Solving Endogeneity in Assessing the Efficacy of Foreign Exchange Market Interventions

Seok Gil Park
Indiana University Bloomington

February 21, 2007

Solving Endogeneity in Assessing the Efficacy of Foreign Exchange Market Interventions

Seok Gil Park[*]

February 13, 2007

Abstract

Sterilized foreign exchange market interventions have been suspected of being inefficient by many empirical studies, but they are plagued by endogeneity problems. To solve the problems, this paper identifies a system that depicts interactions between the interventions and the foreign exchange rate. The model shows that the interventions are effective when the interventions alter the market participants' conditional expectations of the rate without decreasing the conditional variances. This paper estimates Markov-switching type policy reaction functions by conditional MLE, and market demand/supply curves by IV estimation with generated regressors. The empirical results verify that the interventions of the Bank of Korea from 2001 to 2002 were indeed effective.

Keywords: Sterilized intervention; Endogeneity; Markov-switching policy function
JEL classification: F31; E58; G15

1 Introduction

The effectiveness of foreign exchange market interventions has been one of the intensively discussed topics in central bank policy analysis. After myriads of papers have investigated the topic, a skeptical view that the sterilized interventions do not have meaningful impacts on the nominal exchange rate has prevailed. (Craig and Humpage(2001)) At best, the results are mixed in general.[1] However, it is still true that the debate is not closed yet, because the literatures are plagued by endogeneity problems. Through the identification of the system and valid instrumental variables(IVs), this paper estimated the effect with minimizing the endogeneity bias described as follows.

The first endogeneity problem comes from the simultaneity between the intervention decision and the contemporary exchange rate. That is, the intervention may have changed the current spot rate, but it may also be true that the current spot rate movement leads to the intervention. If we regress the rate movements on interventions with a single equation such as

$$\Delta S_t = \beta_0 + \beta_1 INT_t + \boldsymbol{\beta}_2 \mathbf{X}_t + \varepsilon_t \tag{1}$$

where ΔS_t is a difference in the exchange rate, INT_t is the central bank intervention, and $\mathbf{X}_t$ is other explanatory variables, this well known problem makes INT_t endogenous, thus we will have an inconsistent estimator for β_1. (Neely(2005), Kearns and Rigobon(2005))

Endogeneity also comes from omitted variables in equation (1). To be clearer on this point, let's assume that the interventions are decided regardless of the current spot rate. Although INT_t is exogenous now, it is still debatable whether $\mathbf{X}_t$ catches all the other factors to be controlled other than interventions: if $\mathbf{X}_t$ fails to include variables which have an explanatory power on ΔS_t, β_1 will be inconsistent again. Of course, most empirical research has the omitted variables problem more or less, but unfortunately, it is particularly difficult to find a valid $\mathbf{X}_t$ for the daily nominal exchange rate model. Existing papers have tried news and(or) day of the week dummy variables, and Macroeconomic variables such as the interest rate spread as $\mathbf{X}_t$[2]. However, in many cases they are not statistically significant.

---

[1] See the literature review of Galati et al., 2005

[2] Bonser-Neal and Tanner(1996) used macroeconomic news announcement dummy variables and sur-

Messe and Rogoff (1983) have showed that macroeconomic models under-performed a simple random work model in monthly out-of-sample prediction. Moreover, we focus on the daily horizon in which it is believed that macro variables are less relevant with the exchange rate than the longer horizon.

How can we avoid the endogeneity problems? For the simultaneous bias, we will have to take into account an intervention reaction function such as

$$INT_t = \alpha_0 + \alpha_1 \Delta S_t + \boldsymbol{\alpha}_2 \mathbf{Y}_t + u_t \tag{2}$$

where $\mathbf{Y}_t$ is other factors that explain intervention decisions. (Neely(2005)) Now we have a system of equations to be estimated, thus valid instrumental variables are needed to estimate the system of equations. However, similar to the difficulties in finding a relevant $\mathbf{X}_t$, a lack of valid IVs now can be problematic.[3] In this paper, 'customer trades' were used as IVs and the empirical results verified that they were valid. In addition, customer trades data were shown to be closely related with the spot rate movements, thus they were used for resolving the omitted variable bias. That is, the equation (1) was split into market demand/supply equations, and then customer demand (supply) trades data were used for identifying supply (demand) curve. Besides, the mechanism that the interventions may affect the rate became more transparent by specifying the demand and supply curves. In specific, if the interventions shift the demand/supply curves to the desired directions without flattening the curves, 'leaning against winds' operations will be effective.

The estimation strategy is as follows. First, Markov-switching type policy reaction functions were estimated by the Conditional Maximum Likelihood method. Both the regimes and latent variables were modeled as functions of ΔS_t, therefore they were endogenous. Then the market demand/supply curves were estimated by Instrumental Variables method with

---

prise component of the announced variables; Dominguez(1993, 1998) took the interest rate spread and day dummy variables; Galati et al.(2005) used macroeconomic announcements; Ito(2002) included only FED interventions; Rogers and Siklos(2003) used macroeconomic variables such as changes in stock market prices, interest rate spreads, and relevant news dummy variables. (Bonser-Near and Tanner(1996), and Rogers and Siklos(2003) regressed implied volatility on explanatory variables, rather than spot rate movement.)

[3] Kearns and Rigobon(2005) identified the system with the intervention regime change of Reserve Bank of Australia and the Bank of Japan using simulation method.

generated regressors from the reaction functions. Finally, the hypothetical exchange rate was calculated to show what would have been the rate if there were no interventions. The empirical results showed that the Bank of Korea intervened when the Korean won market was volatile, and the operations decreased the volatility. Besides, this model was shown to out-perform the random walk model in one-step-ahead prediction. The remainder of this paper is organized as follows. Part 2 describes the Korean foreign exchange market and the data set, and part 3 illustrates the system that specifies the interactions between interventions, market participants' behavior, and the exchange rate. Part 4 shows the empirical results, and the conclusion follows.

2   Facts and Data

As a sample, this paper covers the daily data from 2001 to 2002. In the sample period, the Bank of Korea "allowed the Korean won to fluctuate freely according to demand and supply conditions in the foreign exchange market." But it intervened "to avoid abrupt fluctuations of the exchange rate within a short-term period." (The Bank of Korea(2002, 2003)) In addition, "the objective is to mitigate short-term exchange rate volatility, ... rather than to maintain a certain exchange rate target," most of the intervention transactions occurs in the spot market, and its impacts on money supply are sterilized. (Rhee and Lee(2005)) In this sense, I focused on the effects of sterilized interventions on the foreign exchange rate volatility in the Korean won spot market. For the intervention data, I used the daily change in foreign exchange position of the Bank of Korea as a proxy, since the Bank of Korea kept the data confidential.

Because the Korean won is not internationalized yet, it is traded only in the Korean foreign exchange market. In specific, the Korean won spot rate is determined in the Korean inter-bank market which has a 'limit order book'. That is, the market participants' limit orders to buy (or sell) at certain prices meet each other electronically without dealers. The market participants are mainly commercial banks chartered by the government, thus other entities that want to transact the Korean won spot trade with participant banks. I refer to

these entities as customers.

The customers include a wide range of entities. For example, there are enterprises selling USD (export companies) or selling the Korean won (import companies); individuals who exchange the Korean won to USD at banks' window; foreign investors who need to trade USD/KRW spot to finance their investments on Korean securities; and other trading desks within the banks such as non-deliverable forwards (NDF) desks whose positions are frequently hedged by spot transactions. The data for demand and supply trades from the customers were accumulated in daily frequency by surveying the participant banks.

3   The model

To specify the channel through which interventions affect the exchange rate, a model for the rate determination should be set up. Various models have been proposed for the rate determination. However, regardless of whether they are *ad hoc* macroeconomic models or new open macroeconomics models based on agents' optimization problems, no model succeeded in acquiring a unanimous approval so far. (Sarno and Taylor(2002)) Moreover, when it comes to daily data, there is more skepticism about such models.

Thus, rather than specifying underlying macroeconomic theory, I focus on the fact that the rate is determined in the inter-bank market. That is, whatever it is, a macroeconomic variable affects the rate only via the market participants' behaviors. In this sense, if we can identify the demand and the supply curves, we will be able to predict the rate validly, thus correctly analyze policy issues such as efficacy of interventions. Specifically, similar to the market microstructure approach to the exchange rate that takes 'order flows' seriously, (Lyons(2001)) I assumed that the daily flow of the demand and the supply will determine the day's rate change, not the stock of the demand and the supply at the end of the day. One of the advantages of identifying the curves is that this model allows the interventions to change not only the value of variables that the market participants take into account, but also the structural parameters which depict the participants' behavior.

3.1 The behavior of market participants

Assume that the inter-bank foreign exchange market consists of two representative decision making agents: a demander, and a supplier. The demander receives C_{Dt}(customer demand for USD plus dollar buying interventions) from its customers including the central bank and the supplier receives C_{St}(customer supply for USD plus dollar selling interventions) at day t. However, they are assumed to have no information on the magnitude of interventions. That is, the demander (supplier) only knows the aggregate magnitude of customer demand (supply). But the presence of the central bank in the market is assumed to be known to both parties. By denoting $\Omega_{Dt}(\Omega_{St})$ as an information set for the demander (supplier) at day t, assumptions on information are summarized as follows.

Assumptions on information

$C_{Dt} \in \Omega_{Dt}$, $C_{St} \in \Omega_{St}$, $C_{Dt} \notin \Omega_{St}$, $C_{St} \notin \Omega_{Dt}$

BUY_t, $SELL_t \notin \Omega_{St} \cup \Omega_{Dt}$, $I_{\{BUY_t \neq 0\}} \in \Omega_{St} \cap \Omega_{Dt}$, $I_{\{SELL_t \neq 0\}} \in \Omega_{St} \cap \Omega_{Dt}$

BUY_t: USD buying intervention, $SELL_t$: USD selling intervention,

$I_{\{\}}$: Indicator function

Given the customer demand (supply) flows, coupled with their own speculative views, they form a daily demand (supply) schedule. To show this, let's suppose that the demander and the supplier maximize the expected utility from a wealth defined as follows:

$$W_{Dt} \equiv (\Delta S_{t+1} - \Delta S_t)Q_{Dt} \tag{3}$$

$$W_{St} \equiv (\Delta S_t - \Delta S_{t+1})Q_{St} \tag{4}$$

where $W_{Dt}(W_{St})$ is a wealth of demander (supplier), $Q_{Dt}(Q_{St})$ is a quantity demanded (supplied), ΔS_t is $S_t - S_{t-1}$, and S_t is the spot rate of Korean won against USD at day t.[4] For tractability, assume that the expected utility functions of the demander and the supplier are negative exponential functions with the absolute risk averse coefficients, γ_D and

---

[4]This definition of wealth is implicitly assuming that the demander and the supplier know that they will switch their roles in near future, thus trade with each other at ΔS_t at day t.

γ_S. Additionally, for a simple closed form objective function of the maximization problem, assume ΔS_{t+1} follows normal distribution conditional on the information available to demander (supplier). To show this normality, let's partition the time interval from t to $t+1$ into N sub-intervals, $t = k_0 < k_1 < k_3 < ... < k_N = t+1$, i.e. time index t is for day-by-day index, and k is for tick-by-tick index. Thus, if the rate differentials for small fraction of times in day $t+1$ are independent and identically distributed conditional on the information at day t, by the Central Limit Theorem, we have

$$\sum_{n=1}^{N} \Delta S_{k_n} \mid \Omega_{Dt} = \Delta S_{t+1} \mid \Omega_{Dt} \sim N(\mu_{Dt}, \sigma_{Dt}^2) \tag{5}$$

$$\sum_{n=1}^{N} \Delta S_{k_n} \mid \Omega_{St} = \Delta S_{t+1} \mid \Omega_{St} \sim N(\mu_{St}, \sigma_{St}^2) \tag{6}$$

where $\mu_{D(S)t} = E[\Delta S_{t+1} \mid \Omega_{D(S)t}]$, $\sigma_{D(S)t}^2 = Var[\Delta S_{t+1} \mid \Omega_{D(S)t}]$. This generates the maximization problems for the demander and the supplier as follows:

$$\max_{Q_{Dt}} \{E[W_{Dt} \mid \Omega_{Dt}] - \frac{\gamma_D}{2} Var[W_{Dt} \mid \Omega_{Dt}]\} \tag{7}$$

$$\max_{Q_{St}} \{E[W_{St} \mid \Omega_{St}] - \frac{\gamma_S}{2} Var[W_{St} \mid \Omega_{St}]\}. \tag{8}$$

From the first order conditions, we have the optimal choice of the demander and the supplier as follows:

$$Q_{Dt}^* = \frac{E[\Delta S_{t+1} \mid \Omega_{Dt}] - \Delta S_t}{\gamma_D Var[\Delta S_{t+1} \mid \Omega_{Dt}]} \tag{9}$$

$$Q_{St}^* = \frac{-E[\Delta S_{t+1} \mid \Omega_{St}] + \Delta S_t}{\gamma_S Var[\Delta S_{t+1} \mid \Omega_{St}]}. \tag{10}$$

Now the issue is how we can model the expected values and variances of the future exchange rate differentials which are conditional on the participants' information. The conditional expected value of the demander (supplier) was modeled as a linear function of several explanatory variables. First, the customer demand (supply) was included because it may used as a daily proxy variable for macroeconomic fundamentals such as current account and

capital inflow as described in part 2. Second, the lagged value of transaction volume was included. The past volume is what was actually demanded (supplied) in the past, thus they were assumed to capture the unknown factors that influence the quantity demanded (supplied) in an autoregressive way. For the last, the difference of Japanese yen rate was included to reflect a speculative motive in Korean won market. As illustrated in figure 1, the Korean won was synchronized with the Japanese yen for the sample period, and the movements of the yen had a significant impact on the sentiment of the Korean won traders in that period.

For conditional variance, I hypothesized that it remains constant for the sample period. However, since market participants were assumed to know whether the central bank is intervening or not, the conditional variance may be different between the days with and without intervention. Whether there was difference in the conditional variance will be tested. Under these assumptions, the demand and the supply curve to be estimated is

$$Q_t = \beta_{D0} + \sum_{k=1}^{3} \beta_{Dk} Q_{t-k} + \beta_{D4} C_{Dt} + \beta_{D5} C_{Dt-1} + \beta_{D6} \Delta JPY_t + \beta_{D7} \Delta S_t + \varepsilon_{Dt} \qquad (11)$$

$$Q_t = \beta_{S0} + \sum_{k=1}^{3} \beta_{Sk} Q_{t-k} + \beta_{S4} C_{St} + \beta_{S5} C_{St-1} + \beta_{S6} \Delta JPY_t + \beta_{S7} \Delta S_t + \varepsilon_{St} \qquad (12)$$

where ΔJPY_t is the USD/JPY rate differential, $C_{D(S)t}$ is decomposed into $\tilde{C}_{D(S)t} + BUY_t$ ($SELL_t$) with $\tilde{C}_{D(S)t}$ as the customer demand (supply) flow without interventions and ε's are error terms.

In this simple mean-variance argument, the sterilized interventions matter in two ways. First, they can affect the conditional expectations. In this model, the central bank can change $C_{D(S)t}$ to shift the demand (supply) curve, thus affect the rate. I will denote this effect as a 'liquidity effect'. However, interventions can make behavioral parameters (β's) distinct across the days with and without intervention. For example, if the interventions decrease uncertainty in future rate ($Var[\Delta S_{t+1} \mid \Omega_{D(S)t}]$), $|\beta_{D7}|$ and $|\beta_{S7}|$ will increase and the demand (supply) curve will be flattened. This will decrease the impact of shifting the curves.

7

3.2 Reaction function of central bank

As explained in part 2, the Bank of Korea is assumed to lean against winds in the sample period. That is, it intervened when the rate abruptly moved, thus simple reaction functions modeling this behavior are as follows.

$$BUY_t^* = \alpha_{D0} + \alpha_{D1}BUY_{t-1} + \alpha_{D2}\Delta S_t + u_{Dt} \tag{13}$$

$$SELL_t^* = \alpha_{S0} + \alpha_{S1}SELL_{t-1} + \alpha_{S2}\Delta S_t + u_{St} \tag{14}$$

where BUY_t^* and $SELL_t^*$ are latent intervention values, and u's are error terms. However, there are many clustered zeros in the intervention series, thus a threshold type model is more plausible for the reaction function. That is, interventions should be expressed as

$$BUY_t = d_t \times BUY_t^* \tag{15}$$

$$SELL_t = d_t \times SELL_t^* \tag{16}$$

where $d_t = 1$ when there was an intervention and $d_t = 0$ otherwise.

This reaction function postulates a two-step decision on the intervention. First, the central bank decides whether it will intervene ($d_t = 1$). Then, it will choose the magnitude of the interventions (BUY_t^* and $SELL_t^*$). Therefore, d_t is also a function of ΔS_t. To model this endogeneity in the intervention regime, a Markov-switching probability is defined as follows:

$$p_t \equiv \Pr(d_t = 1 \mid d_{t-1} = 0, \tilde{\Omega}_t, \Delta S_t) = \frac{\exp(\gamma_0 + \gamma_1(|S_t - S_t^{trend}|))}{1 + \exp(\gamma_0 + \gamma_1(|S_t - S_t^{trend}|))} \tag{17}$$

$$q_t \equiv \Pr(d_t = 1 \mid d_{t-1} = 1, \tilde{\Omega}_t, \Delta S_t) = \frac{\exp(\gamma_2 + \gamma_3(|S_t - S_t^{trend}|))}{1 + \exp(\gamma_2 + \gamma_3(|S_t - S_t^{trend}|))} \tag{18}$$

where p_t is the probability of switching from 'no intervention regime' to 'intervention regime', q_t is the probability of remaining in the 'intervention regime', $\tilde{\Omega}_t$ is the information set of the central bank and S_t^{trend} is a moving average trend of the rate. That is, according to this reaction function, the central bank will intervene when the rate is deviated from the trend;

and the amount of the intervention will depend on the previous day's intervention and ΔS_t.

To estimate the reaction functions, the conditional log likelihood functions are set up as follows:

$$
\begin{aligned}
f(BUY_t \mid \tilde{\Omega}_t) &= f(d_t BUY_t^* \mid \tilde{\Omega}_t) \\
&= f(BUY_t^* \mid d_t = 1, \tilde{\Omega}_t) \times f(d_t = 1 \mid \tilde{\Omega}_t),
\end{aligned}
\tag{19}
$$

$$
\begin{aligned}
f(SELL_t \mid \tilde{\Omega}_t) &= f(d_t SELL_t^* \mid \tilde{\Omega}_t) \\
&= f(SELL_t^* \mid d_t = 1, \tilde{\Omega}_t) \times f(d_t = 1 \mid \tilde{\Omega}_t),
\end{aligned}
\tag{20}
$$

$$
f(BUY_t^* \mid d_t = 1, \tilde{\Omega}_t) = f(BUY_t^* \mid d_t = 1, \tilde{\Omega}_t, \Delta S_t) \times f(\Delta S_t \mid d_t = 1, \tilde{\Omega}_t),
$$

$$
f(SELL_t^* \mid d_t = 1, \tilde{\Omega}_t) = f(SELL_t^* \mid d_t = 1, \tilde{\Omega}_t, \Delta S_t) \times f(\Delta S_t \mid d_t = 1, \tilde{\Omega}_t),
$$

$$
f(d_t = 1 \mid \tilde{\Omega}_t) = \{ p_t I_{\{d_{t-1}=0\}} + q_t I_{\{d_{t-1}=1\}} \} \times f(\Delta S_t \mid d_t = 1, \tilde{\Omega}_t)
$$

where $BUY_t^* \mid (d_t = 1, \tilde{\Omega}_t, \Delta S_t) \sim N(\alpha_{D0} + \alpha_{D1}BUY_{t-1} + \alpha_{D2}\Delta S_t, \sigma_D^2)$, $SELL_t^* \mid (d_t = 1, \tilde{\Omega}_t, \Delta S_t) \sim N(\alpha_{S0} + \alpha_{S1}SELL_{t-1} + \alpha_{S2}\Delta S_t, \sigma_S^2)$, and $\Delta S_t \mid (d_t = 1, \tilde{\Omega}_t) \sim N(\delta_0 + \delta_1 Q_{t-1} + \delta_2 Q_{t-2} + \delta_3 Q_{t-3} + \delta_4 \tilde{C}_{Dt} + \delta_5 \tilde{C}_{Dt-1} + \delta_6 \tilde{C}_{St} + \delta_7 \tilde{C}_{St-1} + \delta_8 BUY_{t-1} + \delta_9 SELL_{t-1} + \delta_{10}\Delta JPY_t, \sigma_Z^2)$.
Under these settings, the maximization problems are

$$
\max_{\theta_{BUY}} \sum_{t=1}^{T} \ln f(BUY_t \mid \tilde{\Omega}_t), \quad \max_{\theta_{SELL}} \sum_{t=1}^{T} \ln f(SELL_t \mid \tilde{\Omega}_t)
\tag{21}
$$

where $\theta_{BUY} = [\alpha_{D0}, \alpha_{D1}, \alpha_{D2}, \sigma_D, \gamma_0, \gamma_1, \gamma_3, \gamma_4, \delta_0, \delta_1, \delta_2, \delta_3, \delta_4, \delta_5, \delta_6, \delta_7, \delta_8, \delta_9, \delta_{10}, \sigma_Z]$ and $\theta_{SELL} = [\alpha_{S0}, \alpha_{S1}, \alpha_{S2}, \sigma_S, \gamma_0, \gamma_1, \gamma_3, \gamma_4, \delta_0, \delta_1, \delta_2, \delta_3, \delta_4, \delta_5, \delta_6, \delta_7, \delta_8, \delta_9, \delta_{10}, \sigma_Z]$.

4 Empirical results

4.1 Estimation on coefficients

Simple descriptive statistics for the variables were shown in Table 1. By the Augmented Dickey-Fuller test, no variables were shown to have a unit root thus I could proceed with the estimation. First, the intervention policy reaction functions were estimated with CMLE. As in Table 2, most of parameters were significant under 5% level. γ_1 and γ_3 were positive, which means that the Bank of Korea actually decided to intervene when the smoothing operations were needed. With the estimated parameters, the fitted value of the interventions was generated. The rule was,

$$\begin{aligned} \text{if } \hat{p}_t &< 0.5 \text{ and } d_{t-1} = 0, \text{ then } \hat{d}_t = 0 \\ \hat{p}_t &> 0.5 \text{ and } d_{t-1} = 0, \text{ then } \hat{d}_t = 1 \\ \hat{q}_t &< 0.5 \text{ and } d_{t-1} = 1, \text{ then } \hat{d}_t = 0 \\ \hat{q}_t &> 0.5 \text{ and } d_{t-1} = 1, \text{ then } \hat{d}_t = 1 \end{aligned}$$

$$\widehat{BUY_t} = \hat{d}_t \widehat{BUY_t^*}, \ \widehat{SELL_t} = \hat{d}_t \widehat{SELL_t^*}$$

where $\hat{p}_t$ and $\hat{q}_t$ are fitted value of transition probabilities, $\hat{d}_t$ is the fitted value of intervention dummy variable and $\widehat{BUY_t}(\widehat{SELL_t})$ is fitted value of buying (selling) interventions. For simplicity, the threshold probability was arbitrarily set to 50%. In the fitted values, the number of the days of interventions decreases by 22.5%; 80.6% of the days with $\hat{d}_t = 1$ coincide with the days with the actual interventions ($d_t = 1$); and 88.7% of the days with $\hat{d}_t = 0$ coincide with the days without the actual interventions ($d_t = 0$).

Next, the demand and the supply curves were estimated. Since I assumed that the market participants only observed the aggregate value of customer trades and the interventions, new explanatory variables were generated as follows:

$$C_{Dt}^* = \tilde{C}_{Dt} + \widehat{BUY_t}, \ C_{St}^* = \tilde{C}_{St} + \widehat{SELL_t}$$

where $\tilde{C}_{D(S)t}$ is the customer trade without the interventions. To avoid the simultaneity bias from ΔS_t in the demand and the supply equations, this paper tried Generalized Method of Moments for estimating coefficients. I could identify the two equations because of the assumption that the customer demand (supply) affects the equilibrium rate, and it is only through the demand (supply) behavior. Specifically, the customer demand (supply) will be a good instrumental variable for the supply (demand) curve. The estimation results were summarized in Table 3 and 4. Pagan-Hall test statistics showed that the errors were homoskedastic, thus simple IV estimation (2SLS) was applied. Except for the constant in the supply curve, all the coefficients were significant under 10% significance level.[5] For the validity of instrumental variables, Anderson canonical correlation likelihood ratio statistic rejected the null hypothesis that the IVs were weak in the both equations under 1% significance level, and Sargan's statistic showed that the IVs were exogenous in the both equations. Portmanteau Q statistic indicated that residuals were white noise with 1, 5 and 10 lags. These features show that the coefficients are consistently estimated.

The signs of coefficients correspond with intuitions. The demand (supply) curve was downward (upward) sloping, and if the price of the USD denominated by the Japanese yen (the USD/JPY rate) increased, the expected USD price denominated by the Korean won, i.e. $E[\Delta S_{t+1} \mid \Omega_{D(S)t}]$, also increased in both equations. The customer trades have a positive relationship with the quantity demanded (supplied) in the same day, but a negative relationship for the quantity in the day after.

The predictive power of the model is another issue. Figure 2 illustrates the in-sample predicted value of the exchange rate which solves the estimated demand and supply curve. For the out-of-sample prediction, I followed Messe and Rogoff(1983)'s arguments. That is, the model was estimated with the first 10 days, and then the one-day-after prediction was made with the estimated coefficients. By expanding the sample size by one day, this procedure was repeated. Results in Table 5 show that this model has lower mean squared errors and mean absolute errors in one-day-after prediction compared with a random walk model.

---

[5]Since generated regressors were used, the standard errors should be corrected. I followed Wooldridge(2002)'s arguments. See page 139-141.

What remains is to check whether the conditional variances were different between the days with and without the interventions. The equation (9) and (10) shows that if they are different, β's should be different. Thus, Chow test was applied, and the result in Table 6 showed that we couldn't reject the null hypothesis that they were same. Therefore, I could conclude that the intervention of the Bank of Korea made no distinction in the participant's behavioral parameters.

4.2   The hypothetical rate and the effect of the intervention

What would have happened in the foreign exchange market if there were no interventions? The answer can be tackled in two ways: the intervention may shift the demand and the supply curves (liquidity effect), and also may change the slopes of the curves. However, this paper shows that the slopes were same across the days with and without intervention, thus what remains is the liquidity effect. Shifted curves were derived by replacing $C_{D(S)t}^*$ with $\tilde{C}_{D(S)t}$ and solving the simultaneous equations. In this way, the hypothetical rate which assumes that there were no interventions is generated, as illustrated in Figure 3.

Since it was assumed that the Bank of Korea tried to minimize the abrupt change in the rate, the sample variance of ΔS_t can be a criterion for assessing the efficacy of the operations. Table 7 shows the final results. The sample variance of ΔS_t was 32.708, but in the hypothetical rate, it was 32.969 in the overall period, which means that the interventions decreased the actual market volatility. More interestingly, this hypothesis rate argument can be used for specifying the causal relationship between the volatile market and the interventions. That is, in the hypothetical world, the sample variance of the ΔS_t was 25.792 for the days without interventions, but it was 55.717 when there were interventions. This means that the Bank of Korea intervened because the market was volatile, but not the other way. Furthermore, the sample variance of the actual rate differentials in the days with intervention was 54.523, which means that the interventions decreased the market volatility measured by the sample variance of the rate differentials.

This paper showed that there was no significant difference in the agents' behaviors with the interventions. Therefore, only the liquidity shock accounts for the effectiveness of in-

tervention. Leaning against winds operations are to supply the liquidity to the market in the opposite direction of the rate movements, thus every leaning against winds operations will always decrease the volatility if the market participants do not change their behavioral pattern. In specific, if the market participants expect that the variance of ΔS_{t+1} will be decreased with interventions of the day t, they will be more willing to change the quantity demanded (supplied) with given change in ΔS_t. But this makes the curves flatter, therefore the liquidity effect (or effect on the expected value of ΔS_t), represented by the shifts of the curves, may be offset.

5 Conclusion

Endogeneity problems impede the analysis on the effectiveness of intervention. In most of the cases, we had to estimate only a reduced form equation taking endogenous variables as regressors, thus the results were obscure. The main motivation of this paper was to clarify the interactions between interventions, market participants' behavior, and the exchange rate. The endogeneity problem can be solved by this clarification.

For the task, a system of equations was specified. Market participants were modeled to solve utility maximization problems, and the central bank secretly intervenes to affect the exchange rate. But again, the central bank reacts to the exchange rate movements. The model predicts that the interventions will be effective, i) if the interventions influence the participants' conditional expectation in the desired direction (liquidity effect), and ii) if the interventions do not decrease the uncertainty perceived by the participants. We cannot guarantee the efficacy of the interventions if any of these two conditions fail.

To consistently estimate the equations, we should have valid IVs. Customer trades were proposed as IVs, and the empirical results showed that the IVs were valid. In addition, the model out-performed the random work model in out-of-sample prediction. More importantly, the interventions of the Bank of Korea in the sample period were shown to have insignificant effects on the behavioral parameters but have the liquidity effect. Therefore, the effectiveness was ensured by the conditions above. With estimated coefficients, the sys-

tem of equations was solved to generate a hypothetical exchange rate assuming that there were no interventions. Compared with the actual rate, it was shown that the Bank of Korea intervened because the market was volatile, and that interventions indeed decreased the volatility.

This finding has an important policy implication. That is, if one-sided large scale interventions are frequently exerted, the effect of operations may be undermined by flattening the demand and supply curves for the foreign currency. Conversely, if operations can only change the expected rate without altering the future variance, the interventions will be effective. This was the case of the Bank of Korea from 2001 to 2002.

References

[1] Bonser-Neal, C., and G. Tanner, 1996, Central bank intervention and the volatility of foreign exchange rates: evidence from the options market, *Journal of International Money and Finance* 15, 853-878.

[2] Craig, B., and O. Humpage, 2001, Sterilized Intervention, Nonsterilized Intervention, and Monetary Policy, Working paper 0110, Federal Reserve Bank of Cleveland.

[3] Dominguez, K.M., 1993, Does Central Bank Intervention Increase the Volatility of Foreign Exchange Rates? Working paper 4532, NBER.

[4] Dominguez, K.M., 1998, Central bank intervention and exchange rate volatility, *Journal of International Money and Finance* 17, 161-190.

[5] Galati, G., W. Melick, and M. Micu, 2005, Foreign exchange market intervention and expectations: The yen/dollar exchange rate, *Journal of International Money and Finance* 24, 982-1011.

[6] Ito, T., 2002, Is Foreign Exchange Intervention Effective? The Japanese Experiences in the 1990s, Working paper 8914, NBER.

[7] Kearns, J., and R. Rigobon, 2005, Identifying the efficacy of central bank interventions: evidence from Australia and Japan, *Journal of International Economics* 66, 31-48.

[8] Lyons, R.K., 2001, *The Microstructure Approach to Exchange rates* (MIT Press, Cambridge).

[9] Meese, R.A., and K. Rogoff, 1983, Empirical Exchange Rate Models of the Seventies, Do they fit out of sample? *Journal of International Economics* 14, 3-24.

[10] Neely, C.J., 2005, An Analysis of Recent Studies of the Effect of Foreign Exchange Intervention. Federal Reserve Bank of St. Louis *Review* 87(6), 685-717.

[11] Rhee, G., and E.M. Lee, 2005, Foreign exchange intervention and foreign exchange market development in Korea, in Foreign exchange market intervention in emerging markets: motives, techniques and implications, BIS Papers 24, May 2005.

[12] Rogers, J.M., and P.L. Siklos, Foreign exchange market intervention in two small open economics: the Canadian and Australian experience, *Journal of Money and Finance* 22, 393-416.

[13] Sarno, L., and M.P. Taylor, 2002, *The economics of exchange rates* (Cambridge University Press, Cambridge).

[14] The Bank of Korea, 2002, *Annual Report 2001*, BOK, Seoul.

[15] The Bank of Korea, 2003, *Annual Report 2002*, BOK, Seoul.

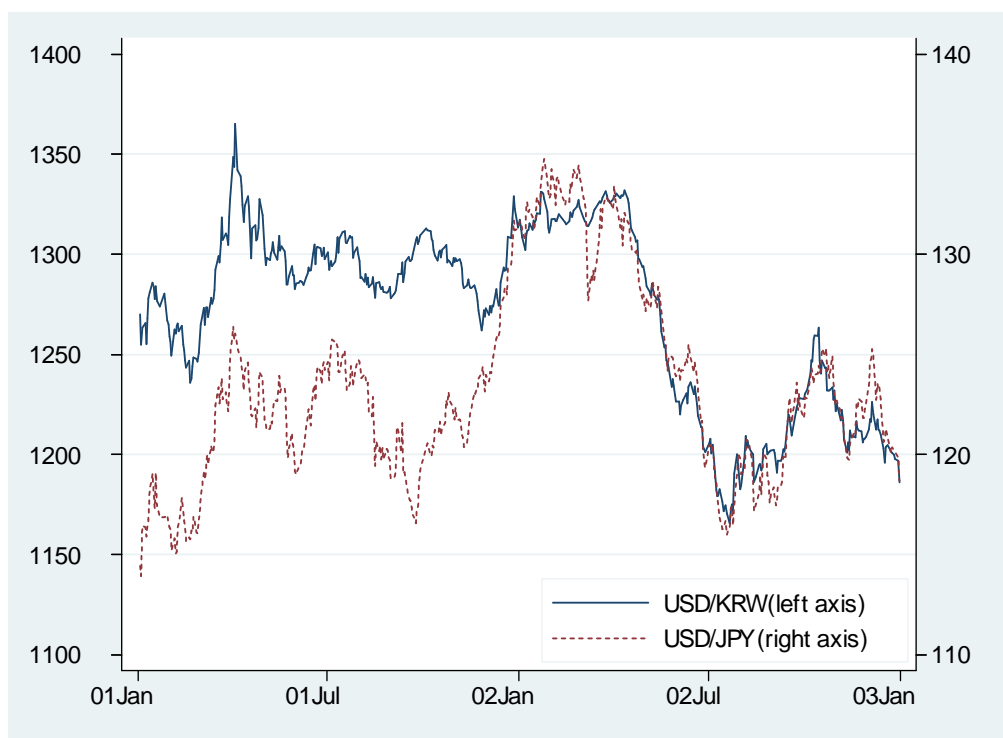[16] Wooldridge, J.M., 2002, *Econometric analysis of cross section and panel data* (MIT press, Cambridge).

Fig.1. The Korean won and the Japanese yen rate in the sample period.

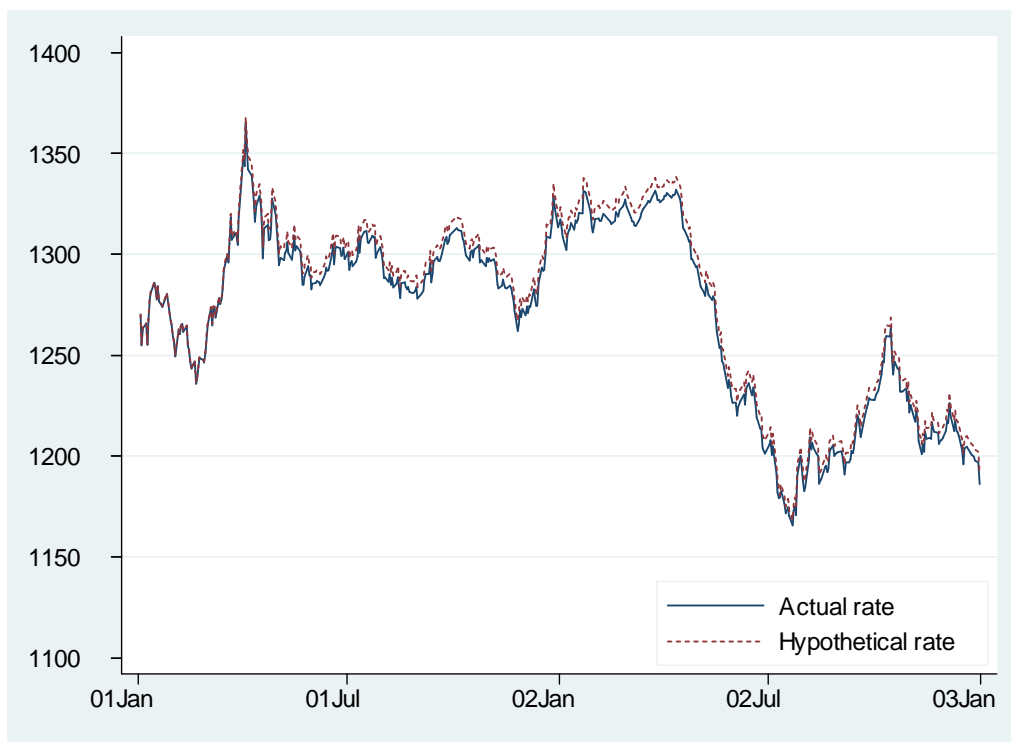Fig.2. The actual rate vs. the predicted rate

16

Fig.3. The actual rate vs. the hypothetical rate

Table 1.
Descriptive statistics for the variables

	Q_t	ΔS_t	ΔJPY_t	$\tilde{C}_{Dt}$	$\tilde{C}_{St}$
Mean	2,634	-0.184	0.009	835	862
Standard deviation	560	5.719	0.769	247	237
Skewness	0.233	0.171	-0.145	0.862	0.501
Kurtosis	2.959	4.364	4.102	4.320	3.202
ADF statistics	-11.07	-22.50	-22.26	-14.88	-15.62
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 2.
CMLE result for the reaction function

$N = 491$

For BUY_t, log likelihood : -5776.6, $\chi^2(2) = 347.29(0.000)$

For $SELL_t$, log likelihood: -5685.5, $\chi^2(2) = 329.22(0.000)$

	Coeff.	S.E.	p-value		Coeff.	S.E.	p-value
α_{D0}	11.907	3.447	0.001	δ_0	0.702	0.997	0.481
$\alpha_{D1}(BUY_{t-1})$	0.641	0.035	0.000	$\delta_1(Q_{t-1})$	-0.0005	0.0003	0.171
$\alpha_{D2}(\Delta S_t)$	-0.970	0.568	0.088	$\delta_2(Q_{t-2})$	0.0003	0.0003	0.365
σ_D	71.943	2.296	0.000	$\delta_3(Q_{t-3})$	0.0001	0.0003	0.729
α_{S0}	10.105	2.869	0.000	$\delta_4(\tilde{C}_{Dt})$	0.006	0.001	0.000
$\alpha_{S1}(SELL_{t-1})$	0.631	0.035	0.000	$\delta_5(\tilde{C}_{Dt-1})$	-0.002	0.001	0.043
$\alpha_{S2}(\Delta S_t)$	-0.442	0.472	0.350	$\delta_6(\tilde{C}_{St})$	-0.007	0.001	0.000
σ_S	59.765	1.907	0.000	$\delta_7(\tilde{C}_{St-1})$	0.002	0.001	0.036
γ_0	-3.322	0.341	0.000	$\delta_8(BUY_{t-1})$	0.004	0.002	0.036
$\gamma_1(|S_t - S_t^{trend}|)$	positive	-	0.000	$\delta_9(SELL_{t-1})$	-0.006	0.003	0.035
γ_2	-1.193	0.441	0.007	$\delta_{10}(\Delta JPY_{t-1})$	4.551	0.179	0.000
$\gamma_3(|S_t - S_t^{trend}|)$	positive	-	0.000	σ_Z	4.252	0.096	0.000

18

Table 3.
Estimation for Demand curve

$$Q_t = \beta_{D0} + \sum_{k=1}^{3} \beta_{Dk}Q_{t-k} + \beta_{D4}C^*_{Dt} + \beta_{D5}C^*_{Dt-1} + \beta_{D6}\Delta JPY_t + \beta_{D7}\Delta S_t + \varepsilon_{Dt}$$

Excluded instrumental variables are $\tilde{C}_{St}$ and $\tilde{C}_{St-1}$.

			$N = 491$
			$F(8, 482) = 46.05$
			$Probability > F = 0.000$
			$Centered\ R^2 = 0.198$
			$Uncentered\ R^2 = 0.965$
	Coefficient	Standard error	p-value
β_{D0}	314.512	166.951	0.060
β_{D1}	0.418	0.058	0.000
β_{D2}	0.212	0.058	0.000
β_{D3}	0.161	0.055	0.003
β_{D4}	0.817	0.108	0.000
β_{D5}	-0.564	0.103	0.000
β_{D6}	388.668	116.096	0.001
β_{D7}	-79.289	23.735	0.001

Anderson canonical correlation LR statistic(IV relevance): 30.501 (p-value: 0.000)

Sargan's statistic: 1.795 (p-value: 0.180)

Pagan-Hall heteroskedasticity test statistic: 10.218 (p-value: 0.250)

Portmanteau Q statistic for e_{Dt} with lag 1: 3.462 (p-value: 0.063)

Lag 5: 4.673 (p-value: 0.457)

Lag 10: 8.763 (p-value: 0.555)

Table 4.
Estimation for Supply curve

$$Q_t = \beta_{S0} + \sum_{k=1}^{3} \beta_{Sk} Q_{t-k} + \beta_{S4} C^*_{St} + \beta_{S5} C^*_{St-1} + \beta_{S6} \Delta JPY_t + \beta_{S7} \Delta S_t + \varepsilon_{St}$$

Excluded instrumental variables are $\tilde{C}_{Dt}$ and $\tilde{C}_{Dt-1}$.

			$N = 491$
			$F(8, 482) = 43.85$
			$Probability > F = 0.000$
			$Centered\ R^2 = 0.158$
			$Uncentered\ R^2 = 0.964$
	Coefficient	Standard error	p-value
β_{S0}	229.842	173.574	0.185
β_{S1}	0.493	0.058	0.000
β_{S2}	0.156	0.056	0.006
β_{S3}	0.149	0.056	0.008
β_{S4}	0.978	0.121	0.000
β_{S5}	-0.614	0.115	0.000
β_{S6}	-327.386	116.595	0.005
β_{S7}	76.426	23.835	0.001

Anderson canonical correlation LR statistic(IV relevance): 28.595 (p-value: 0.000)

Sargan's statistic: 3.230 (p-value: 0.072)

Pagan-Hall heteroskedasticity test statistic: 4.097 (p-value: 0.848)

Portmanteau Q statistic for e_{St} with lag 1: 0.943 (p-value: 0.332)

Lag 5: 3.105 (p-value: 0.684)

Lag 10: 8.462 (p-value: 0.584)

Table 5.
Out-of-sample prediction of the model compared with a random walk model

A random walk model:

$$S_t = \eta_1 S_{t-1} + \eta_2 Q_{t-1} + \eta_3 Q_{t-2} + \eta_4 Q_{t-3} + \eta_4 JPY_t$$
$$+ \eta_5 C^*_{Dt} + \eta_6 C^*_{Dt-1} + \eta_7 C^*_{St} + \eta_8 C^*_{St-1} + e_t$$

	The model	A random walk model
Mean Absolute Error (average)	3.377	6.738
Mean Squared Error (average)	19.695	81.251

Table 6.
Result for the Chow test
H0: The coefficient(s) is(are) same between the days with or without interventions.

Demand curve			Supply curve		
Variable	Statistic	p-value	Variable	Statistic	p-value
Q_{t-1}	-0.211	0.833	Q_{t-1}	-0.044	0.965
Q_{t-2}	0.011	0.992	Q_{t-2}	0.160	0.873
Q_{t-3}	0.267	0.789	Q_{t-3}	-0.114	0.909
C^*_{Dt}	-0.227	0.820	C^*_{St}	0.057	0.955
C^*_{Dt-1}	0.119	0.905	C^*_{St-1}	0.285	0.775
ΔJPY_t	0.053	0.958	ΔJPY_t	-0.037	0.971
ΔS_t	-0.037	0.971	ΔS_t	0.010	0.992

Table 7.
Sample variances of ΔS_t in the hypothetical and the actual rate

	Hypothetical rate	Actual rate
Overall sample period	32.969	32.708
The days without interventions	25.792	25.756
the days with interventions	55.717	54.523