Uncertainty Channel between Stock Prices and Foreign Exchange Rates in Nepal

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Abstract  

In this paper, three different versions of bivariate GARCH in mean models were considered to explain the relationship between uncertainty and average outcomes of the stock index and exchange rate. From the empirical results, the bivariate EGARCH-M is the best model to explain the volatility in the two markets. This paper revealed four important conclusions. First, there is a negative relationship between the exchange rates return and stock prices return, but the current exchange rates return is positively affected by the lagged stock prices return at 5\% significance level. Second, the results provide strong empirical confirmation of the first hypothesis (that uncertainty in foreign exchange market has an effect on average stock prices) and third hypothesis (that uncertainty in stock market has an effect on average stock prices), implying a negative effect of stock index uncertainty and a positive effect of exchange rates uncertainty on average stock index. On the other hand, for the exchange rates equation, the GARCH-in-mean variables in AR modeling are significant. This

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shows that there is a positive effect of exchange rates uncertainty and a negative effect of stock index uncertainty on average exchange rates. Third, the coefficient on the lagged residual variance is greater for stock index than for exchange rates, implying that stock index shocks have longer lived effects on uncertainty in the stock market than exchange rates shock have on uncertainty in the foreign exchange market. Finally, from the magnitude of coefficient that shows the effect of the last period’s shock, volatility is more sensitive to its own lagged values than it is to new surprises in the foreign exchange market.

**Keywords**: Stock Prices, Foreign Exchange Rates, Bivariate GARCH in Mean Models, Asymmetries, Long Memory Process in Conditional Variance, Uncertainty Channel

**JEL Classifications**: C51, G12, G15

## I. Introduction

In the standard macroeconomic model, foreign exchange rates and stock prices played crucial roles in forecasting an economy and managing portfolios and risk. For this reason, numerous researchers and practitioners have investigated the linkages between stock prices and foreign exchange rates. The higher level cross-border flow of financial assets might expose the investors to diverse currency risks. Hence, portfolio and risk managers must consider the linkages between stock prices and exchange rates to design more efficient investment strategies.

From the first moments' perspective, there are two traditional theories about the linkage between foreign exchange rates and stock prices. The first one is the flow-oriented approach of exchange rates suggested by Dornbusch and Fisher (1980). They argued that changes in exchange rates alter the international competitiveness of a firm as well as the balance of trade position, and finally affect stock prices of companies. This implies that the exchange rate changes lead to stock price returns, and that they are positively correlated. In contrast, the other theory suggested by Branson (1983) and Frankel (1983) relates to stock-oriented approach of exchange rates. It implied that stock prices affect exchange rates and these are negatively related. However, the empirical results have been mixed when it comes to the relationship and causal direction between exchange rates and stock prices (Nieh and Lee, 2001; Pan, Fok and Liu, 2007; Phylaktis and Ravazzolo, 2005; Yau and Nieh, 2009).

There are many empirical studies which focused on volatility spillover between exchange rates and stock markets. It indicated strong cross-market dependence in the volatility process. Surprisingly, very few studies have investigated the linkages between returns in both foreign exchange and stock markets, and uncertainties in two markets, which are mutually independent. Higher uncertainty generates turbulence in the foreign exchange markets, with the major currencies being hit by a reduction in international transactions and depreciation in value. An interesting issue is whether financial markets have become more dependent as a result of the uncertainty. Aloui, Aissa and Nguyen (2011), Dufrénot, Mignon and Péguin-Feissolle (2011) and Kenourgios, Samitas and Paltalidis (2011),
among others, indeed found an increase in dependence between international stock markets. Similar findings were reported by Bubak, Kocenda and Zikes (2011) and Coudert, Coularde and Mignon (2011) for foreign exchange markets.

There are four possible hypotheses of whether uncertainties in two markets have an effect on the exchange rates and stock prices returns. The first hypothesis that uncertainty in foreign exchange market has an effect on average stock prices is tested by looking at the coefficient on the conditional variance of exchange rates in the stock market. The underlying idea in this regard is that exchange rate volatility increases the costs of international financial transactions and reduces potential gains from international diversification by making the acquisition of foreign securities such as bonds and equities more risky. This in turn, negatively affects the stock prices across borders (Borensztein and Loungani, 2011; Eun and Resnick, 1988; Fidora, Fratzscher and Thimann, 2007). For the exchange rates equation, the coefficient of the conditional variance of stock index return directly tested the second hypothesis of whether uncertainty in stock market has an effect on exchange rates. During times of financial turmoil, the high volatility of stock markets generates speculative actions by investors and capital flight to value. This may lead to considerable instability in other markets such as the foreign exchange markets (see Caporale, Pittis and Spagnolo, 2002; Granger, Huang and Yang, 2000). The coefficient of the conditional variance of stock prices in the stock index equation tested the third hypothesis which states that the increased uncertainty in stock market raises average stock index. The fourth hypothesis is tested using the coefficient on the conditional variance of exchange rates in the exchange rates equation.

The remainder of the paper is structured as follows. The next section provided the model specifications, and section III discussed the data and the results of preliminary statistical tests. Section IV analyzed the empirical results concerning the lead and lag effects, and the effect of uncertainty in two markets on each market price return in the conditional mean. The final section presented the concluding remarks.

II. Statistical Models

1. Conditional Mean Models

Let $S_t$ and $F_t$ denote, respectively, stock index and foreign exchange rates (in logarithmic form) at time $t$. $R_{St} = S_t - S_{t-1}$ denotes the stock index return and $R_{Ft} = F_t - F_{t-1}$ denotes the exchange rates return. Assuming that the residuals are integrated of order zero and the residuals exhibit long memory and the four possible effects of uncertainty calculated from the different GARCH models are tested, then, we have the following general bivariate error correction model in the mean:

$$R_{St} = \phi_{S} + \sum_{j=1}^{m} \phi_{Sj} R_{St-j} + \sum_{j=1}^{m} \theta_{j} R_{Ft-j} + \lambda_{S}\sqrt{\hat{h}_{S}}$$

$$R_{Ft} = \phi_{F} + \sum_{j=1}^{m} \phi_{Fj} R_{Ft-j} + \sum_{j=1}^{m} \theta_{j} R_{St-j} + \lambda_{F}\sqrt{\hat{h}_{F}}$$

1) However, in turbulent times, decoupling may also occur. When stock markets experience severe downturns, investors may only focus on markets where their assets can be seen as safe regardless of foreign exchange movements. Consequently, there might not be interactions between different markets (see, for example, Hatemi-J and Roca, 2005).
\[ + \delta_F \sqrt{\bar{h}_F} + \eta_F \{ 1 - (1 - L)^{1-d} \} (1 - L)^{d} Z_t + \epsilon_t \]

where \( Z_t = S_t - a - bF_t \), which is the residuals from the regression of the exchange rates on the stock index, and \( \epsilon_S \) and \( \epsilon_F \) are random residual terms.

If \( Z_{t-1} > 0 \), the stock index tends to be decreasing whereas the exchange rates tend to be increasing at time \( t \) to maintain the long-term relationship \( (Z_t = 0) \) between stock index and foreign exchange rates. Similarly, when \( Z_{t-1} < 0 \), the stock index tends to be increasing and the exchange rates tend to be decreasing in the next period. This would lead one to predict that \( \eta_S \leq 0 \) and \( \eta_F \geq 0 \). Let \( L \) denote the lag operator such that \( LZ_t = LZ_{t-1} \) and \( Z_t \) be integrated of order \( d \). Following Granger (1986), the traditional error correction model is encompassed in the fractionally integrated error correction model.2

Different bivariate GARCH in mean models incorporated tests of all four possible hypotheses. The first hypothesis that uncertainty in foreign exchange market raises average stock prices was tested by looking at \( \delta_F \), the coefficient on the conditional variance of exchange rates in the stock market. For the exchange rates equation, the coefficient \( \lambda_F \) on the conditional variance of stock index return, directly tested the second hypothesis of whether uncertainty in stock market has an effect on exchange rates. If uncertainty in stock market adversely affects foreign exchange rates return, \( \lambda_F \) will be negative and significant in equation (2). The coefficient \( \lambda_S \) for the conditional variance of stock prices in the stock index equation tested the third hypothesis that increased uncertainty in stock market raises average exchange rates. Finally, the coefficient \( \delta_F \) on the conditional variance of exchange rates in the exchange rates equation tested the fourth hypothesis.

2. Conditional Correlation GARCH Models

2.1. Univariate GARCH Models

This section briefly outlined asymmetric and nonlinear GARCH models, which have similar structure. It consisted of two equations namely the conditional mean equations and the conditional variance equation. For all models the conditional mean equation for a return series \( \{ y_t \} \) is

\[ y_t = E(y_t | \Omega_{t-1}) + \epsilon_t \]  \hspace{1cm} (3)

where \( \Omega_{t-1} \) is the information set consisting of all relevant information up to and including time \( t-1 \). Here, the conditional variance of \( \epsilon_t \) was allowed to vary over time, that is, \( E(\epsilon_t^2 | \Omega_{t-1}) = h_t \) for some nonnegative function \( h_t = h_t(\Omega_{t-1}) \). A convenient way to express this in general is

\[ \epsilon_t = \zeta_t \sqrt{h_t} \]  \hspace{1cm} (4)

where \( \zeta_t \) is independent and identically distributed with zero mean and unit variance.

In the classic GARCH(p,q) model of Bollerslev (1986), the conditional variance \( h_t \) was postulated to be a linear function of the lagged squared innovations and variance,
which is formally defined by

\[ h_t = \omega + \alpha(L) \varepsilon_t^2 + \beta(L) h_t \] (5)

where \( L \) denotes the lag or backshift operator, and \( \alpha(L) = \alpha_1 L + \alpha_2 L^2 + \ldots + \alpha_L \) and \( \beta(L) = \beta_1 L + \beta_2 L^2 + \ldots + \beta_L \). For stability and covariance stationarity of the \( \{ \varepsilon_t \} \) process, all the roots of \( 1 - \alpha(L) - \beta(L) \) and \( 1 - \beta(L) \) are constrained to lie outside the unit circle.

The first variant of the GARCH model which allows for long memory effects in the conditional variance is the FIGARCH \((p,d,q)\) process for \( \{ \varepsilon_t \} \), which is defined by

\[
h_t = \omega [1 - \beta(1)]^{-1} + \{1 - [1 - \beta(L)]^{-1} \varphi(L)(1 - L)^d \} \varepsilon_t^2 = \omega [1 - \beta(1)]^{-1} + \varphi(L)(1 - L)^d \varepsilon_t^2 \] (6)

where \( \lambda(L) = \lambda_1 L + \lambda_2 L^2 + \ldots \). Of course, for the FIGARCH\((p,d,q)\) process to be well-defined and the conditional variance to be almost surely positive for all \( t \), all the coefficients in the infinite ARCH representation must be nonnegative (see Baillie, 1996 for more details).

The second and earliest variant of the GARCH model which allows for asymmetric effects is the exponential GARCH (EGARCH) model, introduced by Nelson (1991). The EGARCH \((1,1)\) model is given by

\[
\ln(h_t) = \omega + \alpha \ln(\varepsilon_{t-1}) + \gamma |\varepsilon_{t-1}| - E(\varepsilon_{t-1}) \ln(h_{t-1}) + \beta \ln(h_{t-1}) \] (7)

where \( \varepsilon_t = \varepsilon_t / \sqrt{h_t} \) and \( E(\varepsilon_{t-1}) = \sqrt{2/\pi} \).

As the EGARCH model (7) describes the relation between past shocks and the logarithm of the conditional variance, no restrictions on the parameters, \( \alpha, \gamma \) and \( \beta \) has to be imposed to ensure that \( h_t \) is nonnegative. Using the properties of \( Z_t \), it follows that \( g(\chi_t) = \alpha \chi_t + \gamma |\chi_{t-1}| - E(\varepsilon_{t-1}) \) can be rewritten as

\[
g(\chi_t) = (\alpha + \gamma) \chi_t / (\chi_t > 0) + (\alpha - \gamma) \chi_t / (\chi_t < 0) - \gamma E(\varepsilon_{t-1}) \] (8)

The third nonlinear variant model proposed by Glosten, Jagannathan and Runkle (1993), hereafter referred to as GJR, offers an alternative method to allow for asymmetric effects of positive and negative shocks on volatility (see also Rabemananjara and Zakoian, 1993). The GJR model was obtained from the GARCH \((1,1)\) model (5) by assuming that the parameters of \( \varepsilon_{t-1}^2 \) depend on the sign of the shock, that is,

\[
\ln(h_t) = \omega + \alpha \ln(\varepsilon_{t-1}) + \gamma |\varepsilon_{t-1}| - E(\varepsilon_{t-1}) \ln(h_{t-1}) + \beta h_{t-1} \] (8)

where as usual \( |\cdot| \) is an indicator function. The conditions for non-negativity of the conditional variance are \( \omega > 0, (\alpha + \gamma) / 2 \geq 0 \) and \( \beta > 0 \). The condition for covariance-stationarity is \( (\alpha + \gamma) / 2 + \beta < 1 \). The introduction of this indicator variable implied that negative returns have a different impact on volatility than positive returns, depending on the value of \( \gamma \). When \( \delta \) is positive, negative returns have more impact than positive returns.

2.2. Bivariate GARCH Models

It has been well recognized that the variances of asset returns and the covariance
among different asset returns vary over time. To account for this statistical property, multivariate GARCH models with different specifications and restrictions on the conditional variance-covariance matrix have been widely developed. This study considered the conditional constant correlation (CCC) multivariate GARCH model of Bollerslev (1990). The variance-covariance structure should be specified to complete the model.

Allowing the conditional variance and correlation of stock index and foreign exchange rates to change over time, the conditional variance-covariance matrix of residual series, \( e_t = (e_{t1}, \ldots, e_{tN}) \), is denoted by

\[
\text{Var}(e_t | \Omega_t) = H_t = \begin{bmatrix} h_{s,t} & h_{sf,t} \\ h_{fs,t} & h_{f,t} \end{bmatrix}
\]  

where \( \Omega_t \) is the information set at time \( t \). The CCC-BGARCH model is using the original GARCH(1,1) model, which is specified by

\[
\begin{align*}
    h_{s,t} &= \omega_s + \alpha_s e_{t-1}^2 + \beta_s h_{s,t-1} \\
    h_{f,t} &= \omega_f + \alpha_f e_{t-1}^2 + \beta_f h_{f,t-1} \\
    h_{sf,t} &= \rho \sqrt{h_{s,t} h_{f,t}}
\end{align*}
\]  

where \( \rho \) is the correlation coefficient, which is assumed to be constant. The first modification for conditional variances of stock index and foreign exchange rates would allow for long memory properties of the variables, which was originally suggested by Baillie (1996). The second one is using the EGARCH(1,1) model, which was specified by equation (4) for each stock index and foreign exchange rates. The third one was proposed by Glosten et al. (1993), which allowed for asymmetric effects of positive and negative shocks on volatility.

Suppose the vector stochastic process \( \{y_t\} \), \( t = 1, \ldots, T \), is a realization of models (1) to (12) whose the conditional mean and the conditional variance matrix are, respectively, \( \mu_t (\psi_0) \) and \( H_t (\psi_0) \), where \( \psi_0 = (\theta_0, \psi_0) \) is a 2-dimensional parameter vector. All the unknown parameters can be estimated by maximizing the log-likelihood function,

\[
L_T (\psi_0) = \sum_{t=1}^{T} l_t (\psi_0),
\]

and where \( T \) is the total number of observations.

### III. Preliminary Data Analysis

This section described the methodology and the time series characteristics of the data used in the estimation. The daily rates from July 16, 2004 to June 30, 2014 of the stock and foreign exchange markets reported by the Bank of Nepal were used in this study. The NEPSE (Nepal Stock Exchange) Ltd. is a non-profit organization which was established under the Company Act, 2006 and operated under Securities Exchange Act, 1983. It is the only one stock exchange existing in Nepal. It was converted to Securities Exchange Center in 1993. NEPSE opened its trading floor on January 13, 1994 through its newly appointed licensed members and has adopted an "Open Out-Gy" system for the transaction of securities. Following Maslay (2007), Nepal’s choice for a fixed exchange rate with full convertibility to the Indian currency along with supporting
Fig. 1. Time Series of Stock Index and Foreign Exchange Rates

(a) Stock Index Level and Return Series

(b) Exchange Rates Level and Return Series

government policies in April 1960, had contributed significantly to help stabilize confidence both in the domestic currency and in the Nepalese currency-India currency exchange rate. It facilitated the elimination of the dual currency period in 1964.

<Fig. 1> plots the returns and individual level series of the logarithms for the stock index and exchange rates. <Fig. 1> clearly demonstrates that the return series in both variables are rather stable around the mean, but the volatility clusters from exchange rates
are more severe after November 2008. Therefore, market volatility is changing over time, which suggests that a suitable model for the data should have a time varying volatility structure as suggested by the ARCH model. The level of time series from <Fig. 1> also indicates that there are downward and upward trends and provides evidence of structural breaks in both rates.

<Table 1> reports the summary statistics for the level and return series of the stock index and exchange rates. It is evident that the returns are not symmetric as seen from the skewness and kurtosis of the series. This implies a leptokurtic frequency curve, which means that returns do not follow a normal distribution, but exhibit a sharp peak and fat tail distribution. This is confirmed by the Jarque-Bera test for normality. In addition, the Ljung and Box (1978) $Q$ statistics indicated that all return series investigated suffer from long-run dependencies. From the Ljung and Box (1978) $Q^2$ statistics, it is clear that there was a significant, nonlinear temporal dependence in the squared return series, suggesting that the volatility of returns follows an ARCH-type model.

<Table 2> presents the results of short-memory tests. All tests are conducted at a 5% level. Breitung’s (2002) test is for the null hypothesis of non-stationarity and the other statistics test for the null of level stationarity. The KPSS and $S_2$ tests are one-sided, and the other tests are two-sided. The nonlinear stationarity tests led to the clear conclusion that all variables are nonlinearly integrated of order ‘1’, NI(1), but the null hypothesis of non-stationarity was rejected for all variables in Breitung’s nonparametric test.3) <Fig. 2>

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3) For the unit root tests, this study considered the modified rescaled range (R/S) statistic of Lo (1991), the KPSS statistic of Kwiatkowski et al. (1992), the four different types of Cauchy tests statistics ($s_1$, $s_2$, $s_3$, and $s_4$) of Bierens and Gao (1993) and the variance ratio statistic of Breitung (2002). Unlike the first three testing devices, Breitung’s (2002) testing procedure is a non-parametric methodology, as it does not require the practitioner to specify the short-run dynamics of the process and to estimate the long-run variance.
Table 2. Unit Root Tests

| Variables | Stock index | Exchange rates |
|-----------|-------------|----------------|
| KPSS      |             |                |
| Constant  | 8.7361(4)   | 28.0190(4)     |
| Constant and Trend | 6.4829(4) | 5.2438(5) |
| R/S       | 6.6527(3)   | 8.1139(4)     |
| \(\lambda_1\) | -1035775.6 | 1665.6431     |
| \(\lambda_2\) | 2295.0133  | 2294.9963     |
| \(\lambda_3\) | -453.3450  | 148.7916      |
| \(\lambda_4\) | -452.9711(4) | 129.4416(5) |
| Breitung  |             |                |
| Constant  | 0.0190      | 0.0809        |
| Constant and Trend | 0.0141 | 0.0136 |
| Results   | Ni(1)       | Ni(1)         |

Note: All tests were conducted at the 5% level. The critical values are 0.463 and 0.146 for KPSS when including a constant and when including both a constant and a linear trend, respectively. The asymptotical critical value at the 5% level is an acceptance region of [0.809;1.862] for Lo's (1991) modified R/S statistic. The critical value for the Bierens and Guo (1993) test is [-12.706;12.706] for the \(\lambda_1\), \(\lambda_2\) and \(\lambda_3\) statistics, and 6.3137 for the \(\lambda_4\). The critical values at the 5% level are 0.0104 and 0.0035 for the Breitung (2002) statistic when including a constant and when including both a constant and a linear trend, respectively.

Fig. 2. Autocorrelation Coefficients for the Level Series

(a) Stock Index Level

(b) Exchange Rates Level

4) It is noteworthy that the KPSS, R/S and \(\lambda_4\) tests statistics might be fairly sensitive to the choice of lags. Nevertheless, the test statistics with any number of lags in the range from 1 to 12 yield concrete results that are qualitatively similar to the conclusion that all variables are Ni(1), and this is also the case regardless of whether a constant or a deterministic trend was included in the regression.
Table 3. Cointegration Tests

Panel A: Johansen’s cointegration test

| Samples | Hypothesis | Test statistics | Test statistics | 95% critical values |
|---------|------------|-----------------|-----------------|---------------------|
|         | H₀        | H₁              | λ_{trace}       | λ_{max} | λ_{trace} | λ_{max} |
| Stock index and exchange rates | Constant | r = 0          | r = 1          | 2.24    | 2.17    | 15.49  | 14.26  |
|         | r ≤ 1     | r = 1          | 0.07            | 0.08    | 3.84    | 3.84   |
| Trend   | r = 0     | r = 1          | 7.41            | 6.09    | 25.87   | 19.38  |
|         | r ≤ 1     | r = 2          | 1.31            | 1.32    | 12.51   | 12.51  |

Panel B: Breitung’s cointegration test

| Rank | A_{1}^{a} | A_{1}^{b} | A_{1}^{a} | A_{1}^{b} | 95% critical values |
|------|-----------|-----------|-----------|-----------|---------------------|
| 0    | 82.9702   | 172.5312  | 329.9     | 713.3     |
| 1    | 15.9471   | 59.1324   | 95.60     | 281.1     |

Panel C: Fractional Cointegration Test of the residual

Sample 1: 7/16/2004-6/30/2014

| Hypothesis | d | H₀,d=1 | H₀,d=0 | H₀,d=1 | H₀,d=0 |
|------------|---|--------|--------|--------|--------|
| Stock index and exchange rates | 0.95 | -0.67  | 15.45  | 0.97   | -0.55  |
|                | 0.96 | -0.86  | 20.92  |        |

Note: In Panel (A), r represents the number of cointegrating vectors and critical values are from MacKinnon et al. (1999). In Panel (B), the null hypothesis is that the process can be decomposed into a q-dimensional vector of stochastic trend components and a (n – q)-dimensional vector of transitory components. The hypothesis r = r₀ is rejected if the test statistic A₁ exceeds the respective critical value. From Panel (C), Critical values at the 5% level are -2.18 for μ=0.55, -2.13 for μ=0.575, and -2.11 for μ=0.60. Critical values are based on simulated values given in Chung (1997).

Persistence in the exchange rates and it frequently exceed the two 95% Bartlett (1946) confidence bands for very long lags.

The Johansen (1988) test was applied to examine the existence of cointegration between the stock index and exchange rates, and the results were summarized in <Table 3(A)>. The estimated λ_{trace} and λ_{max} statistics showed that the stock index and exchange rates were not cointegrated at the 5% significance level. The Breitung’s (2002) variance ratio statistic was generalized to a Johansen-type multivariate cointegrated system, which allowed for a wide range of nonlinear processes. <Table 3(B)> shows that the test results do not provide clear evidence of cointegration at the 5% level. Furthermore, Geweke and Porter-Hudak’s (1983) test (henceforth, GPH test) was considered to examine whether the two market prices are fractionally cointegrated and its results were reported in <Table 3(C)>.

The results varied little across the different values of μ under consideration. The fractional GPH test statistics were calculated for a cointegration test in which the lower truncation parameter was set to T^{0.1}, and the upper truncation parameter was set to T” with μ = 0.55, 0.575, 0.60 against fractional alternatives.5) The Monte Carlo experiments by Geweke and Porter-Hudak (1983), and Brockwell and Davis (1987) suggest that any values of μ less than 0.5 for the lower truncation parameter and 0.50 ≤ μ ≤ 0.70 for the upper truncation parameter offer the best empirical results.

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5) Monte Carlo experiments by Geweke and Porter-Hudak (1983), and Brockwell and Davis (1987) suggest that any values of μ less than 0.5 for the lower truncation parameter and 0.50 ≤ μ ≤ 0.70 for the upper truncation parameter offer the best empirical results.
statistics showed that all of the estimates of \( d \) lie between ‘0’ and ‘1’, but the null hypothesis of \( d=0 \) was rejected at 5% and the null hypothesis of \( d=1 \) was not, implying that there was no fractional integration relationship between the stock index and exchange rates.

IV. Empirical Analysis

1. Conditional Variance Models for Stock Prices and Exchange Rates

In the discrete time long-memory fractionally integrated I(\( d \)) class of processes, the propagation of shocks to the mean occurred at a slow hyperbolic rate of decay when \( 0<d<1 \), as opposed to the extremes of I(0) exponential decay associated with the stationary and invertible ARMA class of processes, or the infinite persistence resulting from an I(1) process. In order to exemplify the empirical relevance of these ideas for the variances, Fig. 3 plots the lag 1 through 100 sample autocorrelations of squared return series of the stock index and exchange rates. The autocorrelations of the squared returns of the stock index decayed exponentially and appeared in the two 95% Bartlett (1946) confidence bands for no serial dependence.
The above approach was applied to determine possible fractional integration orders of the conditional variances as well as traditional conditional variance specifications such as equations (5), (7), (8) for the stock index and exchange rates. Specifically, the AR(1)-FIGARCH(1,d,1) model from equation (6) was specified by the following:

\[(1 - \phi_1 L) (y_t - \phi_0) = \epsilon_t \quad (14)\]

\[h_t = \omega + \beta h_{t-1} + |1 - \beta L - (1 - \alpha L)| (1 - L)d|\epsilon_t^2| \quad (15)\]

where \(\phi_0, \phi_1, \omega, \alpha, \beta\) and \(d\) are parameters, and \(y_t\) stands for return series of the stock index and exchange rates.

The results were provided in <Tables 4> and <Tables 5>. Evaluated using the Ljung and Box (1978) portmanteau tests for the standardized residuals for the standard GARCH(1,1) model and two asymmetric GARCH(1,1) models reported in the second column to fourth of the table, it appears that these simple traditional models provide dearly the short-run volatility dependencies.

### Table 4. Estimation Results for Stock Index

| Models       | AR(1)-GARCH (1,1) | AR(1)-EGARCH (1,1) | AR(1)-GJR(1,1) | AR(1)-FIGARCH (1,d,0) | AR(1)-FIGARCH (0,d,1) | AR(1)-FIGARCH (1,d,1) |
|--------------|-------------------|--------------------|----------------|-----------------------|-----------------------|-----------------------|
| \(\phi_0\)   | 0.0195 (0.0210)   | 0.0051 (0.0182)    | 0.0228 (0.0221) | 0.0240 (0.0246)       | 0.0237 (0.0245)       | 0.0134 (0.0244)       |
| \(\phi_1\)   | 0.3167 (0.0168)   | 0.3650 (0.0156)    | 0.3165 (0.0171) | 0.3479 (0.0117)       | 0.3480 (0.0122)       | 0.3159 (0.0155)       |
| \(\alpha\)   | 0.1678 (0.0040)   | 0.0112 (0.0072)    | 0.1749 (0.0083) | 0.0840 (0.0091)       | 0.0938 (0.0112)       | 0.0165 (0.0013)       |
| \(\beta\)    | 0.8597 (0.0016)   | 0.9848 (0.0011)    | 0.8589 (0.0018) | 0.1015 (0.0033)       | 0.0904 (0.0032)       | 0.5221 (0.0029)       |
| \(\delta\)   | 0.2964 (0.0066)   | -0.0115 (0.0150)   | -0.0115 (0.0150) |                      | 0.0109 (0.0066)       |                      |
| LLK          | -3441.64 (0.0013) | -3477.59 (0.0020)  | -3441.54 (0.0014) | -3430.77 (0.0091)     | -3430.98 (0.0112)     | -3385.28 (0.0029)     |
| AIC          | 0.0006 (0.0013)   | 0.0013 (0.0014)    | 0.0015 (0.0018) | 0.1082 (0.0091)       | 0.1103 (0.0112)       | 0.0443 (0.0029)       |
| BIC          | 0.0131 (0.0163)   | 0.0163 (0.0083)    | 0.0165 (0.0083) | 0.1207 (0.0292)       | 0.1228 (0.0292)       | 0.0593 (0.0352)       |
| \(\sigma^2\) | 0.9963 (0.0985)   | 0.9961 (0.0996)    | 0.9963 (0.0996) | 1.1094 (0.0985)       | 1.1117 (0.0985)       | 1.0399 (0.0985)       |
| \(Q(10)\)   | 13.28 (0.20)      | 9.27 (0.50)        | 13.18 (0.21)    | 11.34 (0.33)          | 11.36 (0.32)          | 18.29 (0.05)          |
| \(Q^2(10)\) | 2.58 (0.98)       | 1.50 (0.99)        | 2.51 (0.99)     | 0.61 (0.99)           | 0.60 (0.99)           | 1.15 (0.99)           |

Note: The numbers in parentheses are the corresponding t-statistics and LLK denotes the value of log likelihood. AIC = 2(LLK+2k) and SIC = 2(LLK+klog(T)), where k is the number of estimated parameters from the corresponding models and T = 2002. \(\sigma^2\) denotes the residual variance. The \(Q(10), Q^2(10)\) and \(CQ(10)\) are the Ljung-Box statistics for tenth-order serial correlation in the residuals, squared residuals and cross-product of residuals, respectively. The critical values at the 0.05 significance level is 18.31 for 10 degrees of freedom.
### Table 5. Estimation Results for Exchange Rates

| Models | AR(1)- | AR(1)- | AR(1)- | AR(1)- | AR(1)- | AR(1)- |
|--------|--------|--------|--------|--------|--------|--------|
|        | GARCH  | EGARCH | FIGARCH| GARCH  | FIGARCH| FIGARCH|
|        | (1,1)  | (1,1)  | (1,1)  | (1,d,0)| (1,d,0)| (1,d,1)|
| $\phi_0$ | -0.0099| 0.0096 | -0.0039| -0.0117| -0.0122| -0.0119|
|        | (0.0091)| (0.0075)| (0.0091)| (0.0086)| (0.0085)| (0.0083)|
| $\phi_1$ | 0.0929 | 0.0815 | 0.1020 | 0.0981 | 0.0981 | 0.0991 |
|        | (0.0226)| (0.0217)| (0.0227)| (0.0244)| (0.0251)| (0.0259)|
| $D$    |        |        |        |        | 0.4252 | 0.3579 | 0.7362 |
|        |        |        |        |        | (0.0330)| (0.0278)| (0.0623)|
| $\omega$ | 0.0035 | 0.0480 | 0.0035 | 0.0128 | 0.0154 | 0.0035 |
|        | (0.0002)| (0.0056)| (0.0002)| (0.0013)| (0.0021)| (0.0005)|
| $\alpha$ | 0.1074 | 0.0696 | 0.1494 | 0.1246 | 0.3346 |
|        | (0.0070)| (0.0072)| (0.0110)| (0.0267)| (0.0332)|
| $\beta$ | 0.8847 | 0.9577 | 0.8837 | 0.2301 | 0.8136 |
|        | (0.0064)| (0.0032)| (0.0065)| (0.0324)| (0.0318)|
| $\delta$ | 0.1802 | -0.0854 |        |        |        |        |
|        | (0.0095)| (0.0111)|        |        |        |        |
| LLK    | -1228.15| -1203.42| -1213.61| -1224.88| -1229.31| -1211.12|
| AIC    | 0.0010 | 0.0005 | 0.0000 | 0.0238 | 0.0426 | 0.0086 |
| BIC    | 0.0114 | 0.0155 | 0.0150 | 0.0063 | 0.0551 | 0.0236 |
| $\hat{\sigma}^2$ | 0.9946 | 0.9953 | 0.9948 | 1.0196 | 1.0390 | 1.0034 |
| $Q(10)$ | 20.55 | 24.93 | 22.61 | 22.60 | 23.83 | 22.74 |
|        | (0.02)| (0.05)| (0.01)| (0.01)| (0.006)| (0.01)|
| $Q^2(10)$ | 3.55 | 5.17 | 3.82 | 3.89 | 4.26 | 2.12 |
|        | (0.96)| (0.87)| (0.95)| (0.95)| (0.93)| (0.99)|

Note: The numbers in parentheses are the corresponding t-statistics and LLK denotes the value of log likelihood. AIC=2*LLK+2*k and SIC=2*LLK+k*log(T), where k is the number of estimated parameters from the corresponding models and T=2062. $\hat{\sigma}^2$ denotes the residual variance. The $Q(10)$, $Q^2(10)$ and $CQ(10)$ are the Ljung-Box statistics for tenth-order serial correlation in the residuals, squared residuals and cross-product of residuals, respectively. The critical values at the 0.05 significance level is 18.31 for 10 degrees of freedom.

Also, entirely consistent with previous findings, the estimated parameters in the traditional conditional variance models, $\alpha + \beta$, is very close to unity, implying integrated GARCH(1,1) behavior. Hence, one might conclude that the integrated GARCH model successfully described the conditional variance process. However, from the FIGARCH model estimates, reported in the fifth column to seventh, it appears that the long-run dynamics are better modeled by the fractional differencing parameter. The long memory parameters in the conditional variance, d, are between zero and one, and all significant at 5%. However, purely from the perspective of searching for a model that best describes the volatility in the stock index and exchange rate return series, the traditional conditional variance models appeared to be the most satisfactory representation.

2. Dynamics in the Conditional Mean of Bivariate GARCH Models

<Table 6> reports estimates of bivariate
Table 6. Estimation Results of Different Bivariate GARCH Models

| Panel A: Conditional mean estimates for the stock index and exchange rates |
|-----------------|-----------------|-----------------|-----------------|-----------------|
|                | Traditional GARCH | GJR GARCH | Exponential GARCH |
| \( \phi_{S0} \) | 0.1291(0.0468) | 0.1281(0.0437) | 0.1563(0.0344) |
| \( \phi_{F0} \) | 0.3151(0.0173) | 0.3162(0.0173) | 0.3284(0.0175) |
| \( \theta_{f} \) | -0.0578(0.0319) | -0.0565(0.0401) | -0.0876(0.0238) |
| \( \lambda_{S} \) | -0.1484(0.0478) | -0.1800(0.0460) | -0.2647(0.0359) |
| \( \delta_{S} \) | 0.0181(0.0705) | 0.0873(0.0853) | 0.1295(0.0600) |
| \( \phi_{F0} \) | -0.0002(0.0205) | -0.0268(0.0181) | -0.0250(0.0083) |
| \( \phi_{F1} \) | 0.0897(0.0230) | 0.0829(0.0224) | 0.0822(0.0214) |
| \( \theta_{F} \) | 0.0078(0.0056) | 0.0070(0.0063) | 0.0123(0.0047) |
| \( \lambda_{F} \) | 0.0581(0.0550) | 0.0777(0.0556) | 0.1006(0.0357) |
| \( \delta_{F} \) | -0.0304(0.0025) | 0.0147(0.0148) | -0.0189(0.0020) |

Panel B: Conditional variance estimates for the stock index and exchange rates

|                | Traditional GARCH | GJR GARCH | Exponential GARCH |
|----------------|-----------------|-----------------|-----------------|-----------------|
| \( \omega_{S} \) | 0.0235(0.0020) | 0.0192(0.0021) | 0.0519(0.0026) |
| \( \omega_{F} \) | 0.0024(0.0002) | 0.0014(0.0002) | 0.0365(0.0062) |
| \( \alpha_{S} \) | 0.1729(0.0044) | 0.1796(0.0047) | 0.0013(0.0087) |
| \( \alpha_{F} \) | 0.1058(0.0067) | 0.0908(0.0052) | 0.0648(0.0072) |
| \( \beta_{S} \) | 0.8534(0.0033) | 0.8477(0.0037) | 0.9803(0.0021) |
| \( \beta_{F} \) | 0.8934(0.0057) | 0.9058(0.0048) | 0.9658(0.0360) |
| \( \pi_{S} \) | 0.0295(0.0057) | 0.0295(0.0057) | 0.3164(0.0078) |
| \( \pi_{F} \) | -0.0006(0.0001) | 0.0147(0.0148) | -0.0189(0.0020) |

Panel C: Conditional Correlation Coefficient

| \( \rho \) | 0.0080(0.0212) | 0.0031(0.0212) | 0.0056(0.0216) |

Panel D: Diagnostic tests on standardized residuals

| variables | \( R_{S_{t}} \) | \( R_{F_{t}} \) | \( R_{S_{t}^2} \) | \( R_{F_{t}^2} \) |
|-----------|-----------------|-----------------|-----------------|-----------------|
| LLK       | -4663.1460      | -4646.6639      | -4641.1418      |
| AIC       | 9360.29         | 9331.32         | 9320.28         |
| BIC       | 9457.84         | 9440.35         | 9429.31         |
| \( \sigma^2 \) | 0.9981          | 0.9941          | 0.9983          | 0.9928          | 0.9969          | 0.9959          |
| Q(10)     | 36.5767 [0.0001] | 58.7179 [0.0000] | 14.5391 [0.1497] | 21.7137 [0.0166] | 15.5881 [0.1120] | 25.8185 [0.0039] |
| Q2(10)    | 2.4876 [0.9910] | 4.2166 [0.0006] | 2.3345 [0.9930] | 5.0002 [0.0166] | 1.9340 [0.9968] | 6.1329 [0.0039] |
| CQ(10)    | 16.2772 [0.0619] | 58.7179 [0.0000] | 14.5391 [0.0001] | 21.7137 [0.0001] | 15.5881 [0.9952] | 25.8185 [0.0039] |
| CQ2(10)   | 2.4876 [0.0004] | 2.3345 [0.0006] | 5.0002 [0.0001] | 1.9340 [0.0001] | 6.1329 [0.0007] | 1.9340 [0.0001] |

Note: The numbers in parentheses are the corresponding t-statistics and LLK denotes the value of log likelihood. AIC=-2(LLK+2k) and SIC=-2(LLK+k*log(T)), where k is the number of estimated parameters from the corresponding models and T=2062. \( \sigma^2 \) denotes the residual variance. The Q(10), Q(10) and CQ(10) are the Ljung-Box statistics for tenth-order serial correlation in the residuals, squared residuals and cross-product of residuals, respectively. The critical values at the 0.05 significance level is 18.31 for 10 degrees of freedom.
AR-GARCH-M models for the stock prices and exchange rates of Nepal. The lag orders of all models were identified as one. The GARCH parameters in the residual variance equation are significant at 5% significance level. The GARCH-in-mean variables in AR modeling in stock index equation are significant both in the EAGARCH specification, showing that the negative effect of stock index uncertainty and positive effect of exchange rates uncertainty on average stock index was found. For the other two models of traditional GARCH and GJR-GARCH, the coefficients on the conditional variance of stock index in the stock market are both negative and significant, but the coefficients on the conditional variance of exchange rates in the stock market are not significant at 5% level.

On the other hand, for the exchange rates equation, the GARCH-in-mean variables in AR modeling are significant both in the EAGARCH specification, showing that a positive effect of exchange rates uncertainty and a negative effect of stock index uncertainty on average exchange rates were found. The GARCH-in-mean variables in AR modeling in exchange rates equation are not significant both in the GJR-GARCH specification. From the traditional GARCH in mean model, the coefficients on the conditional variance of stock index in the foreign exchange market is not significant, but the coefficients on the conditional variance of exchange rates in the foreign exchange market is negatively significant at 5% level.

The estimates of the mean as well as conditional variances of stock index and exchange rates for bivariate GARCH-M, GJR-GARCH-M and EGARCH-M models are also reported in <Table 6>. Mean reversion was clearly observed such that the previous stock prices return (the previous exchange rates return) has a significant positive impact on the current stock prices return (the current exchange rates return). The current stock prices return was negatively affected by the lagged exchange rates return for the EGARCH-M model at 5% significance level, implying that large previous exchange rates return decreases the current stock prices return. In contrast, the current exchange rates return was positively affected by the lagged stock prices return for the EGARCH-M model at 5% significance level, implying that large previous stock prices return increases the current exchange rates return.

The GARCH parameters in the residual variance equation are all significant in all models. However, the coefficients on the lagged residual variance for GARCH-M, GJR-GARCH-M models are greater for exchange rates than for stock index, implying that exchange rates shocks have long-lived effects on uncertainty in the foreign exchange market than stock index shock have on uncertainty in the stock market. The magnitude of $\alpha$ that shows the effect of the last period's shock directly was found to be greater for stock index than for exchange rates both in GARCH-M and GJR-GARCH-M models, implying that volatility is more sensitive to its own lagged values than it is to new surprises in the market place.

For stock index and exchange rates returns, it appears to be the case that volatile periods often are initiated by a large negative shock, which suggests that positive and negative shocks may have an asymmetric impact on the conditional volatility of subsequent observations. However, the traditional GARCH models cannot capture such asymmetric effects of positive and negative shocks. As the conditional variance depends only on the square of the
shock, positive and negative shocks of the same magnitude have the same effect on the conditional volatility, that is, the sign of the shock is not important. From Table 6, asymmetric parameters, $\pi_i$ for $i=S$ or $F$ are all significant for the GJR-GARCH-M and EGARCH-M models.

Additionally, the estimation results of the variance and correlation equations are also provided in panel C of Table 6. The estimation results for the traditional CCC (Bollerslev, 1990) models supported the existence of conditional heteroskedasticity for both the stock index and exchange rates. There is strong persistence in the variance movement. As expected, the two series are not highly correlated on the basis of coefficient $\rho$ in the table, implying that there is no need to include dynamic conditional correlation in the conditional variance specifications.

In addition, Panel D of Table 6 reports diagnostic tests on the standardized residuals. The Ljung-Box Q-statistics at 10 lags for the levels, squares and cross-equation products of the standardized residuals for the estimated bivariate ARFIMA-GARCH-M system was calculated. The results reported in Table 6 show that the time series models for the conditional means and the GARCH model for the residual conditional variance-covariance adequately captures the joint distribution of the disturbances. The conditional correlation coefficient is close to zero, suggesting that the residual covariance between equations is not statistically significant.

V. Conclusion

In this paper, three different versions of bivariate GARCH in mean models are considered to explain the relationship between uncertainty and average outcomes for the stock index and exchange rates. First, it was examined if there is significant, persistent conditional heteroskedasticity in both variables and then the tests of four hypotheses about how uncertainty influences the stock index and exchange rates were performed.

From the empirical results, a bivariate EGARCH-M model best explained the volatility in the two markets. There are four key findings. First, there is a negative relationship between the exchange rates return to stock prices return, but the current exchange rates return is positively affected by the lagged stock prices return at 5% significance level. Second, the empirical results provided strong empirical confirmation of the first and third hypotheses, implying that the negative effect of stock index uncertainty and positive effect of exchange rates uncertainty on average stock index were found. In contrast, for the exchange rates equation, the GARCH-in-mean variables in AR modeling are significant, showing that a positive effect of exchange rates uncertainty and a negative effect of stock index uncertainty on average exchange rates were found. Third, the coefficient on the lagged residual variance is greater for stock index than for exchange rates, implying that stock index shocks have long-lived effects on uncertainty in the stock market than exchange rates shock have on uncertainty in the foreign exchange market. Finally, from the magnitude of $\alpha$ that shows the effect of the last period’s shock, volatility is more sensitive to its own lagged values than it is to new surprises in the foreign exchange market.
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