DEPARTMENT OF ECONOMICS
SUFFOLK UNIVERSITY

8 ASHBURTON PLACE, BOSTON, MA 02108

RESEARCH WORKING PAPER NO. 2008-1

Conditional Efficacy of Sterilized Intervention

Jongbyung Jun
Suffolk University
jjun@suffolk.edu

January 2008

Abstract: The noise-trading or coordination channel hypothesis implies that sterilized intervention in the foreign exchange market is effective if certain conditions are satisfied, but ineffective otherwise. The hypothesis is tested with a three-regime threshold model and daily data on actual intervention by US and German central banks. The main finding is that if central banks choose the optimal timing in light of the trend-chasing behaviors of noise traders, such strategic intervention is effective in moving the exchange rate in the desired direction.

JEL classification: C22; E58; F31
Keywords: Central bank intervention; Threshold model; Coordination channel

INTRODUCTION

Numerous empirical studies have investigated the issue of whether sterilized intervention in the foreign exchange markets is effective or not. While earlier studies failed to find substantial evidence for its effectiveness, with the exception of Dominguez and Frankel (1993), more favorable results are reported in recent studies that adopt new approaches. Kearns and Rigobon (2005) find that the effects of intervention by the Reserve Bank of Australia and the Bank of Japan are significant when policy endogeneity is addressed. Fatum and Hutchison (2003 and 2006) show that intervention is effective when it is measured by episodes rather than by daily amounts of purchase or sale. Taylor (2004 and 2005) uses a Markov-switching model and reports that intervention increases the probability of switching from a nonstationary exchange rate regime to a stationary regime when the exchange rate is substantially misaligned.

While the main issue in this literature is whether or not intervention is effective, this paper examines the possibility that intervention operations can be effective if certain conditions are satisfied but ineffective otherwise. This is a reasonable proposition given that the size of intervention is typically quite small relative to the market volume and thus it is hard to expect every intervention operation to be effective.

One advantage of this "conditional effectiveness" approach is that it provides an explanation for the mixed results in the previous studies. Suppose that the majority of the intervention operations in a given sample period fail to satisfy the conditions under which intervention becomes effective. Then, an empirical study will find the intervention operations ineffective on average during the sample period. Nevertheless, it may be the case that the conditions are satisfied in some sub-periods. A study that focuses or puts more weights on these sub-periods will find intervention to be effective.

In addition, the new approach may explain why many central banks continued to intervene in the 1990s, as documented in the survey report of Neely (2001), despite academic cynicism. If the conditional efficacy hypothesis holds, it follows that the monetary authorities may increase the probability of success in their future operations by learning from past experience.

Concerning the specific conditions for effective intervention, it has been shown in the previous literature that joint intervention by two or more central banks tends to be more effective, and the size and frequency of intervention may matter (see Fatum 2002, for example). This paper explores the potential conditions implied by the "noise-trading channel" hypothesis of Hung (1997).

Noise traders or chartists are those who make trading decisions based on technical trading rules rather than economic fundamentals. With regard to the relative importance of noise traders in the markets, Frankel and Froot (1990) note that the majority of the foreign exchange forecasting firms switched from fundamental analysis to technical analysis around the mid-1980s. Taylor and Allen (1992) also report that about 90 percent of the traders in London use some form of technical analysis. Building on these findings, Hung claims that since noise traders may be the main source of short-term exchange rate instability, central banks might improve the effectiveness of intervention by entering the market at the optimal moment implied by the popular trading rules. In particular, Hung suggests that the monetary authorities should wait until noise traders drive the exchange rate sufficiently up (or down). This is due to the notion that breaking the trend is easier in a relatively thin market where more traders agree that the exchange rate has overshot some threshold level, and consequently the momentum toward further deviation is relatively weak.

More recently, Sarno and Taylor (2001) propose a similar transmission mechanism, termed the 'coordination channel', through which intervention can be effective even when the traditional signaling channel and portfolio balance channel fail to work. They claim that the central bank may serve as a coordinator for those market participants who are aware of severe misalignment but reluctant to bet individually against a sustained trend. The empirical works of Taylor (2004 and 2005) provide evidence supporting this coordination-channel hypothesis by revealing that intervention has a stabilizing effect which grows with the degree of misalignment.

This paper tests the implications of the noise-trading/coordination channel on the level of the exchange rate with a three-regime threshold model. In this nonlinear model, the effect of intervention on the daily log-return of the exchange rate is allowed to vary depending on the deviation of the exchange rate from the previous *m*-day moving average. Both the noise-trading channel and the coordination channel imply that intervention will be effective when the exchange rate is sufficiently below the moving average (regime 1) or above the moving average (regime 3), and ineffective otherwise (regime 2).

Using the data on the actual daily intervention in the Deutsche mark/U.S. dollar (DM/USD) market during 1987-1989, this paper shows that the overall effectiveness of intervention measured with a linear-effect model is statistically insignificant. However, the conditional efficacy is significant in regime 1 and regime 3 of the threshold model, as suggested by the noise-trading/coordination channel hypothesis. The regime-switching framework and the findings of this paper are broadly in line with the approaches and findings of Taylor (2004 and 2005). However, this paper extends Taylor's works in a meaningful way. It develops and successfully applies a methodology that can evaluate the conditional effect of intervention on the return or the level of the exchange rate, rather than on the stability of the exchange rate series. Because the threshold variable of the model can be any variable and the thresholds are estimated together with other parameters, the methodology can also be quite useful in identifying other conditions for effective intervention that are not explicitly considered here or in previous studies.

The rest of this paper is organized as follows. Section I discusses some issues specific to modeling the effects of intervention within a threshold-model framework. Section II describes the data. Estimation and test results are presented in Section III and Section IV concludes.

1. MODELING THE EFFECTIVENESS OF INTERVENTION

(a) Linear model for overall effectiveness

Let S_t be the DM/USD spot exchange rate. Then the log-return y_t is defined as

$$y_t \equiv 100[\ln(S_t) - \ln(S_{t-1})], \qquad (1)$$

which is approximately the percentage change of the exchange rate between the market opening time of day t-1 and the market opening time of day t. The linear effect model can be written as

$$y_t = c + \theta\, intv[n]_{t-2} + u_t, \qquad (2)$$

where c is a constant, and the explanatory variable $intv[n]_{t-2}$, measured in 100 million U.S. dollars, is the average amount of daily intervention carried out for n days, from day t-n-1 to day t-2. Thus, the coefficient θ shows the response of the exchange rate, between day t-1 and day t, to the average of the previous n-day intervention. The daily amount of intervention is the sum of U.S. dollars purchased by the Federal Reserve and the Bundesbank. The amount is positive when U.S. dollars are purchased against Deutsche mark and negative when U.S. dollars are sold.

Note that intervention is measured as the n-day average amount rather than the daily amount of purchase or sale based on the assumption that intervention carried out on multiple days can be more effective than an isolated single-day intervention. Additionally, the average amount may capture delayed effects of intervention. The delayed effect can be substantial since intervention is frequently unannounced and small in size and thus full reaction in the market may take time. Alternatively, the average amount $intv[n]_{t-2}$ may be replaced by the amount of intervention on day t-2 and its lags. However, since daily intervention is serially correlated, the alternative multivariate model is likely to suffer from multicolinearity, such that the daily variables may not be significant individually even if significant jointly. In this respect, the more parsimonious model is preferred. When the model is estimated, the value of n that minimizes the sum of squared residuals will be chosen from the range of 1 through 5 days.

The slope coefficient θ in the linear model (2) measures the overall effect of intervention. If intervention is effective on average for the entire sample period, θ should be positive: buying the USD against the DM increases the DM/USD rate and selling the USD decreases the rate. If θ is negative or zero, on the other hand, it means intervention is ineffective, at least on average.

The exchange return series y_t is known to have GARCH type conditional heteroscedasticity, which is typically represented by GARCH(1,1) as

$$u_t = z_t \sigma_t, \qquad \sigma_t^2 = \omega + \beta \sigma_{t-1}^2 + \alpha u_{t-1}^2, \tag{3}$$

where z_t ~ i.i.d. $N(0,1)$, and σ_t^2 is the conditional variance of the error term, u_t.

(b) Threshold model for conditional effect

If the noise-trading/coordination channel exists, intervention could be effective if the exchange rate is sufficiently above or below some threshold levels. These conditional effects can be specified with a three-regime threshold model as

$$\begin{aligned} y_t &= 1(q_t \le \gamma_1)(c_1 + \theta_1 intv[n]_{t\text{-}2}) + 1(\gamma_1 < q_t \le \gamma_2)(c_2 + \theta_2 intv[n]_{t\text{-}2}) \\ &\quad + 1(q_t > \gamma_2)(c_3 + \theta_3 intv[n]_{t\text{-}2}) + u_t, \end{aligned} \tag{4}$$

where $1(\cdot)$ is the indicator function that takes the value of 1 if the expression inside the parenthesis is true and 0 otherwise. The threshold variable q_t is defined as the percentage deviation of the exchange rate on day t-n-1 from its previous m-day moving average:

$$q_t = 100\left(\log(S_{t-n-1}) - \log\left(m^{-1}\sum_{i=1}^{m} S_{t-n-1-i}\right)\right). \tag{5}$$

The m-day moving average serves as the time-varying point of reference in judging whether the exchange rate has been following a rapid upward or downward trend recently. As an alternative to the moving average, we may consider a proxy for the equilibrium exchange rate such as the purchasing power parity (PPP) level, in which case the threshold variable has an attractive economic meaning — the degree of misalignment of the exchange rate. However, the moving average is employed in this paper for two reasons. First, it is available at daily frequencies and widely used by noise-traders to form short-term trading rules. Thus, it reflects the market conditions better than the monthly PPP rate on a daily basis. Second, as long as the moving average order m is not too large, the deviation from the moving average is stationary. Stationarity is required for the threshold variable in a regime-switching model in order to ensure that all the regimes of the model are observed. In contrast, the deviation from PPP (the real exchange rate) is known to be highly persistent and thus nearly nonstationary. Although m is unknown, it can be chosen from some reasonable range. In this paper, up to six months (m = 120 days) of moving averages are considered, starting from one month (m = 20 days), with the step length of one week (5 days).

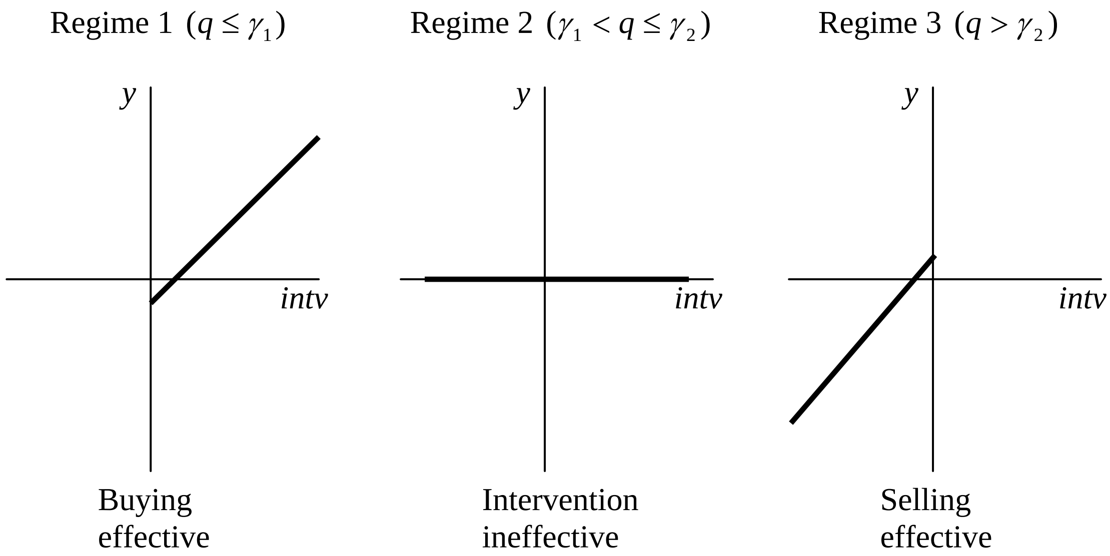
In the threshold model of (4), the regime is determined by the size of q_t relative to the two thresholds γ_1 and γ_2, which will be estimated together with the other parameters in the model. Since each regime shows the reaction of the log return y_t to previous n-day intervention, q_t is assumed to be known before the central banks start the n-day intervention session. That is, at the beginning of day t-(n+1).

The conditional efficacy of intervention implied by the noise-trading/coordination channel is illustrated in Figure 1 within the context of the three-regime threshold model. Noise traders tend to sell a currency when it is depreciating and buy when it is appreciating. If the traders already sold enough of a currency following a depreciating short-term trend, such that the exchange rate is sufficiently below the longer-run trend $(q \leq \gamma_1)$, then buying intervention is likely to be effective, as shown in the far-left graph in Figure 1. In the opposite situation, shown in the far-right graph, when the noise traders are in heavily overbought positions $(q > \gamma_2)$, selling intervention is expected to be effective. In the middle case, in which any upward or downward trend is in its early stage with strong momentum, intervention with limited resources is hypothesized to be ineffective.

(c) Estimation and inference

The linear effect model of (2) can be estimated by ordinary least squares (OLS). The parameters of the threshold model in (4), including the two thresholds γ_1 and γ_2, and the moving-average order m in (5) can be estimated by the method of sequential conditional least squares as explained in Hansen (2000). The overall effectiveness of intervention can be tested with the null hypothesis of $\theta \leq 0$ in (2) against the alternative of $\theta > 0$. The conditional effectiveness implied by the noise-trading/coordination channel can

Figure 1. Hypothesized conditional effectiveness of intervention



Notes: y is the daily log return of the DM/USD rate, *intv* is the average daily purchase of the USD during the previous n-days, and q measures the deviation of the exchange rate from previous m-day moving average. In Regime 1, where the USD is sufficiently undervalued, buying intervention appreciates USD. In Regime 3, where USD is quite overvalued, selling intervention depreciates USD. In Regime 2, where USD is neither overvalued nor undervalued, intervention has little effect on the level of the exchange rate.

be tested with the null hypothesis of $\theta_i \le 0$ against the alternative of $\theta_i > 0$ for $i = 1, 3$ in (4). However, any test involving the parameters of the threshold model is valid only if the thresholds exist. Therefore, the t-tests should be accompanied by an additional test for nonlinearity with the null hypothesis of $c_1 = c_2 = c_3$ and $\theta_1 = \theta_2 = \theta_3$ in (4) in order to see whether significant threshold effects exist.

A simple test for nonlinearity is to compare the values of an information criterion, such as Akaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC), between the linear model and the nonlinear model. A more formal test relies on a test statistic such as

$$F = T(SSR_1 - SSR_3)/SSR_3, \tag{6}$$

where SSR_1 is the sum of squared residuals of the linear model, SSR_3 is the sum of squared residuals of the three-regime model and T is the sample size. When the threshold is known, the asymptotic distribution of this statistic is the Chi-square distribution. However, the thresholds (γ_1, γ_2) are unknown and unidentified under the null hypothesis of no threshold effect while SSR_3 depends on the value of the thresholds. Thus, the asymptotic distribution is not the Chi-square distribution.

The distribution of the *F*-statistic in (6) can be approximated by a bootstrap procedure described in Hansen (1999), with minor modification to reflect the fact that the log return of the exchange rate series has the GARCH property. Thus random draws in each bootstrap replication will not be from the residuals of the linear model (2) but rather from the standardized residuals of $\hat{z}_t = \hat{u}_t / \hat{\sigma}_t$ that can be computed after the estimation of the joint estimation of the linear model (2) and the GARCH model (3) by the method of maximum likelihood (ML). Then the data on u_t and y_t in each replication will be generated, under the null hypothesis of no threshold effect, as

$$\tilde{u}_t = \tilde{z}_t \hat{\sigma}_t , \tag{7}$$

and

$$\tilde{y}_t = \hat{c} + \hat{\theta}\, intv[n]_{t-2} + \tilde{u}_t , \tag{8}$$

where $\hat{\sigma}_t$, $\hat{c}$ and $\hat{\theta}$ are the ML estimates and $\tilde{z}_t$, $\tilde{u}_t$ and $\tilde{y}_t$ are bootstrapped series.

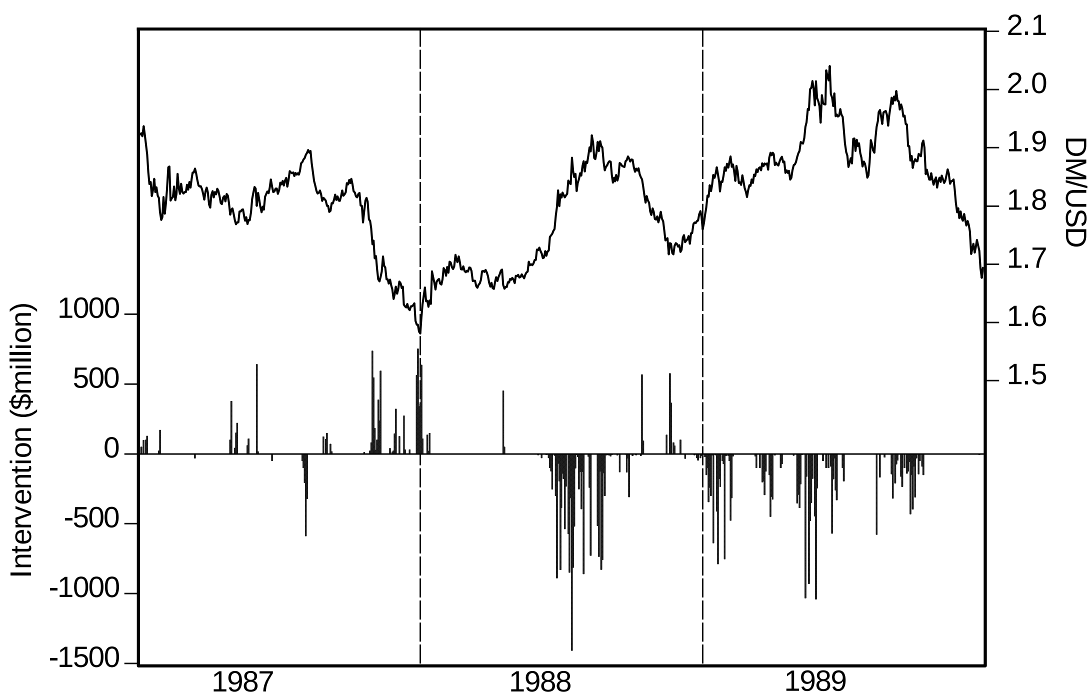
Although the bootstrap data will be generated based on the ML estimates of the parameters, the test statistic in (6) will be computed based on the least-squares estimation in each replication, without explicit consideration of the GARCH property of the errors, for two reasons. First, it is computationally easier to implement, given that the bootstrap procedure involves millions of regressions. Note that the OLS estimators are still consistent and asymptotically normal albeit inefficient. Second, once the GARCH specification is included in the multi-regime model, the regimes may be determined largely by the GARCH parameters rather than by the coefficients in the conditional-mean equation. This possibility itself is interesting. However, the main interest of this study lies in the effect of intervention on the level of the exchange rate. By adopting a threshold model with four or more regimes, it is possible at least theoretically to allow nonlinearity both in the volatility and in the conditional mean. However, such higher-order threshold models can easily become intractable in terms of securing minimum sample size in each regime or achieving convergence in the ML estimation.

2. DATA

The data set used for this study contains daily observations on the DM/USD exchange rate and official intervention by the Federal Reserve and the Bundesbank during the period of 1987 through 1989. The exchange rates are observed at 9:30 AM Paris time and originally recorded by Olsen and Associates of Zurich, Switzerland.

Figure 2 depicts the exchange rate movements and the sum of daily intervention amounts by the two central banks during the sample period. The period roughly covers the "post-Louvre era" in which the two central banks intervened frequently. The relatively high frequency of intervention, including both buying and selling operations, is an attractive feature of this particular sample. Above all, intervention is expected to be nonzero for a substantial portion of the observations in each regime, which makes the

Figure 2. Daily DM/USD exchange rate and the amount of intervention



Notes: The amount of the USD purchased against the DM by either the Federal Reserve or Bundesbank is measured in millions of USD along the left vertical axis. Negative values are for selling USD intervention. The exchange rate of DM per USD is measured on the right vertical axis.

three-regime model a reasonable candidate for the data generating process. Excluding holidays and weekends, the sample includes 723 daily observations with 220 days of intervention. Details by bank and type of intervention are given in Table 1.

Table 1: Days of Intervention in DM/USD market (1987 - 1989)

	Federal Reserve	Bundesbank	Either bank	Both banks
Buy USD	36	48	59	25
Sell USD	100	132	161	71
Total	136	180	220	96

Both in the linear model and the threshold model, the dependent variable y_t is the percentage change in the DM/USD rate from 9:30 AM on day t-1 in Paris to 9:30 AM on day t. To avoid correlation between the errors and the explanatory variable, y_t is matched with the intervention before 9:30 AM on day t-1. Thus, for example, when the 3-day average amount of intervention is chosen as the measure of intervention (n = 3), the explanatory variable $intv3_{t-2}$ is the daily average amount of US dollars purchased between day t-4 and t-2. The amount of intervention on day t-i for i = 2,3,4 is the amount of US dollars purchased between the market closing time on day t-i-1 and the market closing time on day t-i. With this transformation of the data, four observations are lost and the number of usable observations in the regression is 719. The 3-day moving average of intervention ($intv3_{t-2}$), which turns out to be the most appropriate value of n, has 344 nonzero observations with 105 positive values (buying-USD intervention) and 239 negative values (selling-USD intervention).

The threshold variable q_t is the deviation of the exchange rate on day t-n-1 from the previous m-day moving average. To compute q_t, it is necessary to have m+n+1 observations on the exchange rate before 1987. For this necessity, the exchange rate data are augmented by the additional observations available from the Federal Reserve Bank of New York website (www.ny.frb.org/markets/foreignex.html). The supplementary data are the buying USD rate against DM at noon in New York. Although the exchange rates from the two sets of data may differ on a daily basis, the difference cannot affect the empirical results substantially, as the supplementary data are used only to compute the moving averages.

3. RESULTS

The estimation results are reported in Table 2: the linear model in the second column and the three-regime threshold model in the last three columns. With the linear-effect model, the estimated slope parameter is 0.014. That is, the exchange rate is expected to rise by 0.014% when the central banks buy 100 million U.S. dollars against Deutsche mark. The estimate has the expected positive sign but it is not statistically different from zero at any conventional significance level. This result suggests that intervention during the whole sample period is not effective on average.

For the three-regime threshold model, the estimates of θ_i are 0.246 in regime 1 and 0.062 in regime 3. Both estimates have positive signs and are statistically significant. Thus, each of the null hypotheses of $\theta_1 \leq 0$ and $\theta_3 \leq 0$ is rejected against the alternative $\theta_i > 0$, with p-values 0.0003 and 0.0300, respectively. In contrast, the slope estimate is negative in regime 2, implying that intervention is ineffective in that middle regime. The standard errors reported in Table 2 are computed using White's correction, and thus are robust to heteroskedasticity. In fact, the three types of additional adjustments to the White's formula are considered as suggested in the econometrics literature (see Davidson and MacKinnon 2004, p.100), and those reported in Table 2 are the most conservative of the three.

The estimated conditional effect of buying intervention is not only statistically significant but also practically substantial. In regime 1, buying an additional 60 million USD, which is the median of the explanatory variable for buying intervention, is expected to appreciate USD against DM by about 0.15%. This is approximately 1/3 of the sample standard deviation, 0.48, of the positive values of the dependent variable. The conditional effect of selling intervention is estimated to be much weaker but still nontrivial. With the sale of 98 million USD, which is the median value of the explanatory variable for selling intervention, the expected depreciation of USD in regime 3 is about 0.06%. This is approximately 1/8 of the sample standard deviation, 0.47, of the negative values of the dependent variable.

The threshold model is estimated with the restriction that each regime should contain at least 5%, or 36 days, of the total observations. Table 2 shows that 62 days belong to regime 1 and 186 to regime 3. Since USD is depreciating in regime 1, all the observations with intervention are buying operations in this regime. Similarly in regime 3 where USD is appreciating, all the observations with intervention are selling operations. Therefore, the threshold variable, which is estimated to be the deviation of the exchange rate from previous 45-day moving average, is consistent with the leaning-against-the-wind type intervention. The estimated thresholds are $\hat{\gamma}_1 = -4.84\%$ and $\hat{\gamma}_2 = 1.71\%$.

Table 2. Estimation results for the linear and threshold models

	Linear Model	Threshold Model		
		Regime1	Regime2	Regime3
constant	-0.014	-0.213	-0.063	0.173
	(0.028)	(0.149)	(0.031)	(0.071)
$intv[3]_{t-2}$	0.014	0.246	-0.097	0.062
	(0.024)	(0.072)	(0.044)	(0.033)
Obs.	719	62	471	186
Buy	105	38	67	0
Sell	239	0	108	131
Thresholds		-4.84		1.71
R^2	0.001		0.039	
AIC	4276.4		4248.2	
SBC	4289.6		4287.6	
Q(20)	19.533		20.665	

Notes: The two models are estimated with daily data for the sample period of 1987-1989. In parentheses are the standard errors that are robust to heteroskedasticity. The Ljung-Box statistics are both insignificant with p-values of 0.49 for the linear model and 0.42 for the threshold model, hence no signs of remaining serial correlation in the residuals. Each regime of the threshold model is restricted to have at least 5% of the total observations.

Concerning the existence of threshold effects, both AIC and SBC reported in Table 2 suggest that the three-regime nonlinear model explains the data better than the linear model: the three-regime model has lower AIC and SBC than the linear model. The bootstrap test for nonlinearity based on the *F*-statistic in (6) also suggests that the multi-regime model is better than the linear model. The *F*-statistic is 28.84

with a bootstrap p-value of 0.017. Thus the null hypothesis of no threshold effect is rejected. The bootstrap p-value is computed from 1,000 replications. In each replication, the bootstrap data are generated with the following Linear-GARCH model:

$$y_t = -0.01 + 0.006\,intv3_{t-2} + u_t,$$
$$u_t = \sigma_t z_t, \text{ and}$$
$$\sigma_t^2 = 0.019 + 0.088 u_{t-1}^2 + 0.879 \sigma_{t-1}^2.$$

The above empirical results provide strong evidence for the conditional efficacy of intervention and the existence of the noise-trading/coordination channel. However, since intervention is found effective only after the exchange rate is substantially appreciated or depreciated, one may claim that the effects are not caused by intervention but by the increased momentum towards the purchasing power parity. This is a plausible assertion and there is plenty of evidence in the literature supporting this claim. For example, see the survey of Taylor (2003).

Interestingly, however, the estimated intercepts of the threshold model in Table 2 lead to a notable counter-argument. In Regime 1, the estimate of the constant is -0.213, which is significant at 10% level with a one-tailed test. The implication is that without intervention the USD is expected to further depreciate in this regime where the USD is already depreciated substantially. If the PPP claim holds, the opposite should be true. Similarly, the estimated intercept in Regime 3, which is positive and significant at the 1% level, implies that without intervention the USD is expected to appreciate further rather than depreciate. One explanation for this result is that the regimes of the threshold model are determined by the deviation of the exchange rate from the 45-day moving average which is quite different from the PPP level or the long-run equilibrium level of the exchange rate.

4. CONCLUSION

This paper examines the hypothesis that sterilized intervention in the foreign exchange market could be effective under certain conditions but ineffective otherwise. In order to identify the potential conditions for effective intervention, it is first assumed that trend-chasing noise-traders are the main source of short-run fluctuations in the exchange rate. With the further assumption that intervention is effective only if the noise-traders are in heavily overbought or oversold positions, a three-regime threshold model is adopted as the appropriate description of the nonlinear relationship between intervention and the exchange rate return.

The estimation and test results, with the data on the actual intervention in the DM/USD market between 1987 and 1989, strongly support the noise-trading/coordination channel hypothesis, and thus the conditional efficacy of intervention. In particular, the results suggest that the central banks may increase the effectiveness of intervention by waiting until the exchange rate appreciates or depreciates beyond the estimated thresholds, instead of countering new surges in momentum.

The new approach taken in this paper can serve as a practical guide for future studies attempting to evaluate the performance of observed intervention operations, and also for the monetary authorities in designing more effective intervention strategies.

REFERENCES

Davidson, R. and J. G. MacKinnon (2004). *Econometric Theory and Methods*. Oxford and New Yolk: Oxford University Press.

Dominguez, K. M. and J. A. Frankel (1993). "Does foreign-exchange intervention matter? The portfolio effect." *American Economic Review*, 83, 1356-1369.

Fatum, R. (2002): "Post-Plaza intervention in the DEM/USD exchange rate." *Canadian Journal of Economics*, 35, 556-567.

Fatum, R. and M. M. Hutchison (2003). "Is sterilized foreign exchange intervention effective after all? An event study approach." *Economic Journal*, 113, 390-411.

Fatum, R. and M. M. Hutchison (2006). "Effectiveness of official daily foreign exchange market intervention operations in Japan." *Journal of International Money and Finance*, 25, 199-219.

Frankel, J. A. and K. A. Froot (1990). "Chartists, fundamentalists, and trading in the foreign exchange market." *American Economic Review, Papers and Proceedings*, 80, 181-185.

Hansen, B. E. (1996). "Inference when a nuisance parameter is not identified under the null hypothesis." *Econometrica*, 64, 413-430.

Hansen, B. E. (1997). "Inference in TAR models." *Studies in Nonlinear Dynamics and Econometrics*, 2, 1- 14.

Hansen, B. E. (1999). "Testing for linearity." *Journal of Economic Surveys*, 13, 551-576.

Hansen, B. E. (2000). "Sample splitting and threshold estimation." *Econometrica*, 68, 575-603.

Hung, J. H. (1997). "Intervention strategies and exchange rate volatility: a noise trading perspective." *Journal of International Money and Finance*, 16, 779-793.

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.

Neely, C. J. (2001). "The practice of central bank intervention: Looking under the hood." *Review, Federal Reserve Bank of St. Louis*, May/June 2001, 1-10.

Sarno, L. and M. P. Taylor (2001). "Official intervention in the foreign exchange market: Is it effective and, if so, how does it work?" *Journal of Economic Literature*, 39, 839-868.

Taylor, M. P. (2003). "Purchasing power parity." *Review of International Economics*, 11, 436-452.

Taylor, M. P. (2004). "Is official exchange rate intervention effective?" *Economica*, 71, 1-11.

Taylor, M. P. (2005). "Official foreign exchange rate intervention as a coordinating signal in the dollar-yen market." *Pacific Economic Review*, 10, 73-82.

Taylor, M. P. and H. Allen (1992). "The use of technical analysis in the foreign exchange market." *Journal of International Money and Finance*, 11, 304-314.