estimate stochastic volatility models.[6] One attractive feature of the MCMC method is that it offers a unified framework to a) estimate parameter coefficients, b) conduct inferences, and c) estimate latent variables and, hence, unobservable volatilities. Further, MCMC allows inferences to be drawn from finite-sample distributions rather than from asymptotic distributions. The MCMC algorithm used in the current study is described in Cheng and Cheung (2006).

3.1 A Two-Latent-Factor Model for Return, Trading Volume, and Open Interest

According to theoretical models, the dynamics of return, trading volume, and open interest are driven by several types of information. Thus, we start with a trivariate stochastic volatility model with two latent factors. The results pertaining to univariate and trivariate models with one latent factor are reported in Cheng and Cheung (2006). Let r_t, v_t, and o_t be the generic notations for currency futures return, trading volume and open interest at time t. A trivariate stochastic volatility model with two latent factors can be written as:

$$r_t = \mu_0 + \mu_1 r_{t-1} + \sigma_r \exp(a_{r1}h_{1t} + a_{r2}h_{2t})(\sqrt{1-\rho_1^2-\rho_2^2}\,\varepsilon_{rt} + \rho_1\varepsilon_{1t} + \rho_2\varepsilon_{2t}) \tag{1}$$

$$v_t = \sigma_v \exp(a_{v1}h_{1t} + a_{v2}h_{2t})\varepsilon_{vt}$$

$$o_t = \sigma_0 \exp(a_{01}h_{1t} + a_{02}h_{2t})\varepsilon_{ot}$$

$$h_{jt} = \phi_j h_{j,t-1} + \sqrt{1-\phi_j^2}\,\varepsilon_{jt}\,;\, j = 1,\, 2, \text{ and}$$

$$\varepsilon_{jt} \sim iid\ N(0,1)\,;\, j = r,\, v,\, o,\, 1,\, 2$$

The lagged return r_{t-1} is included to capture autocorrelation of returns on currency futures. The h_{jt}'s are the latent factors driving the evolution of the unobservable volatilities. The coefficients a_{jk}; $j = r, v$, and o, and $k = 1$ and 2 capture the strengths of latent factors on the volatilities. $(\sqrt{1-\rho_1^2-\rho_2^2}\,\varepsilon_{rt} + \rho_1\varepsilon_{1t} + \rho_2\varepsilon_{2t})$ is a composite error term that represents innovations in r_t. The contemporaneous correlations between shocks to latent factors and currency futures returns are incorporated in the specification via ρ_1 and ρ_2. The scale parameters σ_r, σ_v, 25 and σ_o are included in place of a constant in the h_{jt} equations. The persistence of a latent factor is measured by ϕ_j. The terms $\sqrt{1-\phi_j^2}$; j = 1 and 2 are included so that (1) is identifiable.

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6 Jacquier, Polson and Rossi (1994) demonstrate the superior performance of the MCMC approach. Andersen (1994, footnote 6) offers an alternative view. Ghysels, Harvey and Renault (1996) and Jacquier, Polson and Rossi (2004) describe other estimation methods.

During the pilot analysis, the terms $\mu_v \exp(h_{j,t})$ and $\mu_o \exp(h_{j,t})$ were included in the trading volume and open interest equations. However, in all instances, the two terms were insignificant and, hence, were dropped from the exercise. It is noted that (1) does not pre-designate the links between the latent factors and the three variables r_t, v_t and o_t. Instead, the model allows the data to reveal the individual effects of each latent factor through the parameters a_{jk}'s. The results of estimating (1) are reported in Table 2.

The coefficient estimates associated with the latent factors are mostly significant. The result supports the notion that there is more than one type of information affecting the three variables. Interestingly, for all these currency futures contracts, there is one persistent latent factor and one transitory latent factor. The persistent one is characterized by a value of ϕ-estimate larger than 0.93 and the transitory one has a value of ϕ-estimate that ranges around 0.25. Thus, the two latent factors correspond to two types of information; one has a short-term impact and one has a long-term effect on these three variables.

The a_{jk} estimates are in accordance with the postulation that the latent factors have different impacts on return, trading volume, and open interest dynamics. For the British pound and Japanese yen data, the return volatility is mainly driven by the transitory latent factor. On the other hand, their trading volume and open interest volatilities depend on both latent factors.

The Canadian dollar, on the other hand, displays a slightly different dependence pattern. While both latent factors contribute to return volatility, only the transient latent factor affects the volatilities of trading volume and open interest. Indeed, we acknowledge that the behavior of Canadian data is different from the other two currencies in some of the subsequent analyses. While it is beyond the scope of the current study, we note that the economic tie between the US and Canada is much stronger than the ties between the US and the other two countries. A close economic tie can lead to exchange rate behavior that is different from others. However, such an explanation is quite speculative in nature and requires further evidence to substantiate it.

The return autocorrelation captured by the μ_1 coefficient is significant for the British pound and Japanese yen but insignificant for the Canadian dollar. The significant estimates have a negative sign and are quite small in absolute value; indicating a weak mean reverting behavior. The result is in accordance with the usual weak autocorrelation found in returns on currency futures. It is also noted that both the means and the standard errors implied by the estimated models are quite comparable to those calculated directly from the data.

The contemporaneous correlation between shocks to the two latent factors and currency futures returns is weak. Indeed, among the six ρ_j-estimates, only two are significantly different from zero. The two significant estimates have a magnitude around 0.06 – one is negative for Canadian dollar and one is positive for Japanese yen. The weak correlation result is in accordance with those reported for currencies but is in contrast to those for stock market data.

3.2 A Three-Latent-Factor Model

Results reported in the previous subsection attest to the presence of different types of market information and they have different impacts on return, trading volume, and open interest dynamics. Apparently, there is no *a priori* reason to restrict the number of latent factors to two, and there is a possibility that one can identify three latent factors from a system containing three observed variables. To explore such a possibility, we consider the following specification

$$\begin{gathered} r_t = \mu_0 + \mu_1 r_{t-1} \\ +\sigma_r \exp(a_{r1}h_{1t} + a_{r2}h_{2t} + a_{r3}h_{3t})(\sqrt{1-\rho_1^2-\rho_2^2-\rho_3^2}\,\varepsilon_{rt} + \rho_1\varepsilon_{1t} + \rho_2\varepsilon_{2t} + \rho_3\varepsilon_{3t}) \\ v_t = \sigma_v \exp(a_{v1}h_{1t} + a_{v2}h_{2t} + a_{v3}h_{3t})\varepsilon_{vt} \\ o_t = \sigma_0 \exp(a_{01}h_{1t} + a_{02}h_{2t} + a_{03}h_{3t})\varepsilon_{ot} \\ h_{jt} = \phi_j h_{j,t-1} + \sqrt{1-\phi_j^2}\,\varepsilon_{jt}\,;\, j = 1,\, 2,\, 3, \text{ and} \\ \varepsilon_{jt} \sim iid\ N(0,1)\,;\, j = r,\, v,\, o,\, 1,\, 2, \text{ and } 3 \end{gathered} \tag{2}$$

Specification (2) is an extension of (1) and represents a structure for which the data determine the interactions between latent factors and observed dynamics.

The results of estimating (2) are presented in Table 3. The estimated h_{jt} equations are indicative of the presence of three latent factors. The British pound and Japanese yen data have two persistent latent variables with ϕ_j estimates ranging from 0.80 to 0.95, and one less persistent latent factor with ϕ_j estimates equal 0.20 and 0.23. The Canadian dollar data, on the other hand, have one persistent latent factor with a 0.94 ϕ_j estimate and two less persistent latent factors with ϕ_j estimates equal to 0.16 and 0.25.

Again, the three latent factors have different impacts on return volatility, trading volume, and open interest. The return volatility of each currency futures series is affected by, at least, one persistent and one transitory latent factor. That is, the market information affecting return volatility may have a long lasting or a transient effect on return volatility. It is conceived that by reducing the number of variables or the number of latent factors, the resulting restricted model can reveal volatility patterns different from the general model (2). Indeed, in fitting a univariate stochastic volatility model with one latent factor to return data, we picked up the persistent latent factor. However, with a trivariate model with one latent factor, the transitory component shows up prominently.[7]

While the British pound and Japanese trading volume volatilities are mainly influenced by a persistent latent factor, the Canadian dollar trading volume volatility is affected only by transitory factors. Also, the persistent latent factor affecting trading volume is not the same as the one affecting return volatility. Apparently, different types of market information drive the persistent components of return and trading volume volatilities.

7 These results are given in Cheng and Cheung (2006).

The a_{oj} estimates in the open interest equations suggest that the open interest volatility is affected by both persistent and transitory latent factors. The open interest is a proxy for market depth. At the same time, open interest represents the amount of capital that traders are willing to invest in the risky futures market. The amount of committed capital depends on the level of risk in the futures market, which is captured by return volatility. Thus, we expect that information driving return volatility has implications for open interest. Indeed, the two latent factors affecting open interest also influence return volatility. It is also noted that, relative to return volatility, open interest volatility is more responsive to the less persistent latent factor.

In sum, the results are broadly consistent with the notion that there are different types of market information driving return, trading volume, and open interest dynamics. The three latent factors that are proxies of information variables exert different effects on these three variables, and their effects also appear to vary across currency futures.

The return autocorrelation captured by the μ_1 coefficient, again, is quite small and significant in two out of three cases. The contemporaneous correlations between shocks to the latent factors and currency futures returns remain weak. Among the nine ρ_j-estimates, only one of the Japanese estimates is significantly different from zero and the others are insignificant.

3.3 Comparison of Performance

While the estimation results are supportive of a trivariate model with multiple latent factors, not all of the coefficient estimates in Table 3 are significant. A natural question to ask is: Does the three-latent-factor model offer a better explanatory power than, say, the two-latent-factor model?

To compare the performance of stochastic volatility models, we consider the abilities of these models to describe the volatilities of return, trading volume, and open interest. For instance, in assessing the ability of a given model in explaining return volatility, we consider the ratio:

$$\Sigma_t (\tilde{r}_t^2 - h_{r,t|t}^2)^2 / \Sigma_t (\tilde{r}_t^2 - \bar{\tilde{r}}^2)^2 \tag{3}$$

where $\tilde{r}_t$ is r_t adjusted for the conditional mean, $h_{r,t|t}^2$ is the filtered volatility of $\tilde{r}_t$, and $\bar{\tilde{r}}^2$ is the sample mean of $\tilde{r}_t^2$.

The ratio measures the discrepancy between $\tilde{r}_t^2$ and its predictor $h_{r,t|t}^2$ relative to the variability of $\tilde{r}_t^2$. A small ratio (3) implies good explanatory power. The filtered volatility $h_{r,t|t}^2$ is generated with observations up to time t. An alternative measure is the smoothed volatility $h_{r,t|T}^2$ that is derived from all the observations. The corresponding evaluation ratio is

$$\Sigma_t (\tilde{r}_t^2 - h_{r,t|T}^2)^2 / \Sigma_t (\tilde{r}_t^2 - \bar{\tilde{r}}^2)^2 \tag{4}$$

The two volatilities were constructed with the estimates reported in Tables 2 and 3 using the MCMC particle filter method (Zhai and Yeary, 2004).

Similarly, the performance of these models in explaining trading volume and open interest volatilities can be evaluated using (3) and (4) with the return variables replaced by the corresponding trading volume and open interest variables v_t^2, $h^2_{v,t|t}$, $h^2_{v,t|T}$, o_t^2, $h^2_{o,t|t}$, and $h^2_{o,t|T}$.

The evaluation ratios are reported in Table 4. For completeness, we also include the one-factor model in the comparison exercise. Panel A and Panel B give the ratios based on filtered and smoothed volatilities, respectively.

Using the filtered volatility, the British pound trading volume and open interest ratios attain the smallest values under the three-latent-factor model. The return volatility ratio, on the other hand, achieves the smallest value under the two-latent-factor specification. For the Canadian dollar data, the two-latent-factor model is the best for return volatility and trading volume, and the one-factor model is the best for return volatility.[8] The three-latent-factor model yields the smallest ratios for Japanese yen return and open interest volatilities, and the two-latent-factor model gives the smallest ratio for trading volume volatility.

The results based on smoothed volatility also offer split opinions on the choice between the two-latent-factor and three-latent-factor models. The two-latent-factor model yields the four smallest ratios and the three-latent-factor model gives five.

Apparently, if the selecting variable is return volatility, the three-latent-factor model is preferred – the model gives the lowest ratio values for all the three currencies. The two-latent-factor model, however, is chosen if the selecting variable is trading volume because it yields the smallest ratios in all three cases. For open interest, there is no unanimous choice although two of the three currencies favor the three-latent-factor model. Overall, these ratios show that the number of latent factors to be included depends on which variable and which currency are under consideration. In general, these ratios lean toward either the two-latent-factor model or the three-latent-factor model.

Table 4 compares the model performance based upon the size of the ratios (3) and (4) but does not formally test whether the ratios are statistically different from each other. As an additional evaluation procedure, we consider $e^2_{r,t|t} \equiv (\tilde{r}_t^2 - h^2_{r,t|t})^2$, the squared error of using $h^2_{r,t|t}$ to predict $\tilde{r}_t^2$. The relative performance of two models, say i and j, can be formally tested by examining the difference series $d_t = e^2_{r,t|t,i} - e^2_{r,t|t,j}$, where the subscripts i and j identify the models with which $e^2_{r,t|t}$'s are generated. Under the null hypothesis of the models i and j have the same performance, the mean of the difference series $\{d_t\}$ is zero.

The null hypothesis of equal explanatory ability can be evaluated using the statistic:

$$\bar{d} / \hat{V}(\bar{d})^{1/2} \tag{5}$$

8 The ratios calculated for the Canadian dollar trading volume three-latent-factor model are quite large relative to those from other models. It was found that there are a few extreme observations in the $h^2_{v,t|t}$ series. We also used $|v_t|$ and $h_{v,t|t}$ instead of v_t^2 and $h^2_{v,t|t}$ in constructing the ratios; the results are qualitatively the same as those reported in Tables 4 and 5. These results are available upon request.

where $\overline{d}$ is the sample mean of d_t and $V(\hat{\overline{d}})$ is a heteroskedasticity and serial correlation consistent variance estimator. See Diebold and Mariano (1995) for a detailed discussion. Under the assumptions of covariance stationarity and short-memory for d_t, the statistic (5) follows an asymptotic normal distribution under the null hypothesis. By the same token, the similarly defined variables $e^2_{v,t|t} \equiv (v^2_t - h^2_{v,t|t})^2$ and $e^2_{o,t} = (o^2_t - h^2_{o,t|t})^2$ can be used to compare the model performance with respect to trading volume and open interest.

The comparison results based on filtered volatility are presented in Panel A, Table 5. Each model is compared against the other two individually. A positive statistic shows that the first model of the pair has a performance worse than the second one, and its significance is indicated by the robust t-statistic in parentheses. The test results for the British pound data are consistent with those in Table 4 – the two-latent-factor model is best for return volatility and the three-latent-factor model is best for the other two variables. The Canadian data give ambiguous results. The statistics do not reveal any significant difference between, say, the one-latent-factor model and the two-latent-factor model. The Japanese yen data confirm the model choice for trading volume and open interest but are inconclusive for return data.

The results pertaining to smoothed volatility are given in the Panel B of Table 5. In this case, the Japanese yen test results affirm those in Table 4. For the other two currencies, the test results corroborate those of return and trading volume from Table 4 but are inconclusive for open interest. In general, the test results are broadly consistent with the ratios reported in Table 4 and are indicative of the pertinence of modeling return, trading volume, and open interest simultaneously using a two- or three-latent-factor stochastic model, even though there are a few cases in which we cannot conclude if the one-latent-factor model is statistically worse than the other two alternatives.

Both Tables 4 and 5 assess performance by considering a model's fit for return, trading volume, and open interest individually. To gauge the overall performance, Table 6 presents the posterior log likelihood estimates of the stochastic volatility models generated from the MCMC procedure. These likelihood estimates choose the model with three latent factors for the British pound and Japanese yen currency futures and the one with two latent factors for the Canadian dollar series. Indeed, the inference is broadly in line with those from Tables 4 and 5.

4. Spillovers between Currency Futures

The latent factors in stochastic volatility models are commonly interpreted as unobservable information variables. Even though we do not know the exact nature of the underlying information variables, we have estimates of their persistence and evolution paths. The latent factor estimates also facilitate the analysis of information flows between these currency futures markets. For instance, Ross (1989) shows that volatility is associated with information flow in a no-arbitrage economy. The volatility interaction pattern, thus, offers useful insight on the direction of information flow. To assess cross-currency volatility interactions, we adopt the notion of causality in variance discussed in, for example, Cheung and Ng (1996), Granger, Robins and Engle (1986) and Hong (2001).

First, consider the return series. Let u_t^2 be the square of the (estimated) standardized residual defined by:

$$u_t^2 = \tilde{r}_t^2 / h_{r,t|t}^2 \quad (6)$$

We introduce the currency subscripts such that $u_{t,BP}^2$, $u_{t,CD}^2$, and $u_{t,JY}^2$ represent the squares of standardized residuals from the British pound, Canadian dollar, and Japanese yen models, respectively. Under the null hypothesis of no causality in variance, the cross-correlation coefficient $\xi_{i,j,k}$ (= correlation $(u_{t,i}^2, u_{t-k,j}^2)$; $i, j = BP, CD, JY$) adjusted by root-T has an asymptotic standard normal distribution (Cheung and Ng, 1996; Hong, 2001). Thus, for currencies i and j, we use the statistic:

$$S_{1,i,j} = T\Sigma_{k=1}^{25}\xi_{i,j,k}^2 \quad (7)$$

to test the null hypothesis of no-causality against the alternative of j causes i in variance. Similarly, for the alternative of i causes j in variance, we consider the statistic:

$$S_{2,i,j} = T\Sigma_{k=-1}^{-25}\xi_{i,j,k}^2 \quad (8)$$

We chose 25 lags for $S_{1,i,j}$ and $S_{2,i,j}$ to capture the potential causation pattern in daily data. Under the null hypothesis, both statistics have an asymptotic chi-square distribution with 25 degrees of freedom. The choices of 20 and 30 lags gave similar results. The instantaneous causality is assessed using $\xi_{i,j,0}$.

The graphs of $\xi_{i,j,k}$ for $i, j = BP, CD$, and JY and k = -25 to 25 are plotted in the far left column of Figure 1. The corresponding $S_{1,i,j}$, $S_{2,i,j}$ and $\xi_{i,j,0}$ statistics are presented in the second column of Table 7. These statistics indicate the presence of return volatility spillovers. The spillover occurs mainly at the contemporaneous level and there is limited evidence of lead or lag causal relationship between return variabilities. All the instantaneous causality statistics $\xi_{i,j,0}$'s are positive and significant at the 1% level. The result should not be surprising because these futures exchange rates are all dollar-based exchange rates.

Besides $\xi_{i,j,0}$, the only significant statistic is $S_{1,CD,JY}$ that indicates the Japanese yen futures return volatility causes the Canadian dollar one. From the graph, it can be seen that the two return volatilities are positively correlated. According to the informational interpretation, the information flow is from the Japanese yen market to the Canadian dollar market. Note that the former market is more active than the latter one.

The remaining two columns in Figure 1 and Table 7 present the results for trading volume and open interest. The causation patterns found in trading volume data are comparable to those revealed by data on returns. The volatility spillover among trading volume is mainly found contemporaneously. There is significant evidence of positive comovement between trading volume variabilities. The lead/lag causal interaction, similar to the return case, is not widespread. Only one S-statistic $S_{1,BP,JY}$ is significant; indicating the more active Japanese yen market is leading the less active British pound trading volume volatility.

The causation patterns of open interest data are quite different from those of the return and trading volume data. First, the evidence of instantaneous causality is weak. Only one $\xi_{i,j,0}$ statistic; namely the $\xi_{BP,JY,0}$, is significant. Second, the lead/lag causality is quite common in open interest data. Both the British pound/Canadian dollar and British pound/Japanese yen pairs display feedback interactions; that is one currency futures series causes the other one and *vice versa*. For the Canadian dollar/ Japanese yen, the S-statistic indicates the causation is running from the Japanese yen futures open interest to the Canadian dollar futures.

In the previous section, we observed that return, trading volume, and open interest respond differently to different types of information arriving at the market. The results in the current section reinforce the presence of differential information. For instance, information affecting return and trading volume volatilities is likely to be contemporaneously related though it induces limited lead/lag relationships. On the other hand, information affecting open interest volatility tends to generate significant lead/lag interactions.

5. Concluding Remarks

We model the joint dynamics of return, trading volume, and open interest using stochastic volatility specifications that allow the data to reveal the interactions between multiple latent factors and observed variables. Our findings are in accordance with the theoretical prediction that return, trading volume, and market depth are jointly determined and the three observed variables respond differently to different types of information. Models not incorporating the feature are likely to be misspecified.

While the stochastic volatility framework offers a convenient structure to examine the latent factors that drive the observed futures data, it is silent on the economic interpretations of these latent factors. Theoretically, the relevant information includes private against public information, information that has short-term and long-term impacts, and information about payoffs. While we can infer their persistence, we are reluctant to label the estimated latent factors by specific information types. We perceive that an elaborate theoretical model on the joint behavior of these variables is required to identify information variables with the estimated latent factors.

The pattern of information flows inferred from causality in variance test results corroborates the notion of differential informational impacts. The pattern of spillovers is crucial for studying the information transmission mechanism. Our exploratory results are in line with the folklore that active markets lead less active markets. It is fruitful for future research to compare and contrast spillover patterns in different markets and their underlying driving forces.

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Table 1. Descriptive Statistics

	Mean	Std. Errors	Skewness	Kurtosis
Return (r)				
BP	0.0049	0.6171	-0.2460	6.5252
CD	-0.0008	0.3687	-0.0620	4.9759
JY	0.0090	0.7465	0.7726	10.4021
Volume (v)				
BP	-0.0000	0.6041	0.3684	4.3190
CD	-0.0000	0.6046	0.3064	4.2861
JY	0.0000	0.5692	0.3452	3.5883
Open Interest (o)				
BP	-0.0000	0.0755	-3.5835	33.0916
CD	-0.0000	0.0908	-0.3581	66.9981
JY	0.0000	0.0614	-4.0771	35.7515

Autocorrelation	Lag 1	Lag 2	Lag 5	Lag 10
r^2				
BP	0.0833	0.1293	0.1142	0.1180
CD	0.1442	0.1188	0.1508	0.1508
JY	0.1009	0.0673	0.0453	0.0141
v^2				
BP	0.1997	0.0209	0.0304	0.0375
CD	0.2468	0.0110	0.0126	0.0539
JY	0.1714	0.0484	0.0965	0.0275
o^2				
BP	-0.0060	-0.0016	-0.0030	-0.0104
CD	0.4980	-0.0000	-0.0003	-0.0010
JY	-0.0038	-0.0021	-0.0095	-0.0133

Note: The first part of the table presents the sample mean, standard error, skewness, and kurtosis.

BP, CD, and JY stand for British pound, Canadian dollar, and Japanese yen currency futures, respectively. The second part gives the sample autocorrelation coefficients at first, second, fifth, and tenth lags of the squared data. There are 3773 daily observations in the sample period from January 1990 to December 2004.

Table 2. Trivariate Stochastic Volatility Models with Two Latent Factors

	British Pound	Canadian Dollar	Japanese Yen
μ_0	0.0193	0.0057	-0.0195
	(0.0085)	(0.0047)	(0.0107)
μ_1	-0.0525	-0.0163	-0.0526
	(0.0147)	(0.0159)	(0.0151)
a_{r1}	0.0014	0.3767	0.0024
	(0.0014)	(0.0217)	(0.0024)
a_{r2}	0.4748	0.3022	0.4416
	(0.0183)	(0.0190)	(0.0171)
a_{v1}	0.3030	0.0033	0.2609
	(0.0182)	(0.0031)	(0.0179)
a_{v2}	0.1450	0.2015	0.1546
	(0.0181)	(0.0161)	(0.0172)
a_{o1}	0.2042	0.0592	0.1312
	(0.0298)	(0.0257)	(0.0305)
a_{o2}	0.7623	0.8275	0.7177
	(0.0186)	(0.0183)	(0.0182)
ϕ_1	0.9318	0.9951	0.9336
	(0.0295)	(0.0034)	(0.0310)
ϕ_2	0.2607	0.2440	0.2637
	(0.0343)	(0.0339)	(0.0337)
σ_r	0.5032	0.3487	0.6133
	(0.0093)	(0.0158)	(0.0110)
σ_v	0.5608	0.5836	0.5249
	(0.0162)	(0.0077)	(0.0119)
σ_o	0.0372	0.0272	0.0302
	(0.0012)	(0.0009)	(0.0008)
ρ_1	0.0072	-0.0573	-0.0022
	(0.0249)	(0.0540)	(0.0251)
ρ_2	-0.0215	-0.0490	0.0523
	(0.0214)	(0.0243)	(0.0218)

Note: The table presents estimates (with standard errors in parentheses) of (1) for return, trading volume, and open interest. The posterior estimates and standard errors are based on 110,000 MCMC repetitions with 50,000 burn-in periods.

Table 3. Three-Latent-Factor Stochastic Volatility Models

	British Pound	Canadian Dollar	Japanese Yen
μ_0	0.0170 (0.0080)	0.0073 (0.0051)	-0.0283 (0.0108)
μ_1	-0.0500 (0.0158)	-0.0134 (0.0164)	-0.0526 (0.0156)
a_{r1}	0.3593 (0.0188)	0.4054 (0.0192)	0.0090 (0.0088)
a_{r2}	0.0135 (0.0162)	0.2155 (0.0299)	0.3094 (0.0196)
a_{r3}	0.3531 (0.0191)	0.1487 (0.0383)	0.3383 (0.0210)
a_{v1}	0.0032 (0.0035)	0.0065 (0.0131)	0.2560 (0.0170)
a_{v2}	0.2892 (0.0202)	0.1989 (0.0361)	0.0107 (0.0109)
a_{v3}	0.0157 (0.0139)	0.6638 (0.0636)	0.0220 (0.0184)
a_{o1}	0.1664 (0.0194)	0.1279 (0.0518)	0.0318 (0.0229)
a_{o2}	0.0347 (0.0302)	0.0784 (0.0506)	0.1724 (0.0179)
a_{o3}	0.7757 (0.0184)	0.5380 (0.0740)	0.7279 (0.0167)
ϕ_1	0.9463 (0.0234)	0.9403 (0.0242)	0.9177 (0.0381)
ϕ_2	0.8031 (0.1047)	0.2546 (0.0542)	0.9015 (0.0470)
ϕ_3	0.1999 (0.0341)	0.1601 (0.0636)	0.2276 (0.0353)
σ_r	0.4903 (0.0150)	0.3077 (0.0100)	0.6009 (0.0134)
σ_v	0.5444 (0.0118)	0.5798 (0.0078)	0.5219 (0.0116)
σ_o	0.0362 (0.001)	0.0266 (0.0007)	0.0298 (0.0007)
ρ_1	-0.0012 (0.0446)	-0.0495 (0.0480)	0.0482 (0.0499)
ρ_2	-0.0025 (0.0503)	-0.0858 (0.0586)	0.1974 (0.0487)
ρ_3	-0.0002 (0.0247)	0.0488 (0.0697)	0.0118 (0.0265)

Note: The table presents estimates (with standard deviations in parentheses) of the three-latent-factor stochastic volatility model (2) for return, trading volume, and open interest. The posterior estimates and standard errors are based on 110,000 MCMC repetitions with 50,000 burn-in periods.

Table 4. Model Performance Comparison Based on Filtered and Smoothed Volatilities

	British Pound	Canadian Dollar	Japanese Yen
A. Filtered Volatiltiy			
	One-Latent-Factor Model		
Returns ($\tilde{r}$)	0.7055	0.6920	0.7785
Volume (v)	0.7160	0.7049	0.6632
Open Interest (o)	0.7769	0.9207	0.7894
	Two-Latent-Factor Model		
Returns ($\tilde{r}$)	0.6270	0.6762	0.7462
Volume (v)	0.6634	0.6993	0.6122
Open Interest (o)	0.6424	0.9823	0.7286
	Three-Latent-Factor Model		
Returns ($\tilde{r}$)	0.7575	1.0850	0.7195
Volume (v)	0.5603	7.0803	0.6533
Open Interest (o)	0.5026	0.9907	0.5646
B. Smoothed Volatility			
	One-Latent-Factor Model		
Returns ($\tilde{r}$)	0.6819	0.6684	0.7376
Volume (v)	0.7084	0.7024	0.6552
Open Interest (o)	0.6007	0.9369	0.6461
	Two-Latent-Factor Model		
Returns ($\tilde{r}$)	0.6546	0.6138	0.7441
Volume (v)	0.6215	0.6832	0.5714
Open Interest (o)	0.6135	0.9317	0.6566
	Three-Latent-Factor Model		
Returns ($\tilde{r}$)	0.5872	0.5741	0.6822
Volume (v)	0.6334	2.1273	0.6098
Open Interest (o)	0.5831	0.9935	0.6223

Note: Panel A reports the ratio $\sum(y_t^2 - h_{y,t|t}^2)^2 / \sum(y_t^2 - \overline{y}^2)^2$; y = $\tilde{r}$, v, and o based on the filtered volatility. Panel B reports the ratio $\sum(y_t^2 - h_{y,t|T}^2)^2 / \sum(y_t^2 - \overline{y}^2)^2$; y = $\tilde{r}$, v, and o based on the smoothed volatility.

Table 5. Diebold-Mariano Test Statistics

	British Pound	Canadian Dollar	Japanese Yen
A. Filtered Volatility			
	One-Latent-Factor Vs Two-Latent-Factor		
Returns ($\tilde{r}$)	0.0750 (2.78)	0.0014 (0.66)	0.1060 (2.40)
Volume (v)	0.0303 (1.85)	0.0032 (0.86)	0.0192 (3.15)
Open Interest (o)	0.0001 (4.10)	-0.0032 (-1.34)	0.00003 (2.64)
	One-Latent-Factor Vs Three-Latent-Factor		
Returns ($\tilde{r}$)	-0.0502 (-0.56)	-0.0362 (-2.31)	0.1858 (0.69)
Volume (v)	0.0895 (8.79)	-3.6525 (-4.46)	0.0037 (0.51)
Open Interest (o)	0.0003 (4.39)	-0.0036 (-1.37)	0.0001 (4.44)
	Two-Latent-Factor Vs Three-Latent-Factor		
Returns ($\tilde{r}$)	-0.1252 (-1.45)	-0.0376 (-2.43)	0.0804 (0.30)
Volume (v)	0.0592 (5.15)	-3.6557 (-4.47)	-0.0155 (-2.00)
Open Interest (o)	0.0002 (3.18)	-0.0004 (-1.61)	0.0001 (3.22)
B. Smoothed Volatility			
	One-Latent-Factor Vs Two-Latent-Factor		
Returns ($\tilde{r}$)	0.0253 (3.52)	0.0049 (3.44)	-0.0251 (-0.58)
Volume (v)	0.05 (7.15)	0.0104 (4.56)	0.0086 (5.18)
Open Interest (o)	-0.00001 (-0.45)	0.0003 (1.06)	-0.0001 (-4.94)
	One-Latent-Factor Vs Three-Latent-Factor		
Returns ($\tilde{r}$)	0.0919 (4.52)	0.0085 (3.93)	0.1747 (3.32)
Volume (v)	0.0431 (7.46)	-0.8158 (-2.29)	0.0171 (6.62)
Open Interest (o)	0.00002 (0.77)	-0.0029 (-1.43)	0.00001 (1.58)
	Two-Latent-Factor Vs Three-Latent-Factor		
Returns ($\tilde{r}$)	0.0666 (3.98)	0.0036 (2.23)	0.1998 (2.18)
Volume (v)	-0.0069 (-1.64)	-0.8265 (-2.32)	-0.0145 (-5.56)
Open Interest (o)	0.00003 (0.82)	-0.0032 (-1.47)	0.00002 (1.84)

Note: The table reports the Diebold-Mariano statistic given by (5) in the text. Panel A gives results based on filtered volatility and Panel B gives the same statistics based on smoothed volatility. Robust *t*-statistics are given in parentheses next to test statistics.

Table 6. Posterior Log Likelihoods

	British Pound	Canadian Dollar	Japanese Yen
One-Factor	-4299.5	-4194.4	-4330.2
Two-Factor	-4498.7	-4066.7	-4659.3
Three-Factor	-4106.5	-5230.6	-4084.9

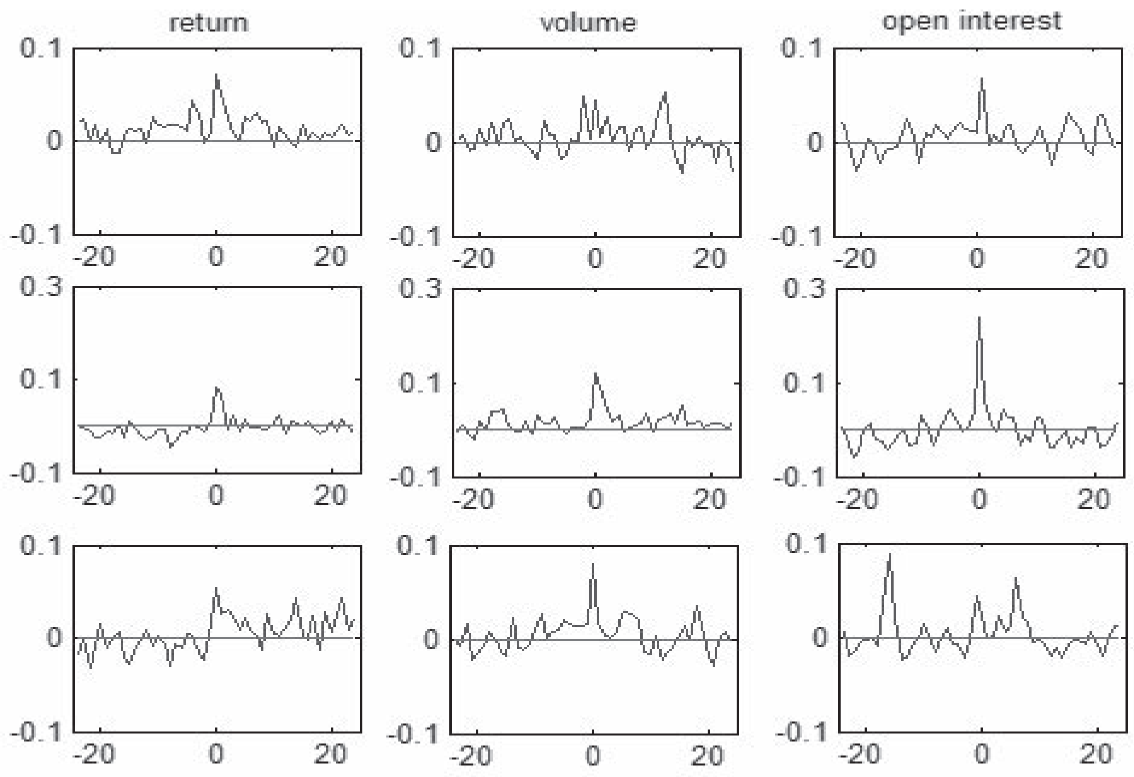
Note: The table presents the *log*-likelihoods of selected trivariate stochastic volatility models of return, trading volume, and open interest based on the posterior estimates from the MCMC procedure. The first column gives the number of latent factors included in the models.

Table 7. The Causality in Variance Test Results

	Return	Trading Volume	Open Interest
$S_{1,BP,CD}$	27.5137	22.2371	39.9514**
$S_{2,BP,CD}$	30.1520	32.4134	38.4438**
$\xi_{BP,CD,0}$	4.4773*	2.7146*	0.6694
$S_{1,BP,JY}$	31.2827	70.9910*	69.7265*
$S_{2,BP,JY}$	31.6596	34.9265	71.6110*
$\xi_{BP,JY,0}$	5.1037*	7.2533*	14.6970*
$S_{1,CD,JY}$	39.574**	17.7143	61.8116*
$S_{2,CD,JY}$	19.9757	26.3830	27.5137
$\xi_{CD,JY,0}$	3.3533*	4.8703*	1.3327

Note: The table reports the causality in variance test results. The S- and ξ -statistics are given in the text. The column labeled "Return" gives results based on the squares of standardized residuals of return series that are derived from the filtered volatility estimates. Similarly, the columns labeled "Trading Volume" and "Open Interest" gives the results pertaining to the trading volume and open interest series. "*" and "**" indicate significance at the 1% and 5% level, respectively.

Figure 1. Cross-Correlation of Squared Standardized Residuals



Plots of cross-correlation of squared standardized residuals based on filtered volatilities are presented. The first column given $\xi_{i,j,k}$ = correlation $(u_{t,i}^2, u_{t-k,j}^2)$; $u_t^2 = \tilde{r}_t^2 / h_{r,t|t}^2$; $i, j = BP$, CD, and JY; k = -25 to 25. The first plot is for $i = BP$ and $j = CD$, the second is for $i = BP$ and $j = JY$, and the third one is for $i = CD$ and $j = JY$. Similar plots for trading volume and open interest are given under the second and the third column.