A microstructural effect of Japanese official intervention in the yen/dollar foreign exchange market

by

Hiroya Akiba, Shinichi Matsuda, Ayano Sato and Yoshihiro Kitamura

Abstract

This study adopts a microstructural approach to examine the effect of Japanese official intervention in the yen/dollar foreign exchange market. Our empirical results show that the number of informed traders after the series of interventions is significantly larger and the degree of the market maker's reaction to the order flow and the cost of the informed trading in the post-intervention term are significantly smaller than that in the pre-intervention one. This implies that the frequent and intense intervention increases the informed traders, and an increasing in them promotes the competition among the informed traders. We interpret that this competition lowers an uncertainty in a market.

Keywords: Intervention of foreign exchange market; microstructure in foreign exchange market

JEL Classification: D82; E58; F31

1. Introduction

The Japanese monetary authority frequently intervened in the yen/dollar markets during from January 2003 to March 2004. As is shown in Ito (2005a), the intervention in this period was unannounced large-scale and the total amount exceeded about 35 trillion yen. By dividing our sample of intervention into the three periods, January 03-March 03, May 03-July 03, and August 03-March04, this paper attempts to examine whether the market microstructure is different between the pre and post days of the above third period using the procedure of Foster and Viswanathan (1995) which applies the simulated method of moment (SMM) to a financial market. Compared to the other two periods, the intensity and sizes of intervention is much larger in the third period.[1] Did the intervention of the Japanese authority in the third period truly have a microstructural effect proposed by Admati and Pfleiderer (1988)? How did the intervention in FX market during this period eliminate the friction and make the market more efficient? The most studies on FX interventions adopt traditional macroeconomic models and consider whether a FX intervention has an impact on an exchange rate through the portfolio and/or signaling channels (Sarno and Taylor, 2001). Unlike the most studies, this paper considers a market microstructure model, which allows us to consider the heterogeneous behaviors among market participants, to examine the effects of the Japanese intervention policy.

As found by Meese and Rogoff (1983) and subsequent literature, no model so far has performed well in predicting short-run foreign exchange (FX) rates.[2] Therefore, as pointed out by Rime (2003), it is reasonable to consider that FX participants have different views on the exchange rate at least over short horizons. The microstructure

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[1] This draft is very primitive. We are also trying to estimate a microstructural effect of the intervention for each month by using our whole sample.

[2] At the longer horizons (well over one year), Mark (1995) shows that the prediction of the monetary model of FX rates, in which the fundamental variable is defined with a linear combination of log-relative money stocks and log-relative real incomes in two countries, outperformed the driftless random walk.

approach, which definition in FX markets is found in Lyons (2001, pp. 5-9), allows us to assume such a heterogeneity regarding FX participants. The availability of high frequency FX data also motivates recent researchers to focus on the microstructure in FX markets. With respect to the topic of FX intervention policy, Dominguez (2003) and Payne and Vitale (2003) examine how FX interventions affect FX market microstructure by using high frequency FX data individually. Dominguez (2003) uses the Deutsche mark/U.S. dollar and the Japanese yen/U.S. dollar data and finds that some traders know that the U.S. Federal Reserve is intervening into those markets at least 1 hour prior to public release of the information regarding the intervention. Payne and Vitale (2003) use the 15 minute interval data of the Swiss franc/U.S dollar and show an empirical result implying that market participants are able to anticipate central bank intervention. Menkhoff (2010) insists that a recent availability of high frequency data in FX markets possibly makes us to consider new microstructure channels of FX intervention such as damping and coordination ones.

Keeping in mind the recent development in the microstructure approach in FX markets, for the discussion of the intervention during our sample period, we consider that it is necessary to focus on an effect of the Japanese authority's interventions to the microstructure of FX market. This paper attempts to explain the twofold. First, Ito (2005a) suggests that the motivation of intervention during the third period differs from those during first and second periods: The Japanese monetary authority intervened in order not to help Japanese economic recovery but to fight the speculative pressures for the yen appreciation. Could this view supported by empirical economic result? To address this issue, we compare the number of uninformed traders between the pre- and post intervention.

Secondly, how asymmetric information between market maker and traders be resolved? We suggest the number of informed traders increase after the interventions and this increase lowers the asymmetric information of market maker. To argue this issue, we examine the sign condition of the impact of current order flow to an increase in the number of informed traders. The sign condition depends on the following two effects: the adverse selection problem faced by market makers and competition among informed traders. We find that the latter effect is relatively significant in the yen/U.S. dollar FX market. Therefore, an increasing in informed traders makes the impact of current order flow small.

The remainder of this paper is organized as follows. The microstructure model developed by Admati and Pfleiderer (1988) and estimation method applied by Foster and Viswanathan (1995) are described in Section 2. Section3 devotes to explanations for our sample data and our empirical results, which contain how the behavior of FX market participants are influenced by intervention. Section 4 concludes this paper.

2. The microstructure model and estimation method

The ultimate goal of this study is to examine a microstructural effect of the FX intervention, which is estimated with the microstructural model developed by Admati and Pfleiderer (1988, hereafter AP). For example, whether do the interventions sweep way an uncertainty about the future yen/dollar movement? If they do, the exchange rate quoted by market makers contains less risk premium component which compensates the market makers for their disadvantageous transactions with informed traders. In other words, the interventions eliminate the friction in the FX market and therefore, make the market more efficient. We hope that the estimation of the microstructural model gives us the answer about this issue.

We assume that information regarding fundamentals includes private information. In this study, traders in the FX market are categorized to informed traders if they can access private information, which is not known by all people, and produces a better forecast than does public information alone (Lyons 2001, p.26). In FX markets, leveraged investors are likely to generate such private information regarding fundamentals because they pursue profits by putting their money into forecasting fundamentals (e.g., Osler, 2009).

By adopting the simulated method of moment to estimate the system of equations describing the equilibrium of AP, we examine the microstructural effect of interventions. We adopt the simulated method of moment (hereafter, SMM), which Foster and Viswanathan (1995) used to estimate the system of equations describing the equilibrium of AP. Since we use the quite similar method of the SMM procedure with Foster and Viswanathan (1995), we limit ourselves to give the summaries of this procedure. Details about the SMM procedure which we adopt here are shown in Section

2 of Foster and Viswanathan (1995).

AP consider a single asset traded over a span of time that we divide into T periods, and assume that the value of the asset in period T is exogenously given by

$$\tilde{F} = \overline{F} + \sum_{k=1}^{T} \tilde{\delta}_k \tag{1}$$

where $\tilde{\delta}_k$, k= 1, 2, .. . , T are independently distributed random variables, each having a mean of zero. The payoff $\tilde{F}$ can be thought of as the liquidation , or fundamentals value of the asset, and $\overline{F}$ is constant asset value. In each period, informed traders receive public information, $\tilde{\delta}_t$, with different error among informed traders, $\tilde{\varepsilon}_t^{\,i}$, which is independently and identically distributed random variable. That is, it is assumed that the ith informed trader observes private signal $\tilde{\delta}_t + \tilde{\varepsilon}_t^{\,i}$ in period t, which will be revealed one period later to all traders.

AP assumes that there exist four types of market participants : an informed trader, two kinds of an uninformed (liquidity or noise) trader and a market maker. nondiscretionary uniformed traders are referred to as agents who trade randomly the asset for exogenous reasons at the prices quoted by a market maker. Discretionary uninformed traders decide their trading timings in order to minimize their trading costs[3]. Thus, in this model, total order flow is defined by the sum of demand of informed traders and two kinds of uninformed traders. Both informed traders and discretionary uninformed traders are treated as strategic players, while the market maker plays a passive role. He can only observe the total current order flow, $\tilde{\omega}$, and sets prices to satisfy the zero expected profit condition.

In the equilibrium, a market maker sets the price which is equal to the expectation of $\tilde{F}$ conditional on the history of public information observed in period t-1 plus an adjustment that reflects the information contained in the current order flow:

$$\tilde{p}_t(\tilde{\Delta}_{t-1}, \tilde{\Omega}_t) = E(F \mid \tilde{\Delta}_{t-1}) + \lambda_t \tilde{\omega}_t$$

[3] AP postulates that nondiscretionary liquidity traders trade a given number of shares in each period, on the other hand, discretionary liquidity traders having liquidity demands need not be satisfied immediately.

$$= \bar{F} + \sum_{k=1}^{t-1} \tilde{\delta}_k + \lambda_t \tilde{\omega}_t \qquad (2)$$

where $\tilde{\Delta}_{t-1} = (\tilde{\delta}_1, \tilde{\delta}_2, \ldots, \tilde{\delta}_{t-1})$, $\tilde{\Omega}_t = (\tilde{\omega}_1, \tilde{\omega}_2, \ldots, \tilde{\omega}_t)$, and λ_t represent the impact of current order flow $\tilde{\omega}_t$ on the corresponding asset price, that is, the market maker's sensitivity to price change with respect to the current order flow. The lemma suggested by AP gives the following equation:

$$\lambda_t = \frac{1}{\tau_t + \tau_t n_t + 2\phi_t} \sqrt{\frac{n_t \tau_t^{\,2} (\tau_t + \phi_t)}{\Psi_t}}, \qquad (3)$$

where n_t is the number of informed traders in period t, $\mathrm{var}(\delta_t) = \tau_t$[4] and $\mathrm{var}(\varepsilon_t^i) = \phi_t$ for all i. Ψ_t is the total variance of the liquidity trading in period t.

By differentiating equation (2), we obtain the following equation:

$$\tilde{p}_t - \tilde{p}_{t-1} = \tilde{\delta}_t + \lambda_t \left[n_t \beta_t s_t + l_t \right] - \lambda_{t-1} \left[n_{t-1} \beta_{t-1} s_{t-1} + l_{t-1} \right], \qquad (4)$$

where l_t is a order flow from liquidity traders. Therefore, $\tilde{\omega}_t$ is again defined to be the sum of order flows from informed, $n_t \beta_t s_t$ (β and s are defined in below), and l_t from uninformed traders at the period t.

Following Foster and Viswanathan (1995), liquidation (fundamentals) value ($\tilde{\delta}_t$), orders from liquidity traders (l_t) and signal observed by informed traders (s_t) at t period are defined as follows:

$$\tilde{\delta}_t = \Gamma_t \sigma_a \upsilon_t^a \qquad (5)$$

$$l_t = \Gamma_t \sigma_b \upsilon_t^b \qquad (6)$$

$$s_t = \tilde{\delta}_t + \varepsilon_t^i = \Gamma_t \sigma_a \upsilon_t^a + \Gamma_t \sigma_d \upsilon_t^d, \qquad (7)$$

where, $\upsilon_t^o \sim N(0,1)$, $o = a, b, d$, and therefore, $\tau_t \equiv \Gamma_t^2 \sigma_a^2$, $\phi_t \equiv \Gamma_t^2 \sigma_d^2$ and $\Psi_t \equiv \Gamma_t^2 \sigma_t^2$. These variables are independent each other. Γ_t is a latent variable which governs the conditional heteroskedasticity in volatility in the model. Foster and Viswanathan (1995) defined the stochastic process of Γ_t as follows:

$$\ln(\Gamma_t) = A + \gamma \ln(\Gamma_{t-1}) + \zeta_t \qquad (8)$$

$$\zeta_t = \sigma_\zeta \upsilon_t^\zeta \quad \upsilon_t^\zeta \sim N(0,1).$$

[4] In AP, information volatility $\mathrm{var}(\delta_t)$ is fixed at 1.

By using the equations (5)-(7), we rewrite equation (3) as follows:

$$\lambda_t = \frac{\sigma_a^2}{\sigma_a^2(1+n_t)+2\sigma_d^2}\sqrt{\frac{n_t(\sigma_a^2+\sigma_d^2)}{\sigma_b^2}}. \tag{9}$$

Similarly, $\beta_t = \sqrt{\Psi_t / \left[n_t(\tau_t + \Psi_t)\right]}$, the reaction of an informed trader to the signal, is rewritten as follows:

$$\beta_t = \sqrt{\frac{\sigma_b^2}{n_t(\sigma_a^2+\sigma_d^2)}}. \tag{10}$$

As shown by AP, the expected profit of each informed trader in the equilibrium, $\pi_t = \lambda_t \Psi_t / n_t$, equals to c the cost which traders must pay to become an informed trader. With this condition, we obtain the following equation:

$$\begin{aligned} c &= \pi_t \\ &= \frac{\lambda_t E\left[\Gamma_t^2 \mid \Delta_{t-1}\right]\sigma_b^2}{n_t} \\ &= \frac{E\left[\Gamma_t^2 \mid \Delta_{t-1}\right]\sigma_a^2}{\sigma_a^2(1+n_t)+2\sigma_d^2}\sqrt{\frac{(\sigma_a^2+\sigma_d^2)\sigma_b^2}{n_t}}, \end{aligned} \tag{11}$$

where $\Psi_t = \mathrm{var}(l_t \mid \Delta_{t-1})$ is used in the second line. Given numerical values for conditional expectation of Γ_t^2 and other parameters, equation (11) gives the number of informed traders. With equation (8), the assumption of log-normal distribution for Γ_t enables us to simulate the conditional expectation of Γ_t^2 [see equation (19) in Foster and Viswanathan (1995)].

Following Foster and Viswanathan (1995), trading volume each period, V_t, is computed as half of the orders from the informed traders, plus half of the orders from liquidity traders, plus half of the orders traded with the market maker:

(12)

By substituting both equations (9) and (10) into each equation (4) and (12), price change and volume equations are expressed with the seven parameters ($\sigma_a, \sigma_b, \sigma_d, \sigma_\zeta, A, \gamma$ and c) and random variables. Then, given arbitrary parameters with equations (4) and (12), generated random variables give the simulated price change and trading volume. With these, we calculate simulated moments for the SMM procedure. Following Table 1 in Foster and Viswanathan (1995), we use the same 52 moments to estimate the parameters. In our simulation, we draw 100,000 simulated values (or equivalently, we generate 10^5 random variables ($\upsilon_t^o, o = a, b, d, \zeta$). Let Θ be a vector of parameters we estimate. Let Θ^* be the true parameters that are consistent with observed data. When we define $f_i^{\Theta^*}$ and f_j^{Θ} to be i and j th the observed and simulated moments respectively, we define the mean difference between these as follows:

$$g_T(\Theta) = \frac{1}{T}\sum_{i=1}^{T} f_i^{\Theta^*} - \frac{1}{10^5}\sum_{j=1}^{10^5} f_j^{\Theta}, \tag{13}$$

where T is a sample size. The SMM procedure searches $\hat{\Theta}$ which minimizes the following quadratic function:

$$g_T(\Theta)' W g_T(\Theta), \tag{14}$$

where W the inverse of the Newey-West estimator, whose lag truncation parameter is $T^{1/3}$ (see, Davidson and MacKinnon, 2004, p.362).

The following section explains the data set for the SMM estimation and also shows the estimation results.

3. Empirical result

3. 1 Data

For empirical analysis, we obtain the trading data from EBS Data Mine ver. 2.0. In order to examine the effect of FX interventions by the Japanese monetary authority, we focus on the Japanese yen/U.S. dollar FX rate. Hereafter, the yen/dollar refers to the yen quoted against the United States dollar spot rate. The sample period ran from December 30, 2002, to April 2, 2004. Throughout this period, the Japanese monetary authority frequently intervened into the yen/dollar FX markets (see Ito, 2005b).

We exclude from our sample all data collected after 20:00 GMT in each day, since trading activity during these hours is minimal. Data in weekends are also excluded. Following Foster and Viswanathan (1995), we convert the original data set into 30-minute intervals. We employ as a price p the midpoint quote of the best bid and ask rates observed at the end of each interval. The unit of trading volume is one million U.S. dollar. We sum reported trading volume at both bid and ask sides in each interval and obtain the variable for trading volume V.

*******Figure 1 around here*******

Figure 1 shows the volume of interventions executed by the Japanese Ministry of Finance at daily frequency. The days of intervention follows the disclosures by the Japanese Ministry of Finance, which has disclosed its daily intervention record dating from April 1991. Figure 1 shows that the Japanese authority intervened into the yen/dollar market highly frequently throughout the sample period. We find the three periods during which the intensity of the Japanese intervention is high; (1) 03/01/15-03/03/07, (2) 03/05/08-03/07/16 and (3) 03/08/29-04/03/16. After the third period, the Japanese monetary authority has never intervened into the yen/dollar market. Here, we come up with the following question; whether the series of interventions during the third period, at which the intensity of intervention is much larger than those of the other two, were successful? To address this issue, we focus on the pre- and post-days of the third period. In other words, we examine whether the market microstructures are significantly different between the pre- and post-days of the third period. If this is true, we possibly conclude that the Japanese interventions during the third period affected the market microstructure of the yen/dollar market. We hope that this attempt leads us to have a new evaluation method for the effect of FX intervention policy, which effect is still under controversy in recent literatures on this topic. Ito (2005a) suggests that the motivation of intervention during the third period differs from those during the first and second periods: The Japanese monetary authority intervened into the yen/dollar market in order not to help Japanese economic recovery but to fight the speculative pressures for the yen appreciation. As shown below, our estimation result supports this view.

3. 2 Estimation results

Since our sample enables us to have the 13 days after 04/3/16, after which the intervention has never reported officially, we set the pre- and post-13 days to 03/8/12-03/8/28 and 04/3/17-04/4/12 (weekends are excluded), respectively.

*******Table 1 around here*******

Table 1 shows the SMM estimated parameters of the pre- and post-days. The row of χ^2 is the value of the chi-square test, which null is that all 52 moment equations are zero [$g_T = 0$ in equation (13)]. Under the null, $Tg_T^{'}Wg_T$ is distributed as a χ^2 with 45 degree of freedom. The figures in parenthesis are *p*-values for this statistics. In terms of the chi-square test, we conclude that our models are well estimated in both the cases. Alternatively, to evaluate our model specification, we can also obtain the standard errors for estimators with the asymptotic distribution of the SMM estimator. However, as mentioned in Foster and Viswanathan (1995), the small-sample properties of our approach are not known for models as complex as ours. Therefore, we adopt the chi-square test to evaluate our model specification.

*******Table 2 around here*******

Table 2 shows descriptive statistics for the simulated model parameters. The estimated parameters and random variables generated by simulations enable us to obtain the simulated impact of order flows and so on. For example, the rows *n* and λ of Table 2 show descriptive statistics of number of informed traders and of impact of order flows, which are obtained by simulations. We draw 100,000 random variables in our simulation and therefore, the maximum number of the simulated model parameters is 100,000.

By comparing the figures of the impact of order flows, we examine whether the series of the interventions during the 3rd period makes the degree of adverse selection of market makers become lower. λ in equation (2) refers to the degree of adverse selection of the market makers. Here, the term of adverse selection refers to the case when a market maker trades disadvantageously with informed traders. When trading with privately informed investors leads to losses for market makers, the market makers react to observed order flows, which contain the signal of private information, excessively. This is equivalent to the case when λ becomes larger. The mean of λ in the post-intervention days is lower than that of the pre-ones and the difference between the two figures is statistically significant at 1 percent level.

As discussing below, we interpret the above finding as the result from the competition among informed traders. In equation (9), the effect of informed trading on the impact of the order flow depends on the following condition:

$$\text{sign}\left(\frac{\partial \lambda_t}{\partial n_t}\right) = \text{sign}[\sigma_a^2(1-n_t)+2\sigma_d^2]. \tag{15}$$

Equation (15) implies that an increase in the number of informed traders has two effects. The first effect is explained by the adverse selection problem faced by market makers. Because the probability that market makers will face disadvantageous deals increases with increasing numbers of informed traders, the sensitivity of market makers to the order flow increases with more informed traders, so that the former can hedge against their losses caused by deals with the latter. The case $\sigma_d^2 >> n_t$ (or equivalently, $1+2\sigma_d^2/\sigma_a^2 > n_t$) corresponds to the period when the information gathered by the informed traders is sufficiently imprecise. The second effect is due to competition among informed traders, which in turn decreases the market uncertainty and lowers the cost of liquidity trading.

The row $\sigma_a^2(1-\overline{n})+2\sigma_d^2$ of Table 2 shows the results of that condition of equation (15), where σ_a and σ_d are estimated parameters reported in Table 1 and $\overline{n}$ is the mean of the proxies for informed trading that are generated by the simulation. In both of the cases, the values are negative, indicating that the impact of order flow is a *decreasing* function of informed trading. We consider that this is due to the transparency of FX spot markets. Unlike an equity market, there is no-analog to inside information in FX markets (Ito, Lyons and Melvin, 1998). In FX markets, it is market participants who predict the variables regarding economic fundamentals such as an unemployment rate accurately to be informed traders (Osler, 2009).[5] The competition

[5] Of course, it is a common view that the variables regarding economic fundamentals are useless to predict intraday FX rate movements. However, in turn, it is also a common view that those variables are *useful* to predict FX rate movements at medium and long runs (Cheung and Chinn, 2001). Moreover, the market survey of Cheung and Chinn (2001) reveals that interest rates and a surprise of macroeconomic announcements always appear to be important for FX rates. Bearing these in our minds, we consider that it is always profitable to predict the variables regarding economic

among informed traders who try to predict the fundamental variables relevant to FX rates continues until they reach consensus. This implies that increasing informed traders enhance the revealing speed and accuracy of information regarding fundamentals of FX rates. Therefore, an increase in informed traders sweeps away the uncertainty regarding fundamentals of FX rate and lowers the adverse selection of the market makers. In other words, the competition among informed traders possibly reduces market dispersion (different opinions among market participants). This makes the market makers feel easy about quoting and leads to less adverse selection of the market makers.

As shown in Table 2, the number of informed traders increases after the interventions and this increase lowers the adverse selection of the market makers. Why do the interventions increase informed traders? In Table 1, the cost to become an informed trader *c* becomes much lower after the interventions than before those. In other words, we possibly suggest that the interventions lower the cost of informed trading and encourage market participants to be informed traders. In turn, why do the interventions lower the cost of informed trading? Before the interventions, the uncertainty regarding the future movements of FX rate was high level in the yen/dollar FX market. Under such market condition, market participants possibly consider that informed trading is so costly because noise factors continue to be dominant over the fundamentals in determining current FX rates even if they predict fundamental variables accurately. If this is true, informed trading is so risky. Once the interventions succeed in sweeping away the uncertainty, they encourage market participants to gather information regarding fundamentals of the yen/dollar rate by lowering the cost of informed trading.

*****Figure 2 around here*****

Ito (2005a) suggests that the interventions during our sample period are practiced partly to fight the speculative pressures for the yen appreciation. Figure 2 is reprinted from Ito (2005a). The bars in Figure 2 show the net long positions of the yen currency futures (against the U.S. dollar) in Chicago Mercantile Exchange (weekly frequency). The beginning of interventions during the third period corresponds to the increasing net long position and the long positions are offset at the end of the

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fundamentals.

interventions. Ito (2005a) suggests that if the Japanese monetary authority intended to reduce the speculative pressure for the yen appreciation during the third period, the movements of line charts, which are the amounts of interventions, possibly tend to coincide with those of bars in Figure 2.

To address this issue, we compare the numbers of uninformed traders between the pre- and post-intervention. In our empirical model, speculators (noise traders) are classified as uninformed traders. AP assumes that informed traders observe the signal of fundamentals and use it to decide the directions and amounts of their trade. Meanwhile, uninformed traders do not observe the signal; their trade does not reflect information regarding fundamentals. Ito (2005a) suggests that the most speculations during the third period are driven by the disagreement about the Japanese intervention policy among the Japanese government and the other G7 ones. This implies that the reason for the speculations during the third period is attributed to not information regarding fundamentals but other factors (noise).

The row of $l(<0)$ in Table 2 corresponds to the uninformed traders who buy the yen against the U.S. dollar. The result of t-test implies that the absolute number of uninformed yen buyers in the post-intervention period is smaller than that in the pre-intervention one and this difference is statistically significant at a 1 percent level. Therefore, we conclude that our estimation result is consistent with Ito (2005a).

In summary, we conclude that the series of interventions in the third period are successful in terms of not only lowering adverse selection of the market makers and but also offsetting speculations for the yen appreciation.

4. Conclusion

In this paper we have examined how the heavy intervention by Japanese monetary authorities affected the behavior of FX market participants during from January 2003 to March 2004, or whether the intervention changes the FX market structure. For the purpose, using the quoted yen/dollar data extracted from EBS data mine ver.2.0, we divide the sample into before and after the period in which Japanese authorities faced the speculative forces and intervened intensively. We estimate the degree of the market maker's reaction to the order flow and the number both of informed traders and uninformed trader by the SMM procedure.

Our empirical results show that the number of informed traders in the post-intervention term is significantly larger, and the degree of the market maker's reaction to the order flow and the cost of the informed trading in the post-intervention term are significantly smaller than that in the pre-intervention one. This implies that the frequent and intense intervention increases the informed traders, and to increase them promotes the competition among the informed traders. The competition lessens the market uncertainty and grows the market transparency, so that the market maker would expect not to suffer losses from the trade with informed investors. As a result, the degree of the market maker's reaction to an order flow gets low relatively. That is, the frequent and heavy intervention might offer to help sweeping away the market uncertainty and the promotion of the market transparency.

In addition, we find that the number of uninformed traders in the post-intervention period is significantly smaller than that in the pre-intervention one. If speculators are assumed as uninformed traders, this finding enables us to interpret that the intervention was successful to suppress the speculation in the sample period. If this is true, we are able to conclude that the exchange rate intervention policy is effective, although Japanese authorities have never intervened in the FX market since March, 2004, until today. When the speculative pressure is observed in the yen-dollar market, the intervention by Japanese authorities might be effective, different from that by developing countries. Especially, as Ito (2005a) points out, the Japanese authority should give a careful consideration to implementations of more frequent intervention because, under the Japanese zero interest rate policy, it is not so costly for the Japanese authority to purchase foreign assets for FX interventions.

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Table 1. Estimation Results

	Pre 13 days		Post 13 days	
	Estimates		Estimates	
σ_a	0.211		0.287	
σ_b	392.556		678.884	
σ_d	3.273		4.516	
σ_ς	0.691		0.820	
γ	0.047		0.056	
A	-2.560		-3.258	
c	5.844		3.780	
χ^2	53.260	(.186)	51.822	(.225)
NOB	454		454	

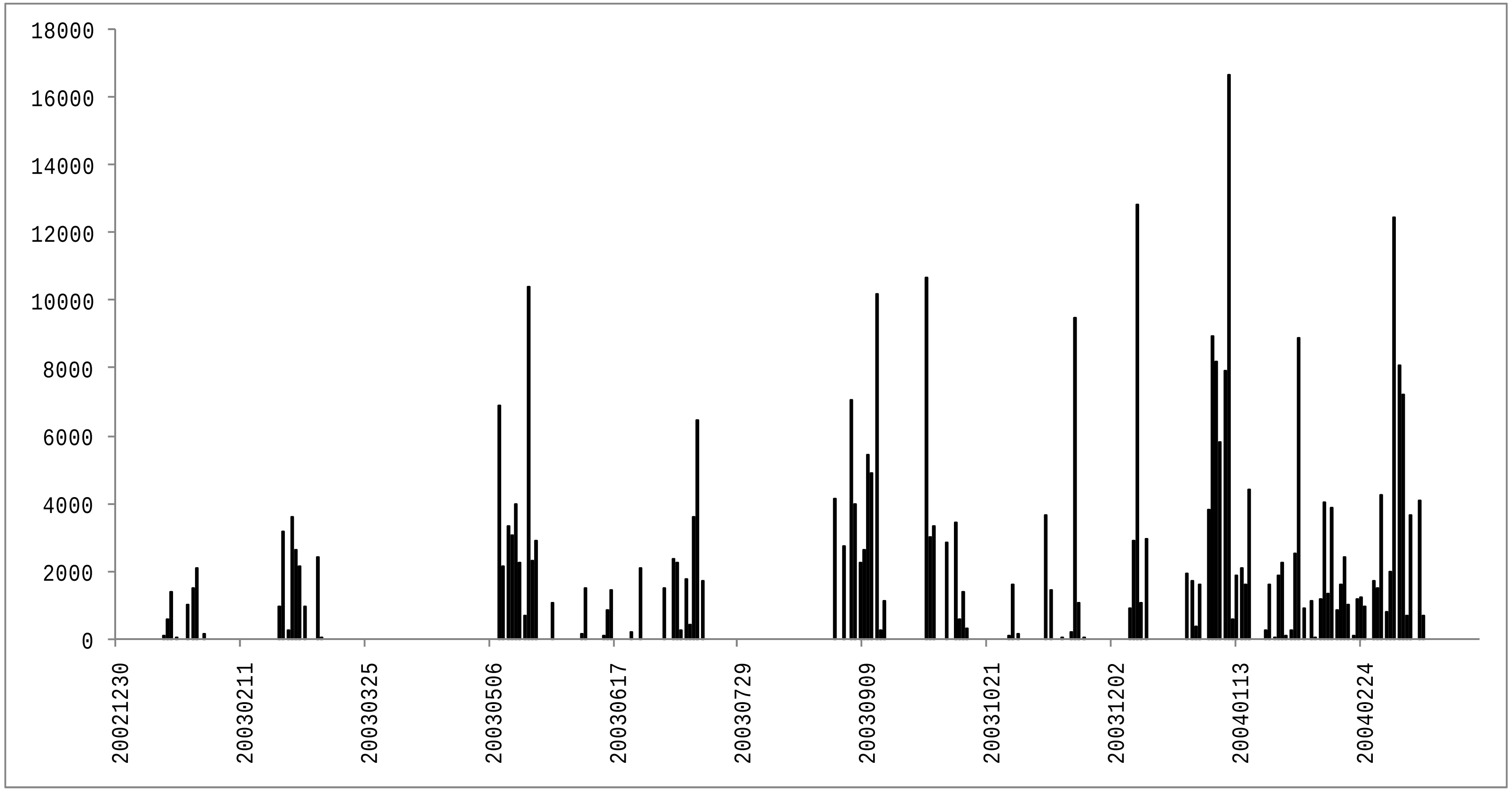
Note: χ^2 is a test statics which null is that all 52 moments [equation (13)] are zero. Figures in parentheses are p-values. *NOB* is the number of observations. Pre (post) 13 days refers to the pre (post) 13 days before (after) the series of interventions during the third period.

Table 2. Descriptive Statistics for Simulated Parameters

	Pre 13 days					Post 13 days					
	Mean	Median	S.D.	Min.	Max.	Mean	Median	S.D.	Min.	Max.	*t-stat.*
Δp	6.59E-05	-1.65E-04	0.092	-1.319	1.477	5.79E-05	-1.14E-04	0.081	-1.670	1.850	0.021
$\lambda(\times 1000)$	0.145	0.145	0.000	0.145	0.145	0.120	0.120	6.18E-06	0.120	0.121	1.3E+06 ***
n	103.430	103.430	0.002	103.430	103.746	122.798	122.798	0.022	122.798	129.061	2.8E+05 ***
l (absolute figure)	27.171	16.620	33.541	1.80E-04	721.801	24.060	13.102	34.460	1.39E-04	941.235	20.46 ***
$l(<0)$	-26.991	-16.608	33.311	-721.801	-0.001	-23.873	-13.098	34.254	-941.235	-0.001	14.57 ***
V	289.209	180.606	349.993	0.023	10843.912	277.852	154.674	395.636	0.026	16345.600	6.80 ***
$\sigma_a^2(1-\overline{n})+2\sigma_d^2$	-6.366					-6.132					

Note: This table shows descriptive statistics for the simulated data at the estimated parameters. Δp and V are defined with equations (4) and (12), respectively. λ is a impact of order flow [equation (9)]. n is the number of informed trader. l is an absolute value of uninformed traders. $l(<0)$ corresponds to the uninformed traders who buy the yen against the U.S. dollar. The row $\sigma_a^2(1-\overline{n})+2\sigma_d^2$ shows the results of that condition of equation (15), where σ_a and σ_d are estimated parameters reported in Table 1 and $\overline{n}$ is the mean of the proxies for informed trading that are generated by the simulation. *t-stat* is a test statistics which null is no difference between means of pre and post 13 days. *** refers to statistical significance at a 1 percent level.

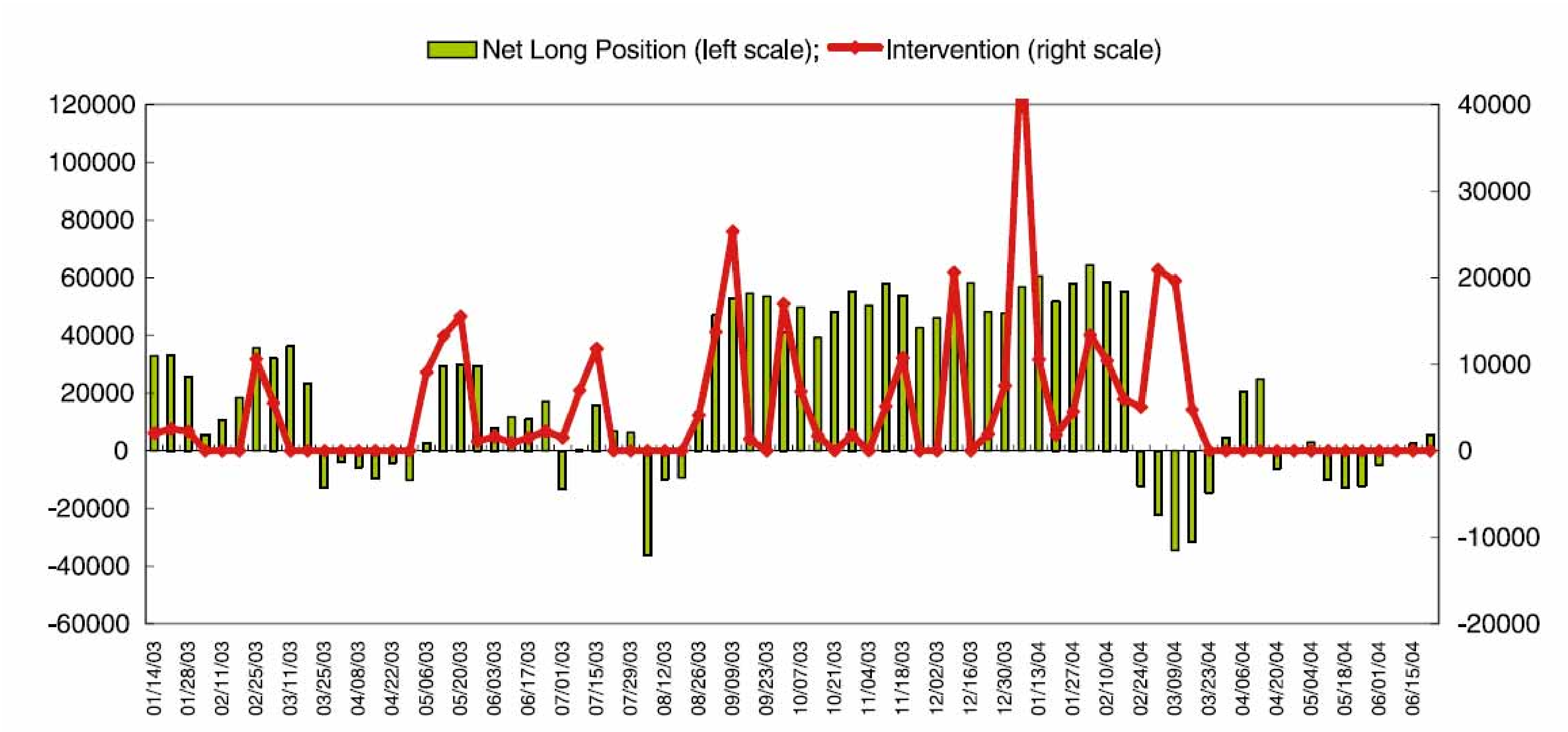
Figure 1. Intervention



Source: Ministry of Finance, Japan

Note: Figure in horizontal axis is an amount of daily intervention, December 30, 2002 to April 2, 2004

Figure 2. Future Position and Intervention



Source: Ito (2005a) Chicago Mercantile Exchange International Monetary Market

Note: Futures position and intervention, January 14, 2003 to June 15, 2004