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Currency Depreciation and Korean Stock Market Performance during the Asian Financial Crisis

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Abstract

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Abstract

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I. INTRODUCTION

Modern theories of asset allocation argue that investor's trade-off expected return and riskiness (volatility). In an early study, Chou (1988) argues that high stock market volatility in 1974 caused the drop in the U.S. stock market, and points to the importance of identifying the sources of volatility. Stock market volatility can reflect changes in money supply and oil prices (Engle and Rodrigues, 1989) and changes in delivery and payment terms (Baillie and DeGennaro, 1989). While asset allocation frequently occurs within a country, some investors, however, allocate portfolios across assets in different countries. International asset allocation must consider the additional complication of currency conversion. Thus, exchange rate risk (volatility) provides an additional channel whereby an asset's expected return trades-off with riskiness (volatility). Such concern is heightened in small open economies where the stock market is small, or emerging.

The Asian financial crisis provides an "experiment" where exchange rate riskiness (volatility) may have helped determine the short-run stock-market movements. This paper investigates the effects of daily currency depreciation on stock market returns during the Korean financial turmoil of 1997 to 2000.

After participating in the East Asian miracle (World Bank, 1993), Korea's stock market suffered severely during the 1997 Asian financial crisis, falling by 42.62 percent in 1997. It then rose by 48.04 and 85.12 percent in 1998 and 1999 and fell by 50.92 percent in 2000. The Korean won depreciated by 68.25 percent in 1997 against the U.S. dollar. It then appreciated by 14.74 and 5.45 percent in 1998 and 1999 and depreciated by 9.90 percent in 2000.

The depreciation of domestic currency against the dollar raises the return on dollar assets. Investors shift funds from domestic assets such as stocks toward dollar assets due to higher expected returns. The shift in portfolio composition favors dollar assets over domestic stocks, leading to declining stock market prices and returns. According to the portfolio balance model, a depreciating domestic currency should negatively correlate with stock market returns.[1]

Investigations of the effects of currency depreciation on stock market returns are scant and inconclusive, and little attention assesses this issue using data from the 1997 financial turmoil. Solnik (1987) employs OLS regression analysis for eight industrial countries and finds both a negative and a positive relation between domestic stock returns and currency appreciation over different sample periods. Although Ratner (1993) fails to find cointegration between the dollar foreign exchange rates of six industrial countries and a U.S. stock market index, Mukherjee and Naka (1995) and Ajayi and Mougoue (1996) find that a stock market index cointegrates with the exchange rate in Japan and seven other industrial economies. Koutoulas and Kryzanowski (1996) and Kearney (1998) provide evidence that stock market volatility responds significantly to exchange rate volatility in Canada and Ireland. Jorion (1991) finds no evidence that unconditional exchange rate risk affects the U.S. stock market. Chiang, Yang and Wang (2000) and Fang (2001) find a significant negative relation between stock returns and currency depreciation in both bivatiate and univariate GARCH(1,1) processes for some Asian countries.

This paper considers structural shifts in volatility of stock and foreign exchange markets and applies a bivariate GARCH-M model using Korean data during the Asian financial crisis to provide more evidence for the effects of currency depreciation on stock market returns. Generalized autoregressive conditional heteroskedasticity (GARCH) models (Bollerslev, 1986; Engle, Lilien, and Robins, 1987; and Bollerslev, Engle, and Wooldridge, 1988) have proved successful in modeling asset returns and volatility by allowing the mean of the asset return to depend on its time-varying variance (and other causes). Our unrestricted bivariate GARCH-M approach differs from and improves on prior research in that the model jointly estimates stock returns and the variance structures of stock returns and currency depreciation, with two variances and currency depreciation as explanatory variables.

II. DATA, COINTEGRATION, AND GAUSALITY TESTS

The data consist of daily closing stock market prices and the exchange rates from January 3, 1997 to December 21, 2000. The stock market price (*P*) is the Korea Composite Price Index of South Korea. The stock market return with no dividend adjustment (*R*) is calculated by the logarithmic difference of the stock market price index, $R_t = 100 \times (\ln P_t - \ln P_{t-1})$. The exchange rate (*S*) is expressed as Korean won per U.S. dollar. The depreciation rate or the exchange rate return (*E*) is the logarithmic difference of the spot exchange rate, $E_t = 100 \times (\ln S_t - \ln S_{t-1})$.

We first test to see if the Korean won exchange rate cointegrates with the Korean stock market price. The reported results of the ADF unit root test in Table 1 indicate the rejection of non-stationarity in first differences, suggests that both the stock market price and the exchange rate are integrated once, I(1). Accordingly, we consider the Johansen test for cointegration (Johansen, 1991) between those two variables. The results of the cointegration test can be sensitive to the lag length. The likelihood ratio (LR) test statistic selects 6 lags for the VAR model. The insignificant λ_{max} and *Trace* statistics suggest that the null hypothesis of non-cointegration is not rejected for the two markets.

The 1997 Asian financial crisis may produce structural breaks in the long-run relation between the two market prices, leading to non-cointegration. Gregory and Hansen (1996) suggest residual-based cointegration tests with structural breaks – either a change in the intercept (level shift), a change in the intercept with a time trend (level shift with trend), or a change in the cointegrating coefficients (regime shift). In table 1, the three residual-based augmented Dickey-Fuller test statistics for those specifications are –2.4348(8), -3.3572(0), and –2.5081(2), respectively, where the number in parentheses is the lag truncation using the t-test suggested by Perron and Vogelsang (1992). We set the maximum lag length to 12 and test downward until the last lag difference included is significant at the 5-percent level. We fail to reject the null hypothesis of no cointegration in each instance. So including potential structural shifts due to the 1997 Asian financial crisis leaves our cointegration findings unaltered.

No cointegration suggests the use of first-differenced data in the VAR model to investigate Granger causality (Granger, 1988). The lag length for the causality test matches that of the test for cointegration. The two significant F-statistics suggest that bidirectional Granger causality exists between the two markets.

III. STRUCTURAL SHIFT IN UNCONDITIONAL VARIANCE

Table 2 displays preliminary statistics for the daily stock market and exchange rate returns over the sample period. The means of the stock market and exchange rate returns are negative and positive, respectively. Both are close to zero. The standard deviation of the stock market return exceeds that of the exchange rate return. The stock market return exhibits a negative skewness, although not significantly different from zero. The exchange rate return exhibits positive and significant skewness. Investors should have a preference for positive skewness, for they should prefer portfolios with a larger probability of large payoffs. The two series are leptokurtic. The Ljung-Box test (L-B Q) suggests the presence of autocorrelation for both series up to 12 lags. The Ljung-Box statistics for the squared series ($L-B^2\ Q$) are all highly significant, implying the possible presence of time-varying volatility in stock and foreign exchange markets.

Since squares of serially correlated data may yield results in favor of presence of heteroskedasticity, the time-varying property of the variances for the two series is further examined with Lagrange Multiplier (LM) tests for ARCH(q) errors (Engle, 1982). Table 3 reports results of the test. The Ljung-Box Q-statistics showing no autocorrelations up to 12 lags suggests that the AR(1) and AR(14) processes are appropriately modeled to obtain white noise errors for the stock market and exchange rate returns. After considering autocorrelations, the LM statistics for the ARCH effect confirm heteroskedastic variances for stock market and exchange rate returns.

We use the GARCH(1,1) specification, since it adequately represents most financial time series.[2] Lamoureux and Lastrapes (1990) suggest the use of dummy variables to correspond to shifts in the unconditional variance. Negligence of such shifts may bias upward GARCH estimates of persistence in variance and thus vitiate the use of GARCH in estimating the mean equation, especially when the degree of permanence is important. The Korean experience provides an interesting case on this issue due to the 1997 Asian financial crisis and its effect on Korean stock and foreign exchange markets.

Figure 1 shows the behavior of stock market and exchange rate returns. Starting on October 24, 1997, the stock market return became more highly variable and remained at the higher level of volatility to the end of 2000. In the same way, the exchange rate return began fluctuating more widely after October 24, 1997, but returned to a less volatile level after August 21, 1998. The visual evidence suggests that the stock market return volatility has one and the exchange rate return volatility has two structural breaks in this sample period. Accordingly, in our GARCH(1,1) specification, a dummy variable D enters the stock market variance equation with D=1 for the period October 24, 1997 to the end of December, 2000; 0 otherwise. For the foreign exchange market variance, we include two dummies: D_1=1 for October 24, 1997 to August 21, 1998; 0 otherwise, and D_2=1 for August 22, 1998 to December 21, 2000; 0 otherwise.

The mean return in the unrestricted GARCH(1,1) model, which includes shift dummies, is specified as an AR(1) process to account for nonsynchronous trading. Estimation results are reported in Table 4. The significant estimates of the dummies (i.e., α_3, β_3, and β_4) support our expectation that structural shifts in the variance emerge for both stock and exchange rate returns. Without the dummies, the restricted GARCH(1,1) model of the exchange rate returns emerges as an unstable variance process in which the sum of the GARCH estimates is greater than one. The inclusion of the shift dummies to decrease GARCH estimates is strongly argued by Lamoureux and Lastrapes (1990). To investigate further, we cannot reject the Lagrange multiplier test (LM) for the constancy of the variance parameters, under the assumption of non-normality, against the alternative hypothesis of a one-time shift in the unrestricted GARCH models (Chu, 1995). Autocorrelation and heteroskedasticity tests indicate that the unrestricted GARCH(1,1) specification sufficiently accounts for time dependence in the conditional variance of R and E.

Each variance process is positive, finite, and stationary as $\alpha_0, \alpha_1, \alpha_2, \alpha_3, \beta_0, \beta_1, \beta_2, \beta_3, \beta_4 > 0$; $(\alpha_1 + \alpha_2) < 1$, and $(\beta_1 + \beta_2) < 1$. The significant estimates of α_1, α_2, β_1 and β_2 confirm the presence of GARCH effect in the two series.

IV. AN UNRESTRICTED BIVARIATE GARCH-M MODEL

The finding of a causal relation running from exchange rate depreciation to the stock market returns (Table 1) implies that changes in currency depreciation induce changes in the stock market returns and its volatility. The statistical evidence of stationarity (Table 1), leptokurticity (Table 2), heteroskedasticity (Table 3), and structural shifts in variances (Table 4) in the two series of stock market and exchange rate returns suggests the use of unrestricted bivariate GARCH models to analyze the effect of currency depreciation on the stock market return. The following eclectic GARCH model provides a framework for investigating the effects of currency depreciation on the stock market return.

$$R_t = d_0 + \sum_{i=0}^{n} a_i E_{t-i} + \sum_{i=0}^{n} b_i h_{E,t-i} + \sum_{i=0}^{n} c_i h_{R,t-i} + \sum_{i=1}^{n} d_i R_{t-i} + \varepsilon_{R,t} \tag{1}$$

$$E_t = \omega_0 + \omega_1 E_{t-1} + \varepsilon_{E,t} \tag{2}$$

$$\varepsilon_{R,t} = v_{R,t}(h_{R,t})^{0.5} \tag{3}$$

$$\varepsilon_{E,t} = v_{E,t}(h_{E,t})^{0.5} \tag{4}$$

$$h_{R,t} = \alpha_0 + \alpha_1 \varepsilon_{R,t-1}^2 + \alpha_2 h_{R,t-1} + \alpha_3 D_t \tag{5}$$

$$h_{E,t} = \beta_0 + \beta_1 \varepsilon_{E,t-1}^2 + \beta_2 h_{E,t-1} + \beta_3 D_{1,t} + \beta_4 D_{2,t} \tag{6}$$

$$h_{RE,t} = \gamma_0 + \gamma_1 \varepsilon_{R,t-1} \varepsilon_{E,t-1} + \gamma_2 h_{RE,t-1} \tag{7}$$

where $v_{R,t}$ and $v_{E,t}$ are i.i.d. with constant mean and unit variance; $h_{R,t} = Var(\varepsilon_{R,t})$ and $h_{E,t} = Var(\varepsilon_{E,t})$; $h_{RE,t} = Cov(\varepsilon_{R,t}, \varepsilon_{E,t})$; $\varepsilon_{R,t}$ and $\varepsilon_{E,t}$ are assumed to be white-noise stochastic processes.

The effect of currency depreciation may be instantaneous and also may be distributed over a few days, depending on how fast the market information is utilized. This dynamic feature in the unrestricted version distinguishes our model from most empirical GARCH-M models that include only contemporaneous variables as regressors in restricted specifications. To pick up autocorrelation in the reduced form errors caused by lagged adjustment to changes in the exogenous variables, we specify an AR component in the mean equation of stock market returns.

In the empirical GARCH model, conditional variances and covariance are time-varying. For example, the large shocks of the Asian financial crisis hit the two asset returns of opposite signs. That is, the crisis raised the asset returns of the dollars and lowered the returns of stocks. The crisis increased the variances of the two correlated assets and the covariance between them. The presence of $h_{E,t-i}$ and $h_{R,t-i}$ in the conditional mean equation of the stock market return implies that the system of equation (1) through equation (7) is a bivariate GARCH-M model.[3] The parameters of the model are estimated by maximum likelihood using the BHHH algorithm.

V. EMPIRICAL RESULTS

Table 5 reports the joint estimation results, including the estimated coefficients and asymptotic t-statistics for the general and simple models. Before estimation, the lag length of the mean equation of the stock market return is determined. We start with the lag structure (i.e., n = 6) in the VAR model for cointegration test. The general dynamic model could be overparametrized. Following the general to simple approach suggested by Hendry (1985), we then carry out a data-based simplification to reduce the model by eliminating insignificant estimates through LR χ^2-tests. We report the likelihood ratio statistic that tests the validity of this restriction. The statistic has a χ^2 distribution with 14 degrees of freedom. We also report the Ljung-Box statistics for up to 12th-order autocorrelation on the standardized and squared standardized residuals in $\varepsilon_{R,t}$ and $\varepsilon_{E,t}$.

In the table, the general model has neither autocorrelation nor heteroskedasticity, but too many insignificant coefficients exist. Using the general-to-simple approach, we eliminate fourteen (14) insignificant variables. Diagnostic tests support the statistical appropriateness of the simple unrestricted bivariate GARCH(1,1)-M model. Each variance process is positive and convergent as every estimated coefficient exceeds zero, and ($\alpha_1 + \alpha_2$) and ($\beta_1 + \beta_2$) < 1. The significant GARCH(1,1) coefficients of α_1, α_2, β_1 and β_2 suggest time-varying volatility in the stock and foreign exchange markets. The 1997 Asian financial crisis produced structural shifts in variance for both the stock market return and exchange rate depreciation.

Table 5 indicates that the exchange rate depreciation significantly affects the stock market return. The effect of currency depreciation has a delayed effect, as only lagged effects emerge. The first, fifth, and sixth lagged depreciation effects are -0.0995, 0.1440, and -0.1299, respectively. The sum (= -0.0854) of the coefficients of the exchange rate depreciation terms supports a negative relation between currency depreciation and the stock market return.

The conditional variances of exchange rate depreciation and the stock market return all have significantly lagged effects. First, the conditional variance of exchange rate depreciation has a positive cumulative effect (=0.0103) on the stock market return. The higher is the volatility of exchange rate depreciation, the higher is the stock market return. That result matches our prior expectation that higher exchange rate volatility should reduce the demand for dollar assets and increase the demand for domestic stocks. Second, the conditional variance of the stock market return also has a positive cumulative effect (=0.0065) on the stock market return. That finding provides support for a higher risk premium in the Korean stock market over the period of financial turmoil.

Since both the stock market return and exchange rate depreciation exhibit GARCH (Table 4), we also examine the extent to which changes in the conditional variance of exchange rate depreciation pass through to the variance of stock market returns by specifying $h_{R,t}$ as a function of $h_{E,t}$. To avoid serial correlation, we specify an autoregressive distributed lag model. After allowing for twelve lags and eliminating insignificant effects, the results appear in Table 6 with t-statistics reported in parentheses. The Ljung Box Q-statistics indicate that the simplified model has no autocorrelation in errors. The positive cumulative effect (i.e., $\sum \lambda_i = 0.0074 > 0$) indicates that depreciation rate volatility raises stock return volatility.[4]

The significant depreciation coefficients in the stock return process and the positive effect of depreciation rate volatility on stock return volatility suggest depreciation movements can explain periods of volatility in the stock returns series. The rise in stock market volatility has been argued to be a major reason for declines in stock prices (Malkiel, 1979; Pindyck, 1984; Chou, 1988). It is important to identify any source of the market volatility. Modern internationalization and integration of financial markets have impacts on investors in that asset allocation occurs across countries and assets.[5] In both cases, investors must consider currency conversion. Thus, exchange rate movements can provide a channel affecting stock market prices and volatility. Our findings provide evidence that stock market volatility reflects changes in the exchange rate, at least in the period of financial turmoil for an emerging market.

VI. CONCLUSIONS

We employ an unrestrictive bivariate GARCH-M model of the stock market return to investigate the relationship between currency depreciation and the stock market return. We perform tests for

Korea over the Asian financial turmoil from 1997 to 2000. Our approach incorporates three important elements. First, the dataset covers the Asian financial turmoil era. Second, we include structural shift dummies in the variance processes for both stock and foreign exchange markets because of the financial crisis. Third, by considering adjustment dynamics, we provide estimates of instantaneous and lagged effects of the stock market return to currency depreciation. We find that currency depreciation has statistically significant effects on stock market returns through three channels. First, the level of exchange rate depreciation negatively affects stock market returns. Second, exchange rate depreciation volatility positively affects stock market returns. Third, stock market return volatility responds to exchange rate depreciation volatility.

Our results show that currency depreciation importantly alters the stock market investment decision. The decision to invest in the Korean stock market benefits from knowledge of both the level and volatility of the Korean won. Investment actions generate stock market returns that are, at best, uncertain, if investors ignore the level, as well as the volatility, of exchange rate depreciation.

FOOTNOTES

[1] Financial markets adjust rapidly and reach their equilibrium in the short run. This paper examines short-run properties of the portfolio balance model, assuming that the real sector is determined. In the long run, a depreciating domestic currency should favorably affect stock market prices and returns due to increased exports and domestic substitution for imported goods.

[2] Bollerslev, Chou, and Kroner (1992) cite over 200 papers using (G)ARCH techniques in an extensive range of applications.

[3] Engle and Kroner (1995) provide more details about specifying multivariate GARCH models.

[4] Kearney (1998) concludes that exchange rate volatility significantly determines stock market volatility in Ireland.

[5] For example, in the internationalization process, the U.S. stock market was by far the largest in the world, but foreign stock markets have been growing in importance. The increased interest in foreign stocks has prompted the development in the United States of mutual funds specializing in trading in foreign stock markets. American investors now pay attention not only to the Dow Jones Industrial Average but also to stock price indexes for foreign stock markets.

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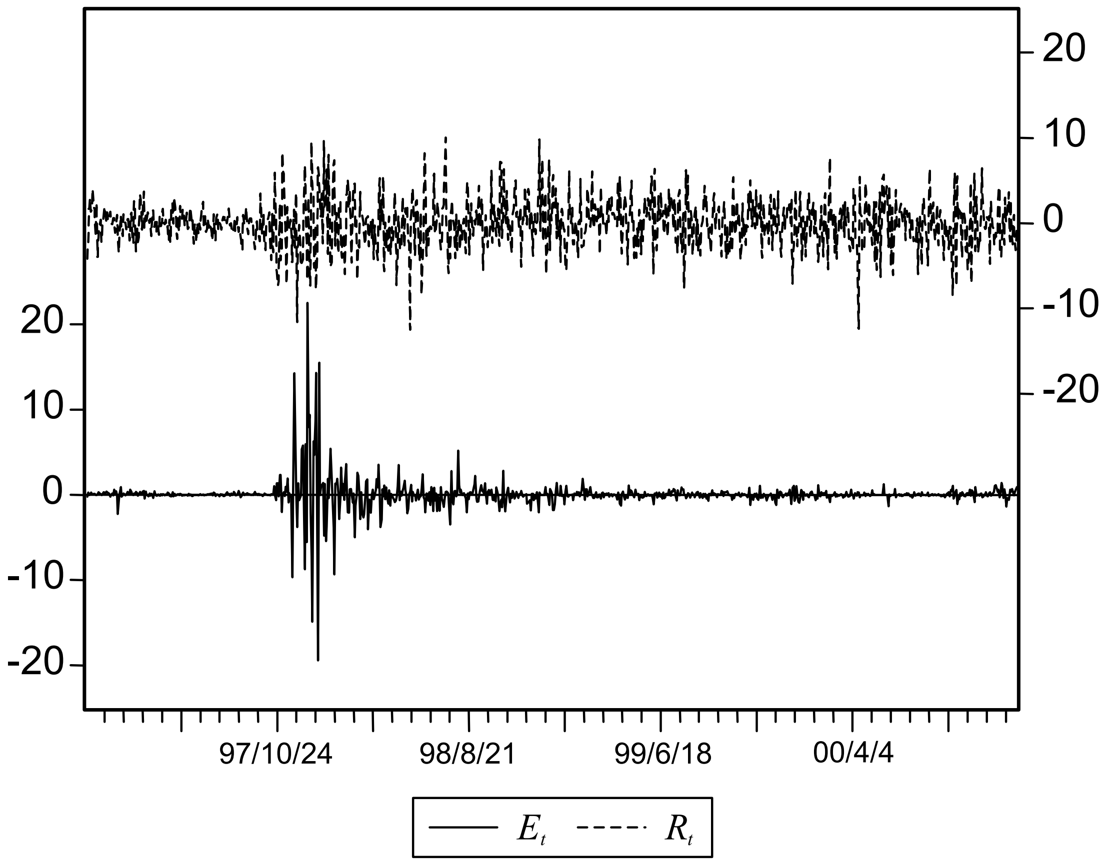

Figure 1. Exchange Rate (E_t) and Stock Market (R_t) Returns

Table 1. Unit-Root, Cointegration, and Causality Tests

ADF Unit-Root Test

Variable	Level	First difference
Stock index (P_t)	-1.3515(2)	-22.3783(1)*
Exchange rate (R_t)	-2.3010(30)	-4.9313(29)*

Johansen Cointegration Test (VAR lags = 6)

H_0	λ_{max}	critical value	*Trace*	critical value
$R=0$	7.60	10.60	9.99	13.31
$R\leq 1$	2.40	2.71	2.40	2.71

ADF Cointegration Test with Structural Breaks

Models	t-statistics	critical value
Level shift	-2.4348(8)	-4.61
Level shift with trend	-3.3572(0)	-4.99
Regime shift	-2.5081(2)	-4.95

Granger Causality Test (VAR lags = 6)

H_0	F(q,N-k)	Granger causality test result
S_t **does not cause** P_t	3.5207*	S_t causes P_t
P_t **does not cause** S_t	2.1326*	P_t causes S_t

ADF(n) is the Augmented Dickey-Fuller test for stationarity with n lags selected to guarantee no autocorrelation in the ADF regression residuals. The likelihood ratio statistics determine a lag length of 6 in the VAR for cointegration and Granger causality tests. R is the number of cointegration vector. The lag length for the ADF cointegration test with structural breaks is selected on the basis of a t –test suggested by Perron and Vogelsang (1992). F(q,N-k) is Wald F statistic with the degrees of freedom of q and N-k.

*denotes significance at the 5% level.

Table 2. Preliminary Statistics for Daily Stock Market and Exchange Rate Returns

	Stock market returns	Exchange rate returns
Sample size	972	972
Mean	-0.0252	0.0389
SD	2.8848	1.8362
Skewness	-0.0386	1.6454*
	(0.1925)	(0.1925)
Kurtosis	4.4884*	59.3951*
	(0.7698)	(0.7698)
L-B Q(6)	20.545*	220.60*
L-B Q(12)	24.303*	328.60*
L-B^2 Q(6)	77.238*	467.23*
L-B^2 Q(12)	114.37*	856.14*

SD is the standard deviation. L-B Q(k) and L-B^2 Q(k) are Ljung-Box statistics for returns and squared returns for autocorrelation up to k lags. The numbers in parentheses beneath the skewness and kurtosis are standard deviations calculated by $\sqrt{6/N}$ and $\sqrt{24/N}$, respectively. *denotes significance at the 5 percent level.

Table 3. ARCH LM test

K	Stock market returns	Exchange rate returns
1	10.4687*	60.9218*
2	8.3037*	105.1889*
3	9.6712*	74.6935*
4	10.3114*	58.2244*
5	10.2403*	46.5011*
6	8.5730*	38.9311*
7	7.7966*	33.8558*
8	6.8555*	30.0013*
9	6.1421*	30.2940*
10	5.7228*	33.6636*
11	5.4863*	30.6141*
12	5.1401*	33.2026*
ARMA(p,q)	(1,0)	(14,0)
L-B Q(6)	9.9010	3.7545
L-B Q(12)	14.4323	12.9256

ARMA(p,q) represents the process in stock and exchange rate returns. L-B Q(k) is the Ljung-Box statistic for residuals from the ARMA process for autocorrelations up to 12 lags. LM statistic follows a χ^2 distribution with k degrees of freedom, where k = 1,2,3,…12.

*denotes significance at the 5 percent level.

Table 4. Unrestricted GARCH Models

Stock Market Returns

$R_t = c_0 + c_1 R_{t-1} + \varepsilon_{R,t}$, where $\varepsilon_{R,t} \mid \Psi_{t-1} \sim N(0, h_{R,t})$

$h_{R,t} = \alpha_0 + \alpha_1 \varepsilon^2_{R,t-1} + \alpha_2 h_{R,t-1} + \alpha_3 D_t$

$$R_t = \underset{(-0.2691)}{-0.0019} \underset{(2.9488)\,*}{+0.1083R_{t-1}} + \varepsilon_{R,t}$$

$$h_{R,t} = \underset{(2.5943)\,*}{0.2200} \underset{(4.0907)\,*}{+0.1130\varepsilon^2_{R,t-1}} \underset{(14.0664)\,*}{+0.7799h_{R,t-1}} \underset{(2.9246)\,*}{+0.8532D_t}$$

$LB\ Q(6) = 7.6631$ $LB\ Q(12) = 11.5856$ $ARCH(6) = 0.5700$ $ARCH(12) = 0.6510$ $LM = 12.3104$

Exchange Rate Returns

$E_t = d_0 + d_1 E_{t-1} + \varepsilon_{E,t}$, where $\varepsilon_{e,t} \mid \Psi_{t-1} \sim N(0, h_{E,t})$

$h_{E,t} = \beta_0 + \beta_1 \varepsilon^2_{E,t-1} + \beta_2 h_{E,t-1} + \beta_3 D_{1,t} + \beta_4 D_{2,t}$

$$E_t = \underset{(1.0426)}{0.0108} \underset{(4.0642)\,*}{+0.1627E_{t-1}} + \varepsilon_{E,t}$$

$$h_{E,t} = \underset{(10.1104)\,*}{0.0079} \underset{(10.1404)\,*}{+0.3113\varepsilon^2_{E,t-1}} \underset{(24.3661)\,*}{+0.6485h_{E,t-1}} \underset{(8.7508)\,*}{+0.7350D_{1,t}} \underset{(6.8877)\,*}{+0.0133D_{2,t}}$$

$LB\ Q(6) = 8.1405$ $LB\ Q(12) = 11.4543$ $ARCH(6) = 0.6446$ $ARCH(12) = 0.5010$ $LM = 9.3219$

L-B Q is the Ljung-Box statistic for standardized residuals for autocorrelation up to 12 lags. ARCH(k) is the LM test for additional ARCH of the standardized residuals. Asymptotic t-values are in parentheses. LM is the Lagrange multiplier test for parameter constancy to the conditional variance in the GARCH model.

*denotes significance at the 5% level.

Table 5. Unrestricted Bivariate GARCH-M Model

$$R_t = d_0 + \sum_{i=0}^{6} a_i E_{t-i} + \sum_{i=0}^{6} b_i h_{E,t-i} + \sum_{i=0}^{6} c_i h_{R,t-i} + \sum_{i=1}^{6} d_i R_{t-i} + \varepsilon_{R,t}$$

$$E_t = \omega_0 + \omega_1 E_{t-1} + \varepsilon_{E,t}$$

$$h_{R,t} = \alpha_0 + \alpha_1 \varepsilon_{R,t-1}^2 + \alpha_2 h_{R,t-1} + \alpha_3 D_t$$

$$h_{E,t} = \beta_0 + \beta_1 \varepsilon_{E,t-1}^2 + \beta_2 h_{E,t-1} + \beta_3 D_{1,t} + \beta_4 D_{2,t}$$

$$h_{RE,t} = \gamma_0 + \gamma_1 \varepsilon_{R,t-1} \varepsilon_{E,t-1} + \gamma_2 h_{RE,t-1}$$

	General model		Simple model	
	Coefficient	t-value	Coefficient	t-value
d_0	-0.0892	-0.6691	-0.0833	-0.6888
a_0	-0.1636	-1.4085		
a_1	-0.1204**	-1.7547	-0.0995*	-1.9708
a_2	-0.0411	-0.5783		
a_3	-0.0055	-0.0886		
a_4	-0.0329	-0.4842		
a_5	0.1218**	1.6855	0.1440*	2.5912
a_6	-0.1264**	-1.7028	-0.1299*	-2.0399
b_0	0.0360	1.3887		
b_1	-0.0283	-0.7139		
b_2	-0.0519	-1.4206	-0.0483*	-2.7799
b_3	0.1048*	3.8779	0.0861*	3.7194
b_4	-0.0869*	-2.4380	-0.0733*	-2.4289
b_5	0.0655	1.5634	0.0762*	2.3829
b_6	-0.0251	-1.3066	-0.0304*	-1.9776
c_0	-0.0388	-0.5923		
c_1	0.0383	0.5067		
c_2	0.0720	1.0933		
c_3	-0.0603	-0.8482		
c_4	-0.1129**	-1.7118	-0.1093**	-1.9226
c_5	0.1293	1.4653	0.1158*	2.0314
c_6	-0.0199	-0.3479		
d_1	0.1036*	2.6706	0.1027*	2.6931
d_2	-0.0630**	-1.8580	-0.0534**	-1.6661
d_3	-0.0154	-0.4598		
d_4	0.0242	0.7850		
d_5	-0.0858*	-2.7516	-0.0772*	-2.6344
d_6	0.0347	0.9953		
ω_0	0.0091	0.9251	0.0092	0.9246
ω_1	0.1545*	4.1253	0.1511*	4.2842
α_0	0.6955*	3.6238	0.6178*	3.8647
α_1	0.1420*	3.6437	0.1424*	3.9542
α_2	0.5506*	5.4007	0.5862*	6.6762
α_3	2.0454*	3.5972	1.8990*	3.6920
β_0	0.0064*	9.1511	0.0065*	9.3437
β_1	0.2459*	10.3208	0.2454*	10.5410
β_2	0.7199*	30.8838	0.7167*	31.2947
β_3	0.5362*	7.3021	0.5477*	7.9403
β_4	0.0090*	6.1685	0.0091*	6.3230
γ_0	-0.0009	-0.3195	-0.0019	-0.6425

	General model		Simple model	
	Coefficient	**t-value**	**Coefficient**	**t-value**
γ_1	0.0742*	3.0770	0.0792*	3.4306
γ_2	0.8937	30.3445	0.8819*	32.7896
LR(14)			10.78	
L-B $Q_R(6)$	0.2672		0.7902	
L-B $Q_R(12)$	3.5500		4.2365	
L-B $Q_R^2(6)$	6.5704		6.4117	
L-B $Q_R^2(12)$	17.1625		16.5574	
L-B $Q_E(6)$	8.8223		8.9009	
L-B $Q_E(12)$	12.5214		12.6353	
L-B $Q_E^2(6)$	3.4224		3.4746	
L-B $Q_E^2(12)$	5.8928		5.9377	

The columns report the coefficient estimates and asymptotic t-statistics for the general and simple models. LR(k) is the likelihood ratio χ^2 statistic that tests this restriction with k degrees of freedom. L-B Q and L-B Q^2 are Ljung-Box statistics for standardized and squared standardized residuals in R , E for autocorrelation up to 12 lags.

*denotes significant at the 5-percent level and
**denote significance at the 10 percent level.

Table 6. Response of stock market return volatility to exchange rate depreciation volatility

$$h_{R,t} = \gamma_0 + \sum_{i=0}^{n} \lambda_i h_{E,t-i} + \sum_{i=1}^{n} \gamma_i h_{R,t-i} + \eta_t$$

$h_{R,t}$ =	0.6264	$+\ 0.6866 h_{R,t-1}$	$+\ 0.0794 h_{R,t-3}$	$+\ 0.0541 h_{R,t-4}$
	(3.7323) *	(26.0458) *	(2.3034) *	(1.6847) * *
	$+\ 0.0985 h_{R,t-12}$	$-\ 0.0194 h_{E,t-8}$	$+\ 0.0444 h_{E,t-9}$	$-\ 0.0176 h_{E,t-12}$
	(4.8211) *	(−1.8373) * *	(3.8005) *	(2.6743) *

$F(3,943) = 6.7293*$ $\quad \sum \lambda_i = 0.0074$ $\quad L - BQ(6) = 3.5177$ $\quad L - BQ(12) = 8.2672$

$\sum \lambda_i$ is the sum of the coefficient estimates of λ_i. L-B Q is Ljung-Box statistic testing for the autocorrelations in residuals up to 12 lags. t-values are in parentheses. F(3,N-3) is Wald F statistic testing for the restriction of zero coefficient in the three lagged $h_{E,t-i}$ variables with the degrees of freedom of 3 and N-3. * and ** denote significance at the 5% and 10% level, respectively.