

Capital Inflows and Exchange Rate Volatility in Korea

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High exchange rate volatility threatens international trade and exacerbates the currency mismatch problem, hence generating economic instability. However, low exchange rate volatility may cause another problem. Low volatility induces speculative capital inflows as speculative investors, who are usually concerned both with the interest rate differential and exchange rate risk, become concerned with the interest rate differential only. In this paper we use several techniques to identify the relationship between exchange rate volatility and capital inflows in Korea. First, estimation of a Markov switching model shows that all kind of capital inflows increase under low volatility regimes, while capital inflows with the exception of FDI all decrease under high volatility regimes. Second, estimation of a multivariate GARCH-in-Mean Model and the impulse response function derived from it provide evidence that lower exchange rate volatility tends to increase most types of capital inflows other than FDI. These results imply that a medium level of exchange rate volatility is most beneficial for economic stability

Keywords: Exchange rate volatility, Capital inflow, Markov switching model, Multivariate GARCH-in-Mean Model

JEL Classification: F31, F32

I. Introduction

The global financial markets have experienced significant turmoil since the 2008 U.S. financial crisis. Not only have the global financial shocks affected advanced economies, but they have also spilled over to emerging countries such as Brazil, Russia and Korea, affecting their financial markets and, in particular, their foreign exchange markets. Increased uncertainty from high exchange rate volatility can affect emerging financial markets in many ways. Notably, it discourages international trade in emerging markets where financial instruments for the hedging of exchange rate risks are not well developed. It also threatens the soundness of financial companies and firms, which usually face currency mismatch problems. Alternatively, however, low exchange rate volatility may cause another problem. It induces speculative investment as speculative investors, who usually take account of both the interest rate differential and exchange rate risk, become concerned about the interest rate differential only when exchange rate volatility is low.¹⁾ It thus seems quite interesting and valuable to investigate the effects of exchange rate volatility on capital inflows during regimes of high and low volatility.

Additionally, emerging country researchers and policymakers should pay special attention to the movements of capital inflows, as their impacts have significant consequences for the recipient countries' economies.

There are many examples of large capital inflows proving to be something of a double-edged sword. On the one hand, capital inflows do bring great benefits. As shown by Mishra et al. (2001), private capital inflows in the form of portfolio flows are

1) A good example of this phenomenon is the so-called "carry trade," which refers to a strategy in which the investor tries to profit from the interest rate differential between two countries while bearing the risk of countervailing exchange rate movements (see, e.g., Chung and Jordà, 2009).

associated with the development of domestic capital markets to diversify investor risk and increase returns, which in turn increases investment and bolsters economic growth. Sudden stops of capital inflows can on the other hand cause devastating effects, however, and hence pose risks and policy dilemmas to the recipient countries. Calvo et al. (1996) insist that capital inflows can lead to inflationary pressures because they are mostly converted into domestic currency. Capital inflows cause the exchange rate to appreciate, which may in turn widen the trade deficit. Mishra et al. (2000) also suggest that capital inflows can increase the vulnerability of a country whose financial markets are weak, and bring about exchange rate crises. Kawai and Lamberte (2008) investigate how capital inflows create maturity and currency mismatches, and possibly reduce the quality of assets, contributing thereby to greater financial fragility.

In this study we focus on capital inflows to Korea, for two reasons. First, in less than 15 years Korea has gone through two major crises. The first originated from the Asian currency crisis of 1997, and the second has arisen more recently due to the global financial crisis. This means that there have been sufficient episodes of exchange rate volatility in the Korean foreign exchange market. Second, Korea has rapidly liberalized its financial market and opened its capital account since the 1997 Asian currency crisis, and capital flows into and out of Korea are now implemented almost freely. This is a quite helpful situation for capturing the relationship between exchange rate volatility and capital inflows.

Explaining both the movements of capital inflows and exchange rate volatility is not an easy task. There are many studies of the relationship between exchange rate volatility and trade flows. Kroner and Lastrapes (1993), for example, show that monthly GARCH conditional variance has a statistically significant impact on international trade for all five industrialized countries considered – the US, the UK, Germany, Japan and France. However, studies on capital inflows and exchange rate volatility are limited.

In this paper, we use several techniques to identify the effects of won/dollar exchange rate volatility on capital inflows to Korea. First, we use a Markov switching

model to distinguish the low and high exchange rate volatility regimes. Second, instead of a pull and push model, we provide a framework for evaluating possible factors explaining the movements of capital inflows to Korea using a multivariate GARCH-in-Mean VAR model, as developed and applied by Elder (2004). We are thereby able to find how the conditional volatility of the won/dollar exchange rate affects capital inflows. The primary goal of this paper is to test the significance of exchange rate volatility as a determinant of capital inflows. Additionally, using the impulse response function analysis also developed by Elder (2004), we show the effects of incorporating exchange rate conditional volatility on the dynamic response of capital inflows to exchange rate shocks.

This paper is organized as follows: Section 2 develops the empirical models employed. Section 3 explains the data used for the empirical work. Section 4 provides the empirical results from the model. In Section 5, we present some concluding remarks.

II. The Empirical Model

1. Detecting the High and Low Volatility Won/Dollar Exchange Rate Regimes

Engel (1994) insists that modeling changes in the log of the exchange rate as a random walk with drift with a two states model provides a good description of exchange rate behavior. We follow the model that he utilizes, the Markov-switching mean and variance model, as follows:

$$\Delta \log(e_t) = r_t = \mu_{S_t} + \varepsilon_t, \varepsilon_t | S_t \sim iid N(0, \sigma_{S_t}^2), \quad (1)$$

$$\mu_{S_t} = \mu_0(1 - S_t) + \mu_1 S_t, \quad (2)$$

$$\sigma_{S_t}^2 = \sigma_0^2(1 - S_t) + \sigma_1^2 S_t, \sigma_0^2 < \sigma_1^2, \quad (3)$$

where $\Delta \log(e_t)$ represents the changes in the log of the Korean won exchange rate relative to the U.S. dollar. The exchange rate changes are measured on a monthly basis in this paper. Here, under regime 0, the parameters are given by μ_0 and σ_0^2 , and under regime 1 they are given by μ_1 and σ_1^2 . S_t is a latent variable modeled as a first-order Markov process (two regimes) with transition probabilities given by:

$$P[S_t = 0 | S_{t-1} = 0] = q, P[S_t = 1 | S_{t-1} = 1] = p, \quad (4)$$

where q and p are the transition probabilities governing the evolutions of S_t in the low and high variance regimes, respectively. The expected duration of the high volatility regimes is given by $E(S_t = 1) = 1 / (1 - p)$.

To estimate this model we derive the joint density of r_t , S_t and S_{t-1} conditionally on the past information I_{t-1} :

$$\begin{aligned} f(r_t, S_t, S_{t-1} | I_{t-1}) &= f(r_t | S_t, S_{t-1}, I_{t-1}) \Pr[S_t, S_{t-1} | I_{t-1}] \\ &= \frac{1}{\sqrt{2\pi\sigma_{S_t}^2}} \exp\left(-\frac{(r_t - \mu_{S_t})^2}{2\sigma_{S_t}^2}\right) \Pr[S_t, S_{t-1} | I_{t-1}]. \end{aligned} \quad (5)$$

We next use equation (5) to derive $f(r_t | I_{t-1})$ as follows:

$$\begin{aligned} f(r_t | I_{t-1}) &= \sum_{S_t=0}^1 \sum_{S_{t-1}=0}^1 f(r_t, S_t, S_{t-1} | I_{t-1}) \\ &= \sum_{S_t=0}^1 \sum_{S_{t-1}=0}^1 f(r_t | S_t, S_{t-1}, I_{t-1}) \Pr[S_t, S_{t-1} | I_{t-1}], \end{aligned} \quad (6)$$

From equation (6), we can find the following log likelihood:

$$\ln L = \sum_{t=1}^T \ln \left[\sum_{S_t=0}^1 \sum_{S_{t-1}=0}^1 f(r_t | S_t, S_{t-1}, I_{t-1}) \Pr[S_t, S_{t-1} | I_{t-1}] \right], \quad (7)$$

where $\Pr[S_t = j, S_{t-1} = i | I_{t-1}] = \Pr[S_t = j | S_{t-1} = i] \Pr[S_{t-1} = i | I_{t-1}]$, for $i, j = 0, 1$. We can compute the weight term, $\Pr[S_t, S_{t-1} | I_{t-1}]$, in equation (7) by updating it once r_t is observed at time t , as follows:

$$\Pr[S_t = j, S_{t-1} = i | I_t] = \frac{f(r_t | S_t = j, S_{t-1} = i, I_{t-1}) \Pr[S_t = j, S_{t-1} = i | I_{t-1}]}{\sum_{S_t=0}^1 \sum_{S_{t-1}=0}^1 f(r_t | S_t = j, S_{t-1} = i, I_{t-1}) \Pr[S_t = j, S_{t-1} = i | I_{t-1}]}, \quad (8)$$

$$\Pr[S_t = j | I_t] = \sum_{S_{t-1}=0}^1 \Pr[S_t = j, S_{t-1} = i | I_t],$$

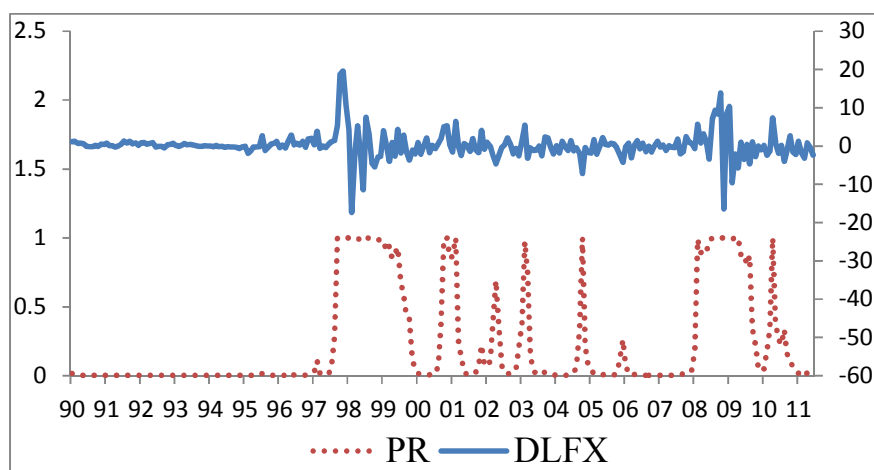
and then iterate equations (7) and (8) for $t = 1, 2, \dots, T$, which will give us the appropriate weighting terms in $f(r_t | I_{t-1})$. (See Hamilton (1989) and Kim and Nelson (1999)).²⁾ We use the algorithm suggested by Kim (1994) to calculate the smoothed probabilities of each regime:

$$\begin{aligned} \mu_{st} &= -0.095(1-s_t) + 1.202(s_t) + \varepsilon_t, \\ &\quad \quad \quad (0.013) \quad \quad \quad (1.219) \\ \sigma_{s_t} &= 1.346(\sigma_0) + 5.654(\sigma_1) \\ &\quad \quad \quad (0.182) \quad \quad \quad (1.139) \\ p_{11} &= 0.956(0.018), \quad p_{22} = 0.853(0.057) \end{aligned}$$

2) The most critical issue in exchange rate volatility is the definition and measurement of volatility. There are several measurements of volatility used in a variety of ways in the literature. It is well known that one of the critical problems of volatility measurement is its ad hoc nature.

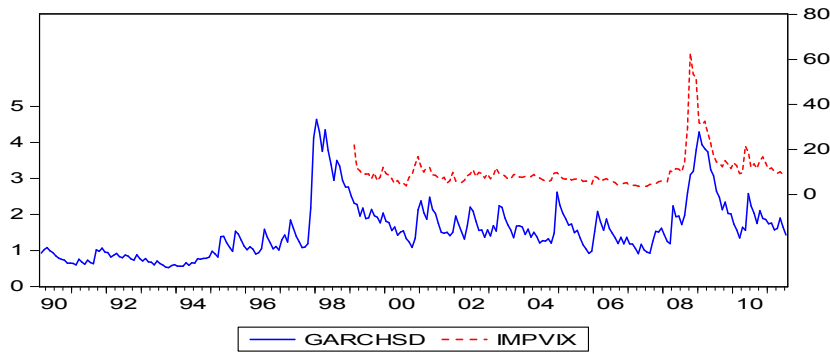
The duration of the low mean and volatility regimes is 23.2 months, and that of the high mean and volatility regimes 6.75 months. Figure 1 illustrates the changes in the log of the exchange rate and smoothed probability of high volatility regimes. When the exchange rate shows volatile movements the probability of high volatility regimes approaches one, and when it shows a stable movement this probability closes to zero. We may therefore conclude that our Markov-switching model captures the high and low volatility regimes quite well:

Figure 1: Smoothed Probability of High Volatility Regimes



Note: This figure describes the changes in the log of the exchange rate(DLFX, right axis) and smoothed probability of high volatility regimes(PR, left axis).

Figure 2: Different Measurements of Volatility



Notes: This figure plots two measurements of exchange rate volatility. GARCHSD represents the generated GARCH standard deviation from the changes in the log of the exchange rate(left axis) and IMPVIX does the implied volatility index derived from FX option formula(right axis).

Here, for a robustness check, we calculate the GARCH volatility from the changes in the exchange rate to see if it matches the smoothed probability of the Markov switching model. Pozo (1992), for example, suggests GARCH volatility as a measure of exchange rate volatility, because it is time dependent and provides better measurement of exchange rate volatility since it uses more information about exchange rate behavior than other commonly employed statistical methods. We in addition also use the implied volatility of the exchange rate, calculated by using the FX option formula. When we compare Figures 1 and 2, the high volatility period of Figure 2 coincides with the high probability period of Figure 1. This again ensures that the Markov switching model successfully captures the high and low volatility regimes of the changes in exchange rates in Korea.

2. Multivariate GARCH-in-Mean VAR model

In this paper, we use Elder's (2003, 2004) methods to analyze the effect of exchange rate volatility on capital inflows to Korea. His method is based on a bivariate GARCH-in-Mean VAR model as follows:

$$By_t = C + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + \Lambda(L)H_t^{1/2} + \varepsilon_t, \quad (10)$$

where B and Φ are an $N \times N$ matrix, $(\varepsilon_t | I_{t-1}) \sim N(0, H_t)$, $\Lambda(L)$ is a matrix polynomial in the lag operator, $H_t^{1/2}$ is a diagonal matrix, and I_{t-1} is information set at time $t-1$.³⁾

In order to test whether exchange rate volatility affects capital inflows, we should test whether $H_t^{1/2}$, the conditional standard deviation of the exchange rate, has any effect on the conditional mean of y_t . We need to be cautious about this estimation method, however, because of the so-called “generated regressor” problem suggested by Pagan (1984). Many studies have used two-stage methods: a volatility variable such as rolling standard deviation is first generated, and this variable is then used in the second stage estimation. Unfortunately, the generated regressor problem results in inefficient estimates in the second stage. When we use the multivariate GARCH-in-Mean VAR model, however, we are able to estimate the time-varying volatility simultaneously in a way that generates internally consistent estimates free from the “generated regressor” problem.

From Bollerslev, Engle and Wooldridge (1988), we see that the most obvious application for multivariate GARCH models is to study the relationships between the volatilities and co-volatilities of several markets. The most general version of the multivariate GARCH model is the BEKK model (Engle and Kroner, 1995), defined as:

3) For more details on the model, see Elder and Serletis (2010).

$$H_t = C^{*'} C^* + \sum_{k=1}^K A_k^{*'} \varepsilon_{t-1} \varepsilon_{t-1}' A_k^* + \sum_{k=1}^K B_k^{*'} H_{t-1} B_k^*, \quad (11)$$

where $C^*, A_k^*, B_k^{*'}$ are $N \times N$ matrices but C^* is the upper triangular. The positive definiteness of the covariance matrix is ensured owing to the quadratic nature of the terms in the right hand side of equation (11).⁴⁾

However, Elder (2004) and Elder and Serletis (2010) suggest a simplified version of this model by adoption of a common identifying assumption in structural VAR. They propose a simple form of H_t that is given a zero contemporaneous correlation of structural disturbances. Assuming the diagonal matrix of H_t :

$$\text{diag}(H_t) = \Theta + \sum_{j=1}^s F_j \text{diag}(\varepsilon_{t-1} \varepsilon_{t-1}') + \sum_{i=1}^k G_i \text{diag}(H_{t-1}). \quad (12)$$

Elder and Serletis (2010) additionally impose restrictions on equation (12), stating that the conditional variance of y_{it} depends only upon its own past square errors and its own past conditional variances. We are thus able to rewrite equation (12) as follows:

$$\begin{aligned} h_{1t} &= \mu_1 + \alpha_1(\varepsilon_{1t-1} \varepsilon_{1t-1}') + \beta_1(h_{1t-1}) \\ h_{2t} &= \mu_2 + \alpha_2(\varepsilon_{2t-1} \varepsilon_{2t-1}') + \beta_2(h_{2t-1}). \end{aligned} \quad (13)$$

The parameters of mean equation (10) and variance equation (12) can be estimated by the full information maximum likelihood (FIML) method. The procedure is to

4) For an excellent survey of multivariate GARCH models, see Bauwens, Laurent and Rombouts (2006).

maximize the log likelihood $\sum_{t=1}^T l_t$ with respect to the structural parameters in equations (10) and (12), where⁵⁾

$$l_t = -\frac{N}{2} \ln(2\pi) + \frac{1}{2} \ln |B|^2 - \frac{1}{2} \ln |H_t| - \frac{1}{2} (\varepsilon_t' H_t^{-1} \varepsilon_t). \quad (14)$$

Another benefit of using Elder's multivariate GARCH-in-Mean VAR model is that it provides an impulse response function based on the model. The impulse response function of the standard VAR model displays the dynamic response of one variable to a shock of another variable, as well as accommodating interaction among the conditional means of the variables in the system. When we use the impulse response function of Elder's multivariate GARCH-in-Mean VAR model, on the other hand, if the shock to the variable of interest shows evidence of the GARCH effect the method of estimation should differ from the standard (homoscedastic) VAR impulse response estimation. The reason for this is that the shock to the variable of interest tends to increase current and future volatility itself. Consequently, the changing volatility has an effect on the variable of interest. Following this line of analysis, Elder (2004) shows the effect that the inflation shocks have on inflation volatility, and the resulting effect of inflation volatility on economic activity.

The impulse response analysis of multivariate GARCH-in-Mean VAR is as follows:⁶⁾

$$y_{t+k} = \Theta(L)(C_0 + \Pi_0 H_{t+k} + B^{-1} \varepsilon_{t+k}), \quad (15)$$

where $C_0 = B^{-1}C$, $\Pi_0 = B^{-1}\Lambda$, $\Theta(L)$ is an infinite order matrix polynomial and $\Theta_0 = I_N$. From equation (15) we are able to expand the term as follows:

5) Note that the current method is different from the standard VAR approach. Standard VAR transforms the first stage reduced form estimates into second stage structural form estimates using some restrictions.

6) For more details, see Elder (2003, 2004).

$\Theta_k = \Phi_1 \Theta_{k-1} + \Phi_2 \Theta_{k-2} + \dots + \Phi_p \Theta_{k-p}$ with $\Theta_0 = I_N$, and $\Theta_s = 0$ for $s < 0$. The standard VAR impulse response function is calculated by $\partial y_{j,t+k} / \partial \varepsilon_{i,t} = \Theta_{i,k}$. However, Elder (2003, 2004) points out that the multivariate GARCH-in-Mean VAR model's $\varepsilon_{j,t}$ also affects $y_{j,t+k}$ through the conditional variance of H_{t+s} , which is a function of $\varepsilon_t \varepsilon_t'$ for $s = 1, 2, \dots, k-1$. He therefore suggests a modified version of the impulse response function for the multivariate GARCH-in-Mean VAR, as follows:

$$H_{t+k-\tau} = \sum_{m=1}^{k-\tau} G^{m-1} [C_v + F(\varepsilon_{t+k-\tau-m} \varepsilon_{t+k-\tau-m}')] + G^{k-\tau} H_t, \quad (16)$$

where $\tau = 1, 2, \dots, k-1$.

Taking the conditional expectation of y_{t+k} , which combines equations (15) and (16), yields

$$E(y_{t+k} | \varphi_t) = \sum_{\tau=0}^{k-1} \Theta_\tau [C_0 + \Pi_0 E(H_{t+k-\tau} | \varphi_t)] + \sum_{t=k}^{\infty} \Theta_\tau [C_0 + \Pi_0 H_{t+k-\tau} + B^{-1} \varepsilon_{t+k-\tau}]. \quad (17)$$

Using the law of iterated expectations and taking the partial derivative gives the forecast of y_{t+k} in response to a shock $\varepsilon_{i,t}$:

$$\frac{\partial E(y_{j,t+k} | \varepsilon_{i,t}, \varphi_{t-1})}{\partial \varepsilon_{i,t}} = \frac{\sum_{\tau=0}^{k-1} \partial \{ \Theta_\tau \Pi_0 (F + G)^{k-\tau-1} F \cdot E[(\varepsilon_t \varepsilon_t' | \varepsilon_{i,t}, \varphi_{t-1})] \}}{\partial \varepsilon_{i,t}} + \frac{\partial \{ \Theta_k B^{-1} \varepsilon_t \}}{\partial \varepsilon_{i,t}}. \quad (18)$$

In equation (18), the second term $\partial \{ \Theta_k B^{-1} \varepsilon_t \} / \partial \varepsilon_{i,t}$ catches the direct effect of a shock $\varepsilon_{i,t}$ on the conditional forecast of $y_{j,t+k}$, while the first term captures the indirect

effect of the shock $\varepsilon_{i,t}$ on the conditional forecast of $y_{j,t+k}$ through the changes in conditional variance. Error bands for the impulse response functions are calculated by the usual Monte Carlo procedure.

III. Data and Specifications

We use eight monthly capital inflow variables. The four main variables are foreign direct investment (FDI), equity (Equity), bonds (Bond), and bank loans (Bankloan). To find the characteristics of both bond and bank loan inflows, we decompose the bond and bank inflows into short- and long-term flows. We thus have four additional variables to consider: short-term bonds (Bond_SR), long-term bonds (Bond_LR), short-term bank loans (Bankloan_SR), and long-term bank loans (Bankloan_LR). To find the high and low volatilities of the won/dollar exchange rate, we use the log differential of that rate (DLFX). These samples cover the period from 1990:02 to 2011:07:

Figure 3: Capital Inflow

(unit: billion)

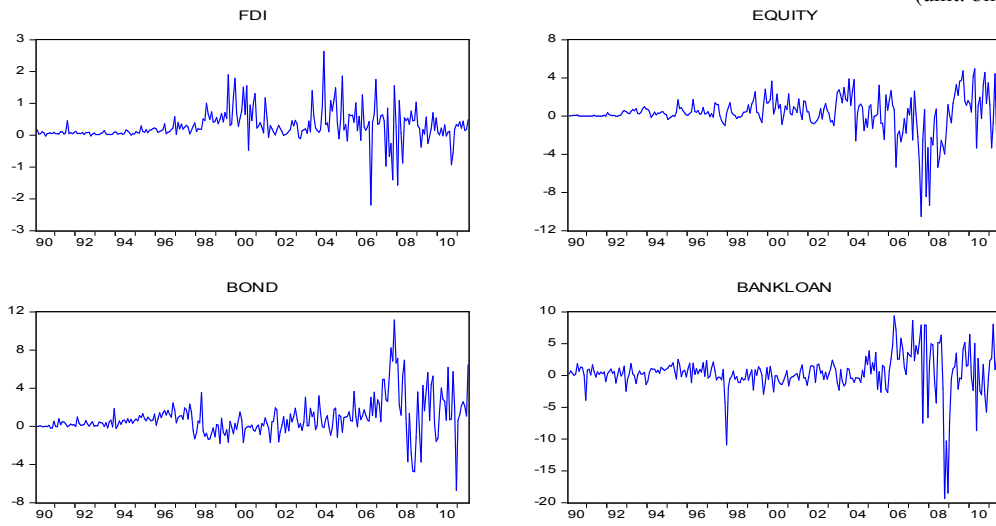
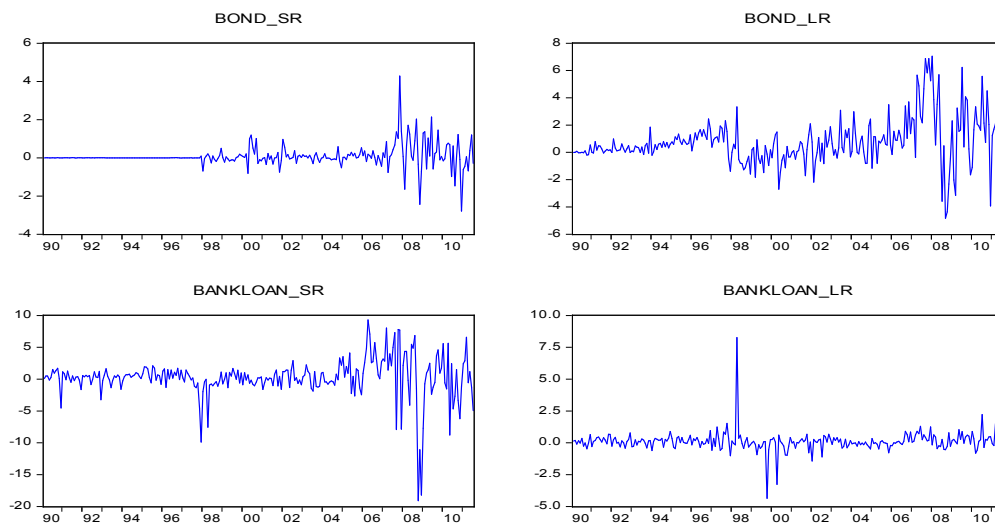


Figure 4: Short- and Long-term Bond and Bank Loan Inflow

(unit: billion)



We see in Figure 2 that when Korea adopted a free floating exchange rate regime, after the 1997 Asian currency crisis, capital inflow volatility became high. It is however clear that, during the recent global financial crisis, the volatility of each inflow rose even more sharply—with the sole exception of long-term bank loan inflows. The descriptive statistics reveal that, among the eight types of capital inflows, bond inflows have the highest mean, followed by bank loan inflows. When we compare the short- and long-term bond inflows in terms of both their means and standard deviations, it is obvious that long-term bond inflows are the dominant factor in bond inflows. In contrast, meanwhile, short-term bank loans are the dominant factor in bank loan inflows: the descriptive statistics show short-term bank loan inflows to be more similar to bank loan inflows itself than long-term bank loan inflows are:⁷⁾

Table 1: Descriptive Statistics

	FDI	Equity	Bond	Bond _SR	Bond _LR	Bank loan	Bank loan_ SR	Bank loan_ LR	DLFX
Mean	0.28	0.28	0.86	0.08	0.78	0.38	0.25	0.13	0.17
S.D.	0.49	1.89	1.96	0.57	1.75	3.13	3.12	0.78	3.56
Skew- ness	0.35	-1.72	1.21	1.35	0.91	-1.89	-1.94	3.51	0.72
Kurto- sis	9.30	11.04	8.42	19.28	5.98	14.84	14.22	52.25	13.58
Max	2.64	4.95	11.15	4.28	7.05	9.36	9.29	8.27	19.56
Min	-2.19	-10.52	-6.72	-2.79	-4.84	-19.34	-19.08	-4.36	-17.35
Jarque- Bera	431.95	821.27	379.42	2926.75	130.84	1661.01	1514.35	26604.54	1225.36

Notes: This table reports the descriptive statistics of different types of capital inflows to Korea and the changes in the log of the exchange rate (DLFX). Samples cover from 1990:02 to 2011:07.

7) The Jarque-Bera statistics show that the distributions of all inflows are not normal distributions.

Table 2: Unit Root Tests

	ADF Test		Phillips-Perron Test	
	Constant	Constant + Trend	Constant	Constant + Trend
FDI	-3.045 ^b (6)	-3.062 (6)	-15.070 ^a (9)	-15.128 ^a (9)
Equity	-3.023 ^b (15)	-3.048 (15)	-10.804 ^a (7)	-10.799 ^a (7)
Bond	-3.184 ^b (11)	-3.872 ^b (11)	-9.912 ^a (8)	-10.469 ^a (8)
Bond_SR	-3.437 ^b (14)	-3.815 ^b (14)	-12.927 ^a (6)	-13.005 ^a (5)
Bond_LR	-4.482 ^a (2)	-4.971 ^a (2)	-10.311 ^a (8)	-10.874 ^a (8)
Bankloan	-5.866 ^a (4)	-5.867 ^a (4)	-10.717 ^a (2)	-10.705 ^a (2)
Bankloan_SR	-5.833 ^a (4)	-5.821 ^a (4)	-10.796 ^a (1)	-10.774 ^a (1)
Bankloan_LR	-3.602 ^a (5)	-3.690 ^b (5)	-14.504 ^a (1)	-14.585 ^a (2)
DLFX	-13.412 ^a (0)	-13.428 ^a (0)	-13.377 ^a (2)	-13.391 ^a (2)

Notes: This table reports the results of two different types of unit root tests. a and b indicate significance levels of 1% and 5%, respectively. The lag order is in the parentheses.

The results of unit root tests are presented in Table 2. The ADF and Phillips-Perron tests show that all variables are stationary. We are therefore able to use the inflow variables without needing to be concerned about the possibility of non-stationary problems. The log differential of the won/dollar exchange rate is stationary as well. From Figures 2 and 3, it is also quite clear that after the 1997 Asian currency crisis the volatility of capital inflows is very high. The Korean exchange rate system was changed from a fixed to a flexible regime from December 1997. The Korean financial market was in addition liberalized after the 1997 crisis; it is quite intuitive to infer that it has been rapidly transformed into a more market-based structure since that time.

IV. Empirical Results

1. Effects of High and Low Exchange Rate Volatility Regimes on Capital Inflows

Out of the high and low volatility regimes from the Markov switching model results, we regress the high regimes on capital inflows. The results of estimation are very interesting. In particular, for the low volatility regimes represented in the beta zero row in Table 3, all of the inflows except for long-term bank loan inflows are statistically significant at the 1% level. We would therefore infer that capital has flowed consistently into Korea under the low volatility regimes. Now let's look at the individual types of capital inflows in detail. We find FDI inflows to be statistically significant at the 1% level under both regimes. When we compare the two regimes, we conclude that FDI inflows during the period considered are more than 0.15 billion dollars higher under the high volatility than the low volatility regimes. Equity inflows are meanwhile statistically significant at the 1% level only under the low volatility regimes. The results of estimation for bond inflows are meanwhile particularly interesting. The bond market is statistically significant at the 1% level under low volatility regimes, and at the 5% level for high volatility regimes.

In comparing the two regimes, we also see that bond inflows are 0.73 billion dollars less under the high volatility than under the low volatility regimes. From the results of bond inflow estimation, we are also able to confirm that long-term bond inflows are the dominant factor, as hypothesized from the descriptive statistics. Bank loan inflows show movements different from those of bond inflows. Under the high volatility regimes bank loan inflows are 1.8 billion dollars less than they are under the low volatility regimes.

Using reasoning similar to that applied to bond inflows, we can conclude that the short-term bank loans dictate the movements of bank loan inflows as a whole.

Table 3: $\text{Cap_Flow} = \beta_0 + \beta_1 \text{Highregime} + \epsilon_t$

	FDI	Equity	Bond	Bond_ SR	Bond_ LR	Bank loan	Bank loan_SR	Bank loan_LR
β_0	0.250 ^a (0.034)	0.315 ^a (0.132)	1.011 ^a (0.135)	0.066 ^a (0.039)	0.945 ^a (0.120)	0.757 ^a (0.212)	0.647 ^a (0.211)	0.110 ^b (0.054)
β_1	0.155 ^a (0.075)	-0.192 (0.291)	-0.734 ^b (0.298)	0.071 (0.087)	-0.805 ^a (0.265)	-1.838 ^a (0.469)	-1.921 ^a (0.465)	0.083 (0.120)
R^2	0.016	0.001	0.023	0.002	0.034	0.056	0.062	0.001

Notes: This table reports the regression results of how high volatility regime in exchange rate affects different types of capital inflows to Korea. a and b indicate significance levels of 1% and 5%, respectively. We state the standard errors in parentheses.

2. Multivariate GARCH-in-Mean Model Estimation Results

We use the monthly data for the bivariate GARCH-in-Mean VAR over the period from 1990:2 to 2011:7. It is a natural procedure to choose the optimal lag, and we use AIC to choose the optimal lags for each model. The point estimates of the variance equations that represent the ARCH or GARCH effects are reported in Table 4. Quite surprisingly, all FX equations show evidence of the ARCH effect but not the GARCH effect. All of the capital inflow equations in contrast provide strong evidence of the GARCH effect. It is interesting to note that Elder and Serletis (2010) also indicate the existence of the ARCH effect in their real price of oil variance equation, and our interpretation is similar to their results. The volatility process of the exchange rate is clearly not very persistent, but the

coefficient on the lagged squared error, the ARCH effect, is very persistent and statistically significant at the 1% level for each exchange rate variance equation. The coefficients of the exchange rate variance equation of the bivariate GARCH-in-Mean VAR for long-term and short-term bank loan inflows show the most persistent effects. The coefficient of the exchange rate variance equation for FDI inflows on the other hand has the least persistent effect. Among the eight equations, the coefficient of the capital inflow variance equation for bond inflows provides the most persistent GARCH evidence. It is very interesting that the coefficient of the capital inflow variance equation for long-term bond inflows also shows highly persistent GARCH estimates, but that for short-term bond inflows does not.

The effects of foreign exchange rate volatility on capital inflows are reported in Table 5. This is the coefficient of $H_{11}(t)^{1/2}$ for each capital inflow equation. The effects of the conditional volatility of the foreign exchange rate on the FDI inflow, short-term bond inflow, bank loan inflow and short-term bank loan inflow equations provide statistically significant estimates. All of the statistically significant estimates except for those of FDI inflows are negative, providing evidence that the higher conditional standard deviations of foreign exchange rates tend to cause decreased capital inflows. The coefficient of the conditional standard deviation of FDI inflows is positive, meaning that a higher conditional standard deviation tends to cause capital inflows to increase.

Table 4: Coefficient Estimates for Variance Function of Bivariate GARCH-in-Mean VAR

	μ_i	α_i	β_i
FDI			
FX	2.229 ^a (0.297)	0.929 ^a (0.057)	0.000 (0.000)
FDI	0.000 (0.000)	0.100 ^a (0.017)	0.895 ^a (0.017)
Equity			
FX	2.074 ^a (0.313)	0.949 ^a (0.082)	0.000 (0.000)
Equity	0.000 (0.000)	0.150 ^a (0.058)	0.906 ^a (0.040)
Bond			
FX	2.242 ^a (0.326)	0.958 ^a (0.050)	0.000 (0.000)
Bond	-0.001 ^c (0.001)	0.089 ^a (0.034)	0.943 ^a (0.029)
Bond_SR			
FX	1.762 ^a (0.282)	0.946 ^a (0.043)	0.000 (0.000)
Bond_SR	0.000 ^b (0.000)	0.470 ^a (0.035)	0.527 ^a (0.035)
Bond_LR			
FX	2.196 ^a (0.291)	0.962 ^a (0.050)	0.000 (0.000)
Bond_LR	-0.001 ^b (0.001)	0.068 ^a (0.024)	0.960 ^a (0.022)
Bankloan			
FX	2.037 ^a (0.308)	0.947 ^a (0.057)	0.000 (0.000)
Bankloan	0.088 ^c (0.052)	0.186 ^a (0.072)	0.799 ^a (0.071)
Bankloan_SR			
FX	2.056 ^a (0.328)	0.963 ^a (0.043)	0.000 (0.000)
Bankloan_SR	0.134 ^b (0.003)	0.268 ^a (0.017)	0.720 ^a (0.017)
Bankloan_LR			
FX	2.037 ^a (0.315)	0.963 ^a (0.043)	0.000 (0.000)
Bankloan_LR	0.006 ^c (0.003)	0.123 ^a (0.017)	0.862 ^a (0.017)

Notes: This table reports the estimation results of bivariate GARCH-in-Mean VAR. For example, FX and FDI row contains two estimation results. FX stands for the result of the exchange rate equation and FDI does the foreign direct investment equation. The other rows have the same interpretations. α_i and β_i indicate ARCH and GARCH coefficients, respectively. a, b, and c indicate significance levels of 1%, 5%, and 10%, respectively. The standard errors are reported in parentheses.

The implications of these results are interesting. FDI inflows are typically long-term investments, and the periods of high volatility that usually accompany high exchange rates (undervalued exchange rates for the recipient countries) give international speculators higher chances of investing successfully.

Table 5: Estimates of Exchange Rate Volatility Coefficients

Measure of capital inflows	Coefficient of $H_{11}(t)^{1/2}$, exchange rate volatility
FDI	0.029 ^a (0.009)
Equity	0.004 (0.020)
Bond	-0.034 (0.025)
Bond_SR	-0.002 ^b (0.001)
Bond_LR	-0.029 (0.022)
Bankloan	-0.147 ^b (0.057)
Bankloan_SR	-0.179 ^a (0.050)
Bankloan_LR	0.006 (0.020)

Notes: This table reports the estimation results of the effects of exchange rate volatility on various capital inflows to Korea. a and b indicate significance levels of 1% and 5%, respectively. We state the standard errors in parentheses.

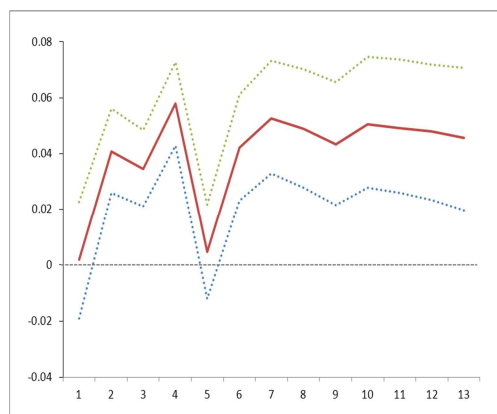
The impulse responses of the Multivariate GARCH-in-Mean VAR model are reported in Figures 5A through 5H. In these figures, the X-axis represents the time intervals and the Y-axis the responses of capital inflows to a foreign exchange rate

volatility shock. Figure 5A shows the dynamic response of FDI inflows to an exchange rate shock, indicating exchange rate shocks to have positive effects on FDI inflows. FDI inflows increase for around three months, and the effects of the shock have not died out even one year later. Figure 5B shows that exchange rate shocks have a negative effect on equity inflows in the initial period, but that the effect returns to a positive level after one month. The impulse responses of bond inflows are reported from Figures 5C through 5E. All three figures show exchange rate shocks to have strong negative effects on several of the bond inflows. The shapes of the three figures are very similar.

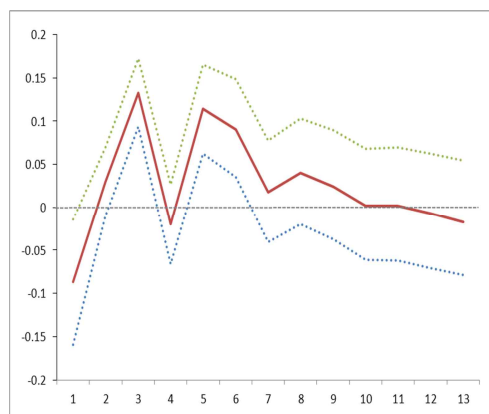
The impulse responses of bank loan inflows are reported in Figures 5F through 5H. The responses to exchange rates shocks of bank loan inflows and short-term bank loan inflows are very similar, and show persistent negative effects. The response of long-term bank loan inflows on the other hand displays a negative effect for up to two months, and then returns to positive levels:

Figure 5: Response of Each Capital Inflow to FX Volatility Shock

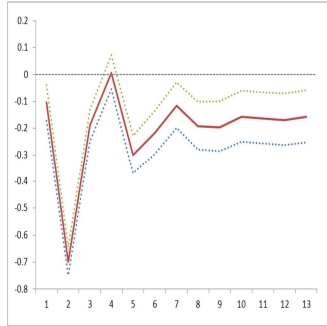
5A: FDI



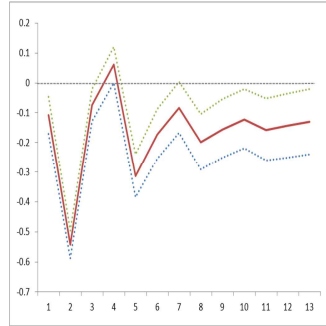
5B: EQUITY



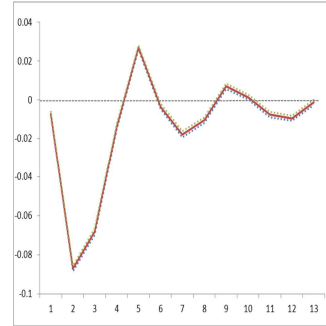
5C: BOND



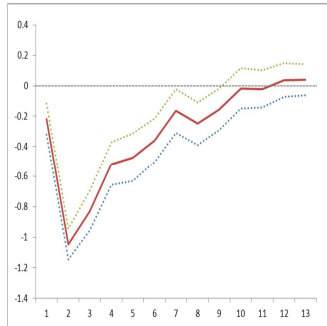
5D: BOND_LR



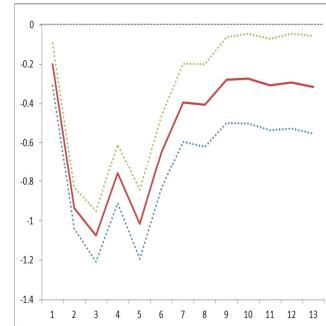
5E: BOND_SR



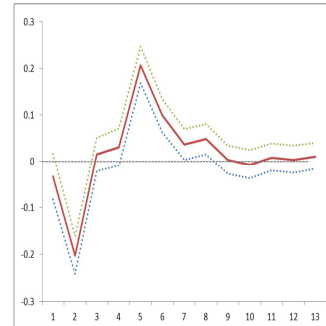
5F: Bank Loan



5G: Bank Loan_LR



5H: Bank Loan_SR



Notes: Figure 5 illustrates the impulse response of each capital inflow to Korea to exchange rate volatility shock. Capital inflows experimented are FDI(5A), Equity(5B), Bonds(5C), Short-Term Bonds(5D), Long-Term Bonds(5E), Bank Loans(5F), Short-Term Bank Loans(5G), and Long-Term Bank Loans(5H). Y axis represents billion and X axis does months.

V. Conclusion

In this study we try to show the relationship between capital inflows and exchange rate volatility. We choose this topic because high exchange rate volatility exacerbates the adverse effects of the currency mismatch problem, and therefore generates great fluctuations in capital flows in emerging markets. Low exchange rate volatility may cause another problem, however. It may induce speculative capital inflows, because the speculative investors become concerned only about the interest rate differential and not about foreign exchange losses.

To show how exchange rate volatility affects capital inflows in Korea, we have used several models. First, we have decomposed the low and high volatility regimes using a Markov switching model. Second, we have regressed the high volatility regimes on capital inflows. All coefficients under the low volatility regimes are positive and statistically significant. Under high volatility regimes the FDI coefficient is positive and significant, while the bond and bank loan coefficients are negative and significant. We would therefore infer that under low volatility regimes, and with the exception of FDI, capital flows consistently into Korea. Bond inflows during the period considered are 0.73 billion dollars less under the high volatility than the low volatility regimes. Since the coefficient of long-term bond inflows is large enough and significant, we are able to conclude that the reason for a change in bond inflows is a change in long-term bond inflows. During the high volatility regimes, bank loan inflows are 1.8 billion dollars less than they are under the low volatility regimes. By reasoning similar to that concerning bond inflows, we conclude that a change in short-term bank loan inflows is the main factor behind fluctuation in bank loan inflows.

Finally, we have used a multivariate GARCH-in-Mean Model to analyze the effect of exchange rate volatility on capital inflows. We found that the effects of the conditional

volatility of the exchange rate on the FDI inflow, the short-term bond inflow, bank loan inflow and short-term bank loan inflow equations provide statistically significant estimates. All of these statistically significant estimates except for those of the FDI inflows are negative, providing evidence that a higher volatility of exchange rates tends to cause capital inflows to decline. Another method we have used is an impulse response function. From impulse response analysis, we have concluded that exchange rate shocks decrease most types of capital inflows with the exception of FDI inflows.

Our empirical studies suggest that maintaining proper levels of exchange rate volatility would further improve stability of the Korean economy. As this study focuses only on analyzing the relationship between exchange rate volatility and capital inflows, we may improve it by focusing on the mechanism by which changes in monetary policy are transmitted to exchange rate volatility, given the findings of previous studies suggesting strong evidence of their interrelatedness.

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