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Modeling Central Bank Intervention as a Threshold Regression: Evidence from Turkey[*]

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Abstract. We conjecture that the Central Bank of Turkey intervenes differently depending on whether or not a single measure of market disorder exceeds a threshold value. In view of such possible measures we consider deviation from the trend and excess volatility of the spot exchange rate. The questions we ask are what is the threshold value and whether the measure of market disorder is consistent with the announced policy of the Bank. Interestingly, during the managed float period we find no support for a threshold in the Bank's reaction function; during the free float period we find evidence of a threshold in volatility, which is in line with the Bank's policy objectives.

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1. Introduction

The response rule of central bank intervention to economic conditions is known as the central bank's intervention reaction function. The determinants of central bank interventions have been a focus of many studies, for example, Kim and Sheen (2002), Baillie and Osterberg (1997), Almekinders and Eijffinger (1994), Almekinders and Eijffinger (1996), and Jun (2004). However, most of these studies consider developed low-inflation economies and free floating exchange rate regimes. In this paper, we model and contrast intervention in both managed and free float regimes using recent data from the Central Bank of the Republic of Turkey, an emerging market economy.

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We adopt a threshold model of intervention determination, assuming that the central bank reacts to market conditions differently depending on whether they surpass a threshold level. We are not testing whether this intervention mechanism is preferred to some other or whether an intervention carried out by this or any other mechanism is effective.

There is an enormous amount of literature concerning the effects of intervention on currency markets. Disyatat and Galati (2005) point out that empirical studies are often done for the large, developed economies, yet few studies are available for developing and small economies and the results on the effectiveness of intervention are mixed and depend on which exchange rate regime is analyzed, what sample period is studied and on the intervention strategy that is followed. The problem stems not only from differences in the data and methodology employed but also from difficulties in defining a "successful" intervention. King (2003) argues that empirical studies show mixed results because foreign exchange intervention may be undertaken to meet a range of objectives and the studies do not adequately address how these objectives may vary over time.

This study focuses on the motivation for intervention. Since no unique measure of the market conditions is given by either the central banks or by the economic theory, economists often rely on econometric methods to test if certain characteristics of the market are closely related to the interventions. One of the main challenges in specifying a reaction function is the fact that the intervention variable has a zero value for the majority of the observations in a sample while the explanatory variables are not zero. This implies a non-linear relationship because the observed quantities of intervention do not increase or decrease approximately in proportion to the level of the explanatory variables. One way to proceed is to approximate this potential non-linear relationship with a linear model. Eijffinger and Gruijters (1991), Ito (2002) and Rogers and Siklos (2003) used OLS models. Another way is to model the probability, rather than the quantity of intervention, using the probit approach, as in Baillie and Osterberg (1997), Dominguez (1998), Kim and Sheen (2002) and McKenzie (2004). Recent studies use ordered probit as in Frenkel, Pierdzioch, and Stadtmann (2003), and Ito and Yabu (2004), or logit as in Frenkel and Stadtmann (2001). If one is interested in the quantity, rather than the probability of intervention, an appropriate model may be a Tobit model. Humpage (1999) follows this approach. However, a Tobit approach involves either buys or sells but not both as the dependent variable. If one wants to explain both types of intervention simultaneously then the friction model may be an appropriate specification for the reaction function as in Almekinders and Eijffinger (1996) and Kim and Sheen (2002).

In this study we adopt a different approach and use a threshold model, with a view to extending our empirical understanding of the determinants of the Central Bank of Turkey's intervention. Jun (2004) uses this model in relation to the US dollar - Deutsche Mark exchange rate. Jun (2004) argues that the friction method adopted by Almekinders and Eijffinger (1996) and Kim and Sheen (2002) is not better than a simple linear model. A friction model involves specifying three separate distributional assumptions for the intervention series that corresponds to the three different states of the intervention outcome. The threshold approach allows a direct modeling of the relationship between the interventions and their determinants. The central bank is assumed to react to market conditions and constraints, but only after an intervention threshold is reached. The thresholds may differ for positive and negative interventions (purchase/sale of the foreign currency) and these may be estimated. Jun (2004) tests the friction hypothesis with a more flexible model using a threshold model that does not restrict the dependent variable to zero in the middle regime. In contrast to the friction model, the threshold variable that determines the regimes is one of the measures of the market conditions and it can be estimated by the method of least squares without assumptions regarding error distribution. Residual based test for misspecification are also applicable using this modeling approach.

We are interested in whether there is support in the data for the Bank's policy. The policy states that it intervenes when the markets are "disorderly". We want to know how "disorderly" should the markets be for the intervention reaction function to change and whether the announced measure of disorder is consistent with data. It has been widely recognized that the motivation for (and the effects of) intervention depends on the exchange rate regime – see, e.g., Neely (2006). So we separately consider two clearly identifiable regimes.

Section 2 describes our intervention data. Section 3 discusses specification, estimation and testing procedures for a threshold model. Section 4 presents estimation and testing results. Section 5 concludes.

2. Data Description

For the period between November 1, 1993 and May 15, 2006, we have 3164 daily values of market purchases and sales of foreign assets (in billions of

USD), provided by the Central Bank of the Republic of Turkey (CBRT). We also use daily spot bid rates at 3:30 pm of the Turkish lira (TRL) to the US dollar (USD). Figure 1 contains plots of the exchange rate. After the liberalization reforms of the 1980s, Turkish foreign exchange market has been through numerous crises and CBRT's official exchange rate policy has significantly changed several times.

In early 1995, a standby agreement was signed with the IMF that aimed the CBRT's policy at curbing inflation using the nominal exchange rate as an anchor. The lira exchange rate defined in terms of a US dollar/German mark basket was supposed to match the targeted inflation rate. The lira depreciated throughout the late 90s. Maintaining the currency peg was clearly the target of interventions.

In early 2001, CBRT announced it would let the lira float. At the same time, more independence of the CBRT coincided with an agreement with the IMF to intervene only in limited amounts in order to dampen excessive volatility (see, e.g., IMF, 2003). Besides, CBRT began conducting pre-announced purchase and sale auctions with the aim of improving the transparency of interventions.

We consider two sub-periods that are free from crises and are clear representations of the two exchange rate regimes and the underlying CBRT intervention policy:

- Period I (managed float): January 2, 1995 - December 31, 1999 (1261 obs.)
- Period II (free float): February 27, 2001 - May 15, 2006 (1312 obs.)

Most interventions during both periods were sterilized. We use the actual net value of purchases. Actual purchases and sales are the official direct interventions during managed float while the actual purchases and sales are the sum of both official direct interventions and the pre-announced auctions during free float. Auctions are also viewed as interventions so they are included in actual purchases and sales. More details of the regimes can be found in annual reports of the CBRT as well as in Guimarães and Karacadag (2004), Akinci, Culha, Özlale, and Sahinbeyoglu (2005) and Herrera and Özbay (2005).

Table 1 describes the empirical distributions of the intervention data in the two sub-periods. The distributions appear to have a domination of moderately sized purchases. During the managed float, CBRT intervened on

71.06% of all trading days: net purchases on 37.91% of trading days, net sales on 33.15% of trading days. The average net purchase was $74.67 mln; the average net sale was $105.27 mln. The average of the absolute values of all interventions was $88.94 mln. More than 62% of interventions were no greater than $50 mln in magnitude.

During the free float period, CBRT interventions were overall less intensive. CBRT intervened on only 58% of all trading days: net purchases on 46.27% of trading days, net sales on 11.73% of trading days. The average net purchase was $78.17 mln; the average net sale was $16.55 mln. The average of the absolute values of all interventions was $75.46 mln. Around 86% of interventions were no greater than $50 mln in magnitude. There are however instances of exceptionally large purchases.[3]

3. The Threshold Model of Intervention

3.1 Model Specification

Suppose we can model central bank intervention as a linear function of market conditions and past interventions:

$$IN_t = \alpha + \sum_{k=1}^{p} \rho_k IN_{t-k} + x_{t-1}b + \varepsilon_t, \tag{1}$$

where IN_t denotes the net purchase of foreign assets, x_t contains characteristics of the market, β is the parameter to be estimated, and ε_t is the error term. An *m*-regime threshold model of Hansen (2000) allows the parameter vector in (1) to change *m* times based on the values of a threshold variable η_t:

$$IN_t = \sum_{i=1}^{m}\left(\alpha^{(j)} + \sum_{k=1}^{p}\rho_k^{(j)} IN_{t-k} + \chi_{t-1}\beta^{(j)} + \varepsilon_t \right) \mathrm{I}\left\{\gamma_1^{(j)} < \eta_t \le \gamma_2^{(j)}\right\} \tag{2}$$

where I(.) is the indicator function, j=1,…,m, $\gamma_1^{(1)} = -\infty$, $\gamma_2^{(m)} = \infty$, and $\gamma_1^{(l)} = \gamma_2^{l-1}$, for l=2,…,m (so there are *m-1* thresholds in an *m*-regime

[4]The amount of purchase/sale is announced regularly at the Bank’s web page http://www.tcmb.gov.tr/.

model). If the right-hand side variables in (2) contain lagged IN_t only, the model is known as a threshold autoregressive (TAR) model. In addition, if η_t is a lagged IN_t, the model becomes a self-exciting threshold autoregressive (SETAR) model – see, e.g., Hansen (1999).

Equation (2) is an intuitive form for a central bank's reaction function for two reasons. First, it does not restrict interventions to be the same linear function of the same set of determinants in all circumstances. Clearly, determinants of interventions, say, in periods of high volatility are different from those in periods of low volatility. The regime-shifting variable η_t (the threshold variable) accounts for that. Second, it provides a way to determine empirically what the regime-switching variable is. It is intuitive that it may vary depending on what drives the market conditions in a particular period.

3.2 Exogenous Variables

Our x_t contains deviations from a 22-day moving average DE_t and excess volatility estimates EV_t. Note that x_t is stationary and is lagged to avoid simultaneity.

We define DE_t as

$$DE_t = s_t - \sum_{n=1}^{22} s_{t-n-1}, \tag{3}$$

where s_t is the logarithm of the spot exchange rate. We view the 22-day horizon sufficiently long to represent the trend or target exchange rate.

We obtain the excess volatility estimates as

$$EV_t = h_t - \sigma^2, \tag{4}$$

where σ^2 is the unconditional variance estimate of the spot exchange rate and h_t is the conditional variance estimates obtained from a GARCH model described below. The unconditional variance represents the target volatility and EV is thought of as another measure of market disorder.

We model conditional volatility as follows:

$$\Delta s_t = \mu + b_1 IN^B_{t-2} + b_2 IN^S_{t-2} + \sum_{k=1}^{4} \delta_k D_k + e_t, \tag{5}$$

$$h_t = \omega + \alpha e^2_{t-1} + \beta h_{t-1} + c_1 IN^B_{t-2} + c_2 IN^S_{t-2} + \sum_{k=1}^{4} \lambda_k D_k, \tag{6}$$

$$e_t = \sqrt{h_t} \cdot z_t, \tag{7}$$

$$z_t \sim N(0,1). \tag{8}$$

It is common in the international finance literature to use a GARCH specification for modeling conditional variance of a time series. Such specifications are known to account for many stylized facts about financial data such as volatility clustering and fat-tailedness.

Table 2 reports estimation results for the conditional variance model during managed float; Table 3 – during free float.

Interventions are jointly insignificant in both conditional mean and the conditional variance equations for managed float, but significant jointly by an LR test for free float. Day dummies are jointly significant in both equations in both periods. There is a significant Monday effect in the managed float period.

Based on the fit indices and joint significance tests, we choose the second specification for managed float (columns 4-5, Table 2) and the fourth specification for free floats (columns 8-9, Table 3).

3.3 Estimation

The parameters $\left\{\alpha^{(j)}, \rho^{(j)}, \beta^{(j)}\right\}_{j=1}^{m}$, and $\left\{\gamma_2^{(j)}\right\}_{j=1}^{m-1}$ can be estimated using conditional least squares.

Given the threshold variable η_t and the thresholds $\left\{\gamma_2^{(j)}\right\}_{j=1}^{m-1}$, the model becomes linear in the rest of the parameters and can be written as

$$y_t = \vartheta_t \theta + \varepsilon_t, \tag{9}$$

where y_t=IN_t, $\theta = \left(\alpha^{(1)}, \rho_1^{(1)}, ..., \rho_k^{(1)}, \beta^{(1)'}, ..., \alpha^{(m)}, \rho_1^{(m)}, ..., \rho_k^{(m)}, \beta^{(m)'}\right)'$, and

$$\vartheta_t = \left((1, IN_{t-1}, ..., IN_{t-k}, x_t) I\left\{\gamma_1^{(1)} < \eta_t \le \gamma_2^{(1)}\right\}, ..., \right. \\ \left. (1, IN_{t-1}, ..., IN_{t-k}, x_t) \mathrm{I}\left\{\gamma_1^{(m)} < \eta_t \le \gamma_2^{(m)}\right\}\right) \tag{10}$$

Now, θ in (9) can be estimated by OLS producing $\left\{\hat{\alpha}^{(j)}, \hat{\rho}^{(j)}, \hat{\beta}^{(j)},\right\}_{j=1}^{m}$.

To find the threshold variable and the threshold estimates, a search is carried out over $\{DE_{t-1}, EV_{t-1}\}, t = 1, ..., T$, for values of the threshold variable that minimize the sum of squared residuals of (2). To be more specific, define a set of the available threshold variable values $\Omega = \{\eta_t \mid t = 1, ..., T\}$. The candidate threshold variables are $\{DE_{t-1}, EV_{t-1}\}$. Then, for each combination $(\eta_{i_1}, ..., \eta_{i_{m-1}}) \in \Omega^m$, for which $i_1, ..., i_{m-1} = 1, ..., T$ and $\eta_{i_1} < ..... < \eta_{i_{m-1}}$, substitute $\gamma_2^{(j)}$ in (2) by η_{i_j}, $j = 1, ..., m-1$. The sum of squared residuals of (9) can then be written as

$$S(\eta_{i_1}, ..., \eta_{i_{m-1}}) = \sum_{t-1}^{T} (y_t - \vartheta_t \theta)^2. \tag{11}$$

The combination that minimizes (11) contains the estimates $(\hat{\gamma}_2^{(1)}, ..., \hat{\gamma}_2^{m-1})$ of the *m*-regime model.

This procedure requires that a LS regression is estimated for each combination of the threshold variable values described above. For example, for a three-regime model for the free float period we would need to run *T*(*T*-1) (over 1.7 mln) regressions for each candidate threshold variable. This is not a problem in the estimation stage but it is a problem in the testing stage, which involves thousands of bootstrap replications of this procedure. We therefore follow Hansen (1999) in using a shortcut proposed by Bai (1997) and Bai and Perron (1998).

Bai (1997) and Bai and Perron (1998) proposed a sequential threshold estimation procedure. First, a two-regime model is estimated. The threshold estimate $\hat{\gamma}_2^{(1)}$ should be the same as either $\hat{\gamma}_2^{(1)}$ or $\hat{\gamma}_2^{(2)}$ in a three-regime model, which reduces the running time of the three-regime model estimation. The sequential approach is as follows:

1. Estimate the two-regime model and obtain $\hat{\gamma}_2^{(1)}$ which is an element of Ω that minimizes the sum of squares in (11);
2. Estimate a three-regime model setting $(\gamma_2^{(1)}, \gamma_2^{(2)})$ equal to either $(\hat{\gamma}_2^{(1)}, \eta_t)$ or $(\eta_t, \hat{\gamma}_2^{(1)})$ for each $\eta_t \in \Omega$.

This results in a consistent estimate. Furthermore, if this method is iterated at least once (by repeating step 2 for $\hat{\gamma}_2^{(1)}$ with $\hat{\gamma}_2^{(2)}$), then estimate precision can be as high as for the joint estimation of both thresholds.

In order to rely on the asymptotic properties of the estimators we have to make sure that there are enough observations in each regime. We follow Hansen (1999) in imposing the requirement that at least 10% of the sample size lie in each regime.

3.4 Testing

The testing procedure for the threshold model is outlined in Hansen (1999). What distinguishes our case from Hansen (1999) is that our model is not a SETAR model. We thus modify his testing procedure to account for the threshold variables used in our model. Yet, the testing is based on the LM test with bootstrapped critical values.

We consider one-, two-, and three-regime models and test each against all the other models. Testing the linear model (one-regime) against the three-regime model is equivalent to testing the null hypothesis:

$$H_0 : \alpha^{(1)} = \alpha^{(2)} = \alpha^{(3)}, \quad \rho_i^{(1)}, \rho_i^{(2)}, \rho_i^{(3)}, i = 1,...., k, \quad \beta^{(1)} = \beta^{(2)} = \beta^{(3)}.$$

The test statistic suggested by Hansen (1999) is

$$F_{13} = T \frac{S_1 - S_3}{S_3},$$

where S_i is the sum of squared residuals of the i-regime model. When the thresholds are known, F_{13} is asymptotically equivalent to the usual F-

statistic. Since the thresholds are unknown and not identified under H_0, however, F follows an unknown asymptotic distribution. Bootstrapping methods are relied on to compute the p-values. These will be different depending on whether the conditional heteroscedasticity assumption holds for the errors.

Under the homoscedastic error assumption, a set of bootstrap errors $\tilde{\varepsilon} = \{\tilde{\varepsilon}_t \mid t = 1,....,T\}$ is obtained by randomly drawing T times with replacement from the OLS residuals $e = \{e_t \mid t = 1,....,T\}$ of the linear model (1). A set of data on the dependent variable is then generated by

$$\tilde{IN}_t = \hat{\alpha} + \sum_{k=1}^{p} \hat{\rho}_k \tilde{IN}_{t-k} + \chi_{t-1}\hat{\beta} + \tilde{\varepsilon}_t, \tag{12}$$

where $\{\hat{\alpha}, \hat{\rho}_1,....., \hat{\rho}_k, \hat{b}\}$ are OLS estimates of (1). Substituting $\tilde{IN}_t$ for IN_t, all the i-regime (i=1,2,3) models are re-estimated to provide one value of $\tilde{F}_{1i}$ defined as

$$\tilde{F}_{1i} = T\frac{\tilde{S}_1 - \tilde{S}_i}{\tilde{S}_i}, i = 2,3,$$

where $\tilde{S}_i$ is the sum of squared residuals from the i-regime model with bootstrapped data. Out of 1,000 replications, the proportion of $\tilde{F}_{1i}$ greater than F is the approximate p-value.

Under the heteroscedastic error assumption, the procedure is a bit more complicated because we have to impose heteroscedasticity on the bootstrap errors $\tilde{\varepsilon}$. First, each element of $\tilde{\varepsilon}$ is divided by an estimate of the conditional standard deviation $\sqrt{\hat{h}_t}$ to obtain a set of homoscedastic errors

$$\approx{\varepsilon} = \left\{ \approx{\varepsilon}_t \,\middle|\, \approx{\varepsilon}_t = \frac{\tilde{\varepsilon}_t}{\sqrt{\hat{h}_t}}, t = 1,...., T \right\}.$$

The conditional variance estimate $\hat{h}_t$ is obtained as a fitted value from an auxiliary regression of e_t^2 on $w_t = \{1, x_t x_t', IN_{t-1}^2, ..., IN_{t-k}^2\}$. Let $\hat{\delta}$ denote that OLS estimates obtained from such a regression.

Now we draw randomly from $\approx{\varepsilon}$. The *t*-th heteroscedastic bootstrap error is

$$\tilde{\varepsilon}_t = \approx{\varepsilon}\sqrt{\tilde{h}_t}, \quad (13)$$

where $\tilde{h}_t = \tilde{w}_t \tilde{\delta}$ and $\tilde{w}_t = \{1, x_t x_t', \tilde{IN}^2_{t-1}, ..., \tilde{IN}^2_{t-k}\}$. Once the value of $\tilde{\varepsilon}_t$ is obtained, the value of $\tilde{y}_t$ is calculated using (12). It is important to note that $\tilde{h}_t \neq \hat{h}_t$ and $w_t \neq \tilde{w}_t$. The rest of the bootstrap procedure is the same as in the homoscedastic case.

Finally, if linearity hypothesis is rejected in favor of a threshold model, it is possible to construct an asymptotically valid confidence interval for the threshold – see Hansen (1997), Hansen (2000), and Gonzalo and Pitarakis (2002). We do not pursue this here.

4. Empirical Results

4.1 Specification Tests

We use a Gauss code based on Hansen (1999) to estimate the CBRT reaction functions for both managed float and free float regime. This estimation precedes hypothesis tests, but we begin by reporting the results of the tests so that we can then focus on the relevant threshold model.

The specification tests for a managed float regime are presented in Table 4. The test statistics F_{12} for testing the one-regime versus the two-regime model is 26.32. The *p*-values are computed as the proportion of those bootstrap replications (out of 1,000) that have the *F*-statistics larger than 26.32.

Under the assumption of homoscedastic errors, the p-value is 0.01. Therefore, we reject the null hypothesis of linearity against a two-regime model at 5% level. Under the assumption of heteroscedastic errors, the p-value is about 0.26 and we do not reject the null of linear reaction function.

With regard to the three-regime alternative, the F_{13} statistic is 43.60. The bootstrap p-value is 0.03 under the homoscedasticity assumption. Therefore we reject the null of the linear reaction function at 5%. Under the heteroscedasticity assumption, the p-value is 0.31 and fail to reject linearity. Since we cannot reject linearity against three-regime non-linearity, it is not surprising to find that the three-regime model is no better than a two-regime model. The F_{23} statistics is not significant under either of the two-variance assumptions.

We test for the validity of the homoscedasticity assumption for both periods as discussed in the next section.

Specification testing results for the free float regime are given in Tables 5. Test statistic F_{12} is as large as 75.13. Under homoscedastic errors, the p-value is 0.01 and we reject the null hypothesis of linearity in favor of a two-regime model at fairly high significance levels. Under heteroscedastic errors, the p-value is about 0.05 and, again, we reject the null of linear reaction function but at a somewhat lower significance level.

With regard to the three-regime alternative, the test statistics is as high as 82.22. The bootstrap p-value is 0.15 under homoscedastic errors and 0.13 under heteroscedastic errors, so we cannot reject the linear model in favor of the three-regime model. The three-regime model does not perform better than the two-regime model – the F_{23} statistics is not significant with or without the heteroscedasticity assumption for the regression errors.

4.2 Estimation of Threshold Model

Tables 6 and 7 report estimation results for managed float and free float, respectively. We only report estimates for one- and two-regime models because the three-regime model was rejected for both periods at the testing stage.

Considering managed float first, estimates for the linear model suggest that both our measures of market disorder are significant at 10%. Deviations from the long-term trend are significant at 5%. The coefficient on *DE* has the expected negative sign implying that the central bank's sales were primarily associated with lira depreciation (the "leaning against the wind" effect). The coefficient on *EV* is positive, indicating that higher net purchases were preceded by high volatility days.

Two out of three auto-regression coefficients are positive and significant at the 1% level. Overall, the implication is that recent interventions increase the expected amount of intervention in the near future. Three lags are enough to eliminate serial correlation in the residuals. Ljung-Box test statistics indicates that there is no significant serial correlation in the residuals up to order 20. However, there is strong evidence of heteroscedasticity. A separate regression of the squared residuals on squared regresses (not reported) confirmed that the errors are heteroscedastic. We therefore report White's heteroscedasticity-consistent standard errors in Table 6.

Based on the evidence of heteroscedasticity and the results in Table 4, we find no support for a threshold in the reaction function during the managed float period. It is however indicative that, from our two measures of market "disorder", *DE* is picked up as the threshold variable. After all, currency peg was the official policy of the Bank in that period.

Now, considering the free float period (Table 7); estimates for the linear model and for regime 2 of the threshold model indicate that the coefficient on excess volatility is significant at the 1% level and has the expected negative sign. The central bank's intervention tends to follow days of high volatility. In the high volatility regime (regime 2), the "leaning against the wind" effect is also noticeable. In the low volatility regime (regime 1), none of the coefficients is significant, suggesting that on these days interventions may be determined by other considerations.

Each auto-regression term is significant at the 10% level in the linear model, and at least at 10% in regime 2. Overall, the implication is that recent interventions increase the expected amount of intervention in the high volatility regime, in particular. The Ljung-Box test statistics indicates no significant serial correlation in the residuals and squared residuals. A separate regression of the squared residuals on squared regresses (not reported) supports homoscedasticity of errors.

Based on the evidence of homoscedasticity and the results of specification testing in Table 5, we conclude that the two-regime model is preferred to both the linear and the three-regime model. At the estimate of the threshold value of 0.211, the algorithm as the threshold variable picks up excessive volatility. The threshold in volatility agrees with the announced policy of the Bank for the free float. The fact that the threshold is so low (almost 90% of observations are in the high volatility regime) suggests that the bank's sensitivity to excess volatility is very high.

5. Conclusion

In this paper, we model and contrast intervention in different exchange rate regimes using recent data from the Central Bank of Turkey, an emerging market economy. We conjecture that the Central Bank of Turkey intervenes differently depending on whether a single measure of market disorder exceeds a threshold value or not. When possible to do so, we consider such measures a deviation from the trend and an excess volatility of the spot exchange rate. The questions we ask are what is the threshold value and whether the measure of market disorder is consistent with the announced policy of the Bank. Empirical evidence on intervention and market "disorder" appears to agree overall with the statements of the central bank in both periods. In the managed float period, we cannot reject the linear model in favor of a multiple-regime model. The linear model, however, indicates that the deviation from the 22-day moving average is a significant determinant of intervention. This is consistent with the exchange rate policy during managed float, which was based on the idea of utilizing exchange rates as a nominal anchor in curbing inflation. The increase in the foreign exchange basket, defined as 1.5 German marks and 1 US dollar, was targeted to increase by as much as the targeted monthly inflation rates.

In the free float period, under the assumption of homoscedastic errors, we reject linearity in favor of the two-regime model, in which excess volatility serves as the threshold variable. In the high volatility regime, excess volatility is more significant than deviation from the trend both in terms of practical and statistical significance. This is consistent with the announced goal to lower excess volatility.

In both regimes, lagged interventions matter a lot for future intervention.

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Table 1: Empirical distribution of interventions

Net Purchase (USD million)	managed float[ι]		free float[ξ]	
	(1)	(2)	(1)	(2)
>500	4	100	13	100
(300; 500]	9	99.68	0	99.01
(200; 300]	29	98.96	0	99.01
(100; 200]	89	96.66	9	99.01
(50; 100]	93	89.61	100	98.32
(0; 50]	254	82.23	485	90.70
0	365	62.09	551	53.74
(-50; 0)	167	33.14	87	11.74
(-100; -50]	96	19.90	37	5.11
(-200; -100]	97	12.29	15	2.29
(-300; -200]	27	4.59	13	1.14
(-500; -300]	23	2.45	2	0.15
<-500	8	0.63	0	0
Min	-878.5		-321.6	
Max	681		5441	
Obs	1261		1312	

Notes: [ι] January 2, 1995 - December 31, 1999.
[ξ] February 27, 2001 - May 15, 2006.
(1) is frequency.
(2) is cumulative frequency, %.

Table 2: Maximum likelihood estimates of GARCH model (5)-(8) for managed float[ζ]:

$$\Delta s_t = \mu + b_1 IN_{t-2}^{B} + b_2 IN_{t-2}^{S} + \sum_{k=1}^{4} \delta_k D_k + e_t,$$

$$h_t = \omega + \alpha e_{t-1}^2 + \beta h_{t-1} + c_1 IN_{t-2}^{B} + c_2 IN_{t-2}^{S} + \sum_{k=1}^{4} \lambda_k D_k,$$

$$e_t = \sqrt{h_t} \cdot z_t, z_t \sim N(0,1).$$

	Coef.	Std.Er.	Coef.	Std.Er.	Coef.	Std.Er.	Coef.	Std.Er.
Conditional Mean								
μ	0.017	0.052	0.007	0.050	-0.011	0.051	0.004	0.050
IN_{t-2}^{B}	-0.00007	0.00012			-0.00014	0.00012	-0.00011	0.00012
IN_{t-2}^{S}	-0.00006	0.00011			-0.00009	0.00012	-0.00005	0.00011
MO	0.333***	0.032	0.340***	0.033	0.334***	0.032	0.337***	0.033
TU	-0.010	0.025	-0.003	0.025	0.006	0.025	-0.004	0.025
WE	0.003	0.026	0.004	0.026	-0.001	0.027	0.001	0.026
TH	0.014	0.026	0.014	0.026	0.008	0.026	0.012	0.026
Conditional Variance	Coef.	Std.Er.	Coef.	Std.Er.	Coef.	Std.Er.	Coef.	Std.Er.
ω	-0.008	0.014	0.00001	0.014	0.012***	0.004	0.002	0.014
$\in_{t-1}^2$	0.140***	0.041	0.146***	0.045	0.183***	0.062	0.146***	0.045
$h_{t\text{-}1}$	0.750***	0.043	0.731***	0.048	0.727***	0.043	0.732***	0.048
IN_{t-2}^{B}	0.00002	0.00003			-0.00001	0.00003		
IN_{t-2}^{S}	0.00001	0.00003			0.00003	0.00005		
MO	0.105***	0.029	0.099***	0.030			0.095***	0.030
TU	-0.045**	0.022	-0.047*	0.024			-0.048**	0.025
WE	0.007	0.016	-0.002	0.016			-0.005	0.016
TH	0.041	0.029	0.032	0.029			0.030	0.029
ln*L*	-326.28		-326.303		-349.796		-325.619	
AIC	0.545		0.539		0.576		0.541	
SIC	0.615		0.592		0.629		0.602	
μ_3	0.319		0.292		0.548		0.289	
μ_4	7.671		7.701		9.353		7.668	
Q(20)	32.212		33.455		27.927		32.170**	
$Q^2(20)$	15.131		16.41		14.185		16.064	
Obs.	1259		1259		1259		1259	

Notes:

[ζ]January 2, 1995 - December 31, 1999.

***,**,* denote significance at the 1, 5, and 10 % level, respectively.

AIC and SIC are Akaike and Schwartz Information Criteria.

μ_3, μ_4 denote skewness and kurtosis, respectively.

$Q(20)$ and $Q^2(20)$ are the Ljung-Box test statistics for linear and squared standardized residuals.

Table 3: Maximum likelihood estimates of GARCH model (5)-(8) for free float[ξ]:

$$\Delta s_t = \mu + b_1 IN^{B}_{t-2} + b_2 IN^{S}_{t-2} + \sum_{k=1}^{4} \delta_k D_k + e_t,$$

$$h_t = \omega + \alpha e^2_{t-1} + \beta h_{t-1} + c_1 IN^{B}_{t-2} + c_2 IN^{S}_{t-2} + \sum_{k=1}^{4} \lambda_k D_k,$$

$$e_t = \sqrt{h_t} \cdot z_t, z_t \sim N(0,1).$$

Conditional Mean								
	Coef.	Std.Er.	Coef.	Std.Er.	Coef.	Std.Er.	Coef.	Std.Er.
μ	-0.016	0.044	-0.112**	0.044	-0.069*	0.037	-0.107*	0.043
IN^{B}_{t-2}	-0.00001	0.0001	0.00001	0.00001				
IN^{S}_{t-2}	0.001	0.002	0.002	0.002				
MO	0.120	0.066	0.102*	0.058	0.104*	0.060	0.099*	0.059
TU	0.089	0.059	0.060	0.056	0.054	0.052	0.059	0.055
WE	0.164***	0.062	0.112*	0.057	0.117**	0.055	0.109*	0.057
TH	-0.033	0.061	0.068	0.058	0.015	0.056	0.066	0.058
Conditional Variance								
	Coef.	Std.Er.	Coef.	Std.Er.	Coef.	Std.Er.	Coef.	Std.Er.
ω	0.254***	0.063	0.045**	0.014	0.039	0.036	0.046***	0.014
$\in^2_{t-1}$	0.171***	0.046	0.282***	0.053	0.206***	0.038	0.284***	0.054
h_{t-1}	0.694***	0.093	0.668***	0.057	0.727***	0.049	0.667***	0.058
IN^{B}_{t-2}	-0.0001***	0.00001	-0.00003	0.00003	-0.00004***	0.00001	-0.00003	0.00003
IN^{S}_{t-2}	0.005	0.006	0.009**	0.004	0.004	0.004	0.010**	0.005
MO	0.051	0.119			0.201**	0.099		
TU	-0.258***	0.097			-0.134*	0.079		
WE	-0.065	0.086			0.017	0.063		
TH	-0.301***	0.093			-0.061	0.063		
ln*L*	-1638.30		-1570.34		-1573.04		-1571.25	
AIC	2.526		2.415		2.434		2.414	
SIC	2.589		2.463		2.479		2.453	
μ_3	0.653		0.523		0.578		0.578	
μ_4	4.734		4.446		4.373		6.065	
$Q(20)$	40.470		30.555		35.265		32.156	
$Q^2(20)$	51.012		13.934		19.395		27.105	
Obs.	1310		1310		1310		1310	

Notes: [ξ]February 27, 2001 - May 15, 2006.
See Notes of Table 2.

Table 4: Specification testing for managed float ς

		p-value	
	F-statistic	Homoscedastic	Heteroscedastic
F_{12}	26.32	0.01	0.26
F_{13}	43.60	0.03	0.31
F_{23}	16.92	0.17	0.41

Notes: ς January 2, 1995 - December 31, 1999.

Table 5: Specification testing for free float ξ

		p-value	
	F-statistic	Homoscedastic	Heteroscedastic
F_{12}	75.13	0.01	0.05
F_{13}	82.22	0.15	0.13
F_{23}	6.70	0.72	0.51

Notes: ξ February 27, 2001 - May 15, 2006.

Table 6: Least Squares estimates of threshold model (2) for managed float ς (m=2)

	Linear		Two-regime			
	Regime 1		Regime 1		Regime 2	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Const	0.079	0.069	0.012	0.085	-0.338	0.520
DE_{t-1}	-0.059**	0.024	-0.023	0.034	0.059	0.139
EV_{t-1}	0.279*	0.166	0.413**	0.209	-0.051	0.422
IN_{t-1}	0.377***	0.048	0.306***	0.047	0.622***	0.124
IN_{t-2}	0.165***	0.042	0.192***	0.046	-0.025	0.097
IN_{t-3}	0.037	0.041	0.021	0.048	0.108	0.078
Obs.	1237		985		252	
Threshold			DE_{t-1}			
$\hat{\gamma}$			3.313			
R^2	0.26		0.272			
μ_3	-0.595		-0.524			
μ_4	13.290		12.470			
$Q(20)$	11.782		11.722			
$Q^2(20)$	109.735		121.709			

Table 7: Least Squares estimates of threshold model (2) for free float $^{\xi}$ (m=2)

	Linear		Two-regime			
	Regime 1		Regime 1		Regime 2	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Const	0.407***	0.079	-5.206	4.512	0.261***	0.041
$DE_{t\text{-}1}$	-0.019	0.012	1.688	1.079	-0.024**	0.011
$EV_{t\text{-}1}$	-0.087***	0.016	42.363	27.360	-0.065***	0.009
$IN_{t\text{-}1}$	0.019*	0.010	-0.066	0.043	0.037**	0.015
$IN_{t\text{-}2}$	0.012*	0.007	-0.063	0.059	0.013*	0.007
$IN_{t\text{-}3}$	0.011*	0.008	-0.045	0.023	0.021**	0.008
Obs.	1287		140		1147	
Threshold			$EV_{t\text{-}1}$			
$\hat{\gamma}$			0.211			
R^2	0.012		0.067			
μ_3	14.876		13.796			
μ_4	266.027		246.624			
$Q(20)$	1.163		0.854			
$Q^2(20)$	0.172		0.102			

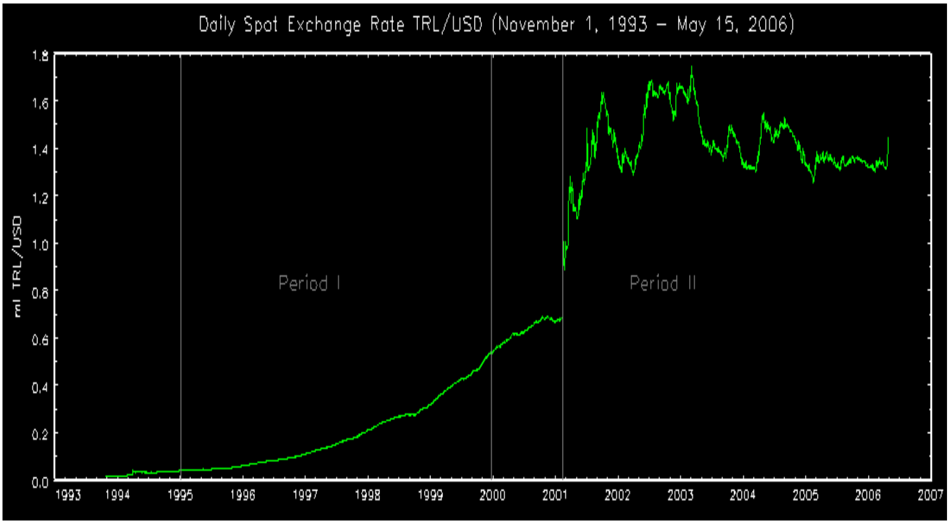

Figure 1: Daily TRL/USD exchange rate.