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Foreign Exchange Intervention Revisited: A New Way of Estimating Censored Models*

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Abstract

Most of the literature on the effectiveness of foreign exchange intervention has yet to reach a general consensus. In part, this is due to the different estimation methods in which exogenous variation is identified. In this sense, the use of heavily-dependent parametric models can sometimes condition the validity of results. In this paper we allow for a more flexible estimation of policy functions by using a censored least absolute deviation model, applied to a time-series framework. We first corroborate the properties of the estimators that we use through simulation exercises for cases in which: (i) the degree of censoring varies, (ii) errors are subject to conditional heteroskedasticity, (iii) the distribution of the errors varies, and (iv) when there are multiple censoring thresholds. The simulation exercises suggest that the estimator used is robust to both conditional heteroskedasticity and heavy tailed distributions in the error term. However, we show that misspecification, when considering a single-valued instead of multiple-valued thresholds, leads to an estimation bias. Finally, we carry out empirical estimations for the case of Turkey and Colombia and compare our findings with the related literature.

Key Words: CLAD; Censored models; Foreign exchange intervention; Central bank's policy function

JEL Codes: C14, C22, C24, E58, F31

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1 Introduction

Central banks conduct foreign exchange operations for a variety of reasons, including calming disorderly markets, influencing exchange rate movements, and to support other market-related transactions (e.g. accumulate or diminish international reserves). As such, there has been an ample strand of empirical work that centers on the effectiveness of central bank intervention.¹ Paradoxically, the literature has yet to reach a general consensus on the matter. In fact, advocates argue that purchases and sales of foreign currency (even if sterilized) can affect the exchange rate by re-balancing agent’s portfolios, which are assumed to be comprised of imperfectly substitutable assets. Alternatively, authors who reject the use of interventions sustain that central banks cannot simultaneously allow for free capital flows, have autonomous monetary policy, and manage the exchange rate due to arbitrage by foreign investors. Essentially, questions such as whether a *portfolio channel* exists or whether a *monetary trilemma* prevents the separate use of policies, have motivated one of the most controversial debates in the history of central banking.

The relating literature mostly differs in the way that exogenous variation in central bank intervention is identified. Namely, specification issues arise in any model-based approach where a policy function needs to be empirically estimated (see Kuersteiner, Phillips, and Villamizar-Villegas (2016)). And, in the context of discretionary intervention, monetary authorities systematically react to informative variables when setting their policy decisions, i.e. the timing and magnitude of interventions are driven by market behavior in order to meet explicit or implicit policy objectives.

To overcome this endogeneity problem and to control for heteroskedastic errors due to the high frequency of exchange rates, authors such as Almekinders and Eijffinger (1996), Guimaraes and Karacadag (2005), Huang (2007) Jun (2008), Humala and Rodríguez (2010), Rincón and Toro (2010), and Echavarría, Melo, Téllez, and Villamizar (2013) model foreign exchange policy through the use of a Generalized Autoregressive Conditional Heteroskedasticity process (GARCH). Alternatively, authors such as Kim, Kortian, and Sheen (2000), Kamil (2008), Adler and Tovar (2014), Villamizar-Villegas (2015), and Onder and Villamizar-Villegas (2015) model policy through a Tobit type-I model in order to capture the marked asymmetries between purchases and sales of foreign currency. The latter imply a censoring process which, in the literature, has been coined as a “*fear of floating*” (see in particular Calvo and Reinhart (2002) and Levy-Yeyati and Sturzenegger (2007)).

Notwithstanding, the use of heavily-dependent parametric models sometimes condition the validity of results (see Arabmazar and Schmidt (1982)). Consequently, in this paper we allow

¹A thorough compilation of empirical findings can be found in Dornbusch (1980), Meese and Rogoff (1988), Dominguez and Frankel (1993), Edison (1993), Dominguez (2003), Fatum and Hutchison (2003), Neely (2005), Menkhoff (2010), and Villamizar-Villegas and Perez-Reyna (2015).

for a more flexible estimation of central banks' policy functions by using quantile regressions; robust to heteroskedasticity and to any error distribution. Specifically, we follow the methodology presented in de Jong and Herrera (2008), in which a Censored Least Absolute Deviation model (**CLAD**) is extended to a time-series framework, i.e. the authors show asymptotic consistency and normality of the estimators. However, through a simulation study, we analyze the small sample properties of the estimators and specific characteristics within our empirical context of foreign exchange intervention, such as: (i) when the degree of censoring varies, (ii) when errors are subject to conditional heteroskedasticity, (iii) when the distribution of the errors varies, and (iv) when there are multiple censoring thresholds. Thus, we believe that this exercise will provide key insights to future research, given that this method has been employed (almost exclusively) in a cross-sectional context.

In the empirical application, we use proprietary data (at a daily frequency) from the Central Bank of Turkey and the Central Bank of Colombia during 2000-2010. The timing and amount of foreign exchange interventions allows us to precisely estimate the set of central bank functions and to sidestep potential endogeneity problems brought forth by liquidity demand or valuation effects.

Our results indicate that the time-series application of CLAD is robust to conditional heteroskedastic behavior and different distributions in the error term. However, misspecification when considering a single-valued threshold (instead of multiple-valued thresholds) leads to an estimation bias. This does not seem to be the problem for the empirical case considered (i.e. Colombia), since we find similar results when considering single and multiple-valued thresholds.

This paper proceeds as follows: Section II describes the methodology of the Censored Least Absolute Deviation model. In this section we consider a stationary bootstrap algorithm in order to estimate the error-covariance matrix. Sections III and IV present simulations applied to a time-series setting, and some empirical results for the case of Turkey and Colombia, respectively. Finally, Section V concludes.

2 Methodology

This section is comprised of two parts. In section 2.1 we provide a discussion of the econometric model and characterize its estimation method. In section 2.2 we describe the covariance matrix estimation.

2.1 Censored Least Absolute Deviation

The Censored Least Absolute Deviation model (**CLAD**) for a censoring threshold of zero was first proposed by Powell (1984) who considered a model based on the following form:

$$y_i = \max\{0, x_i' \beta_0 + \epsilon_i\}, \quad i = 1, \dots, T \quad (1)$$

where x_i is a $k \times 1$ observed regression vector and ϵ_i is a continuously distributed unobserved error term with a positive density function f_ϵ at zero and quantile function $Quant_{0.5}(\epsilon_i|x_i) = 0$.

Under some regularity conditions (see Powell (1984)) it can be shown that a consistent estimator of β_0 is obtained as a solution to:

$$\min_{\beta} \frac{1}{T} \sum_i |y_i - \max\{0, x_i' \beta\}| \quad (2)$$

in which the first order condition is given by:

$$\frac{1}{2T} \sum_i I(x_i' \hat{\beta} > 0) sgn\{y_i - x_i' \hat{\beta}\} x_i \quad (3)$$

where $I(\cdot)$ denotes the indicator function and $sgn(\cdot)$ is the sign function. Under similar conditions Powell (1986) shows that the CLAD estimator is asymptotically normal: $\sqrt{T}(\hat{\beta} - \beta) \xrightarrow{Dist.} N(0, \Sigma)$, where the variance matrix is exemplified by:

$$\begin{aligned} \Sigma = & \frac{1}{4} \left(E \left[f_\epsilon(0|x) I(x_i' \beta > 0) x x' \right] \right)^{-1} E \left[I(x_i' \beta > 0) x x' \right] \\ & \times \left(E \left[f_\epsilon(0|x) I(x_i' \beta > 0) x x' \right] \right)^{-1} \end{aligned} \quad (4)$$

where x stacks x_i vertically. An extension to a time series setting of CLAD is given by de Jong and Herrera (2008) who show that the LAD estimator is consistent even when the regression vector x_i includes p-lags of the observed censored variable. The authors show that a sufficient condition for stationarity in the dynamic censored regression model is for the roots of the lag polynomial $\rho_{max}(z) = 1 - \sum_{i=1}^p \max(0, \rho_i) z^i$ to lie outside the unit circle, where the ρ_i 's denote the coefficients

of the lagged-dependent variables.

In the relating literature, several algorithms for the estimation of CLAD have been suggested and a useful discussion is found in Fitzenberger (1997). In this study we use the Iterative Linear Programming Algorithm (**ILPA**), as suggested by (Buchinsky, 1994).² The idea of the ILPA is to solve for $\hat{\beta}^{(j)}$ in the j^{th} iteration by using observations for which $x_i' \hat{\beta}^{(j-1)} > 0$ and to stop whenever the set of observations in two consecutive iterations are the same.

Finally, in order to avoid a lack of robustness attributed to the starting value of the optimization process, we follow a genetic algorithm as described in Lucasius and Kateman (1993) to obtain the initial values used in the ILPA.

2.2 Covariance Matrix Estimation

Several methods for estimating the asymptotic covariance matrix, Σ , have been proposed for cases in which the distribution of the error term is independent of the regressors, i.e $f_\epsilon(0|x) = f_\epsilon(0)$. This, however, excludes (bounded) heteroskedastic behaviour in the error term, which we believe is essential in the context of high frequency data such as the case of foreign exchange intervention. For this reason we adopt a design matrix bootstrap.³

To account for the (possibly) weak dependence of the data over time and to allow for heteroskedastic behaviour in the error term, we consider the use of the stationary bootstrap proposed by Politis and Romano (1994) over the traditional block bootstrap of Kunsch (1989).⁴

A brief description of the stationary bootstrap algorithm is provided as follows:

Let X_i $i \in [1, T]$ denote the sample of interest and define a block of these observations as:

$$B_{i,b} = \{X_i, X_{i+1}, \dots, X_{i+b-1}\} \tag{5}$$

1. Choose a constant $p \in (0, 1)$.
2. Sample L_1, L_2, \dots, L_k (where k is a number such that $\sum_{i=1}^k L_i = T$) independent and identically distributed random variables from the geometric distribution with parameter p .
3. Sample I_1, I_2, \dots, I_k independent and identically distributed random variables from the discrete uniform distribution in $\{1, \dots, T\}$.

²Fitzenberger (1997) shows that ILPA is not able to interpolate censored observations. However, modifying this aspect does not lead to meaningful improvements on the estimator (see Fitzenberger (1994)).

³For cases in which heteroskedasticity is present, only kernel estimation and design matrix bootstrap are robust to the estimation of the asymptotic covariance matrix (see Buchinsky (1995)).

⁴For a detailed use block bootstrap in a quantile regression setting see Fitzenberger (1998).

4. Sample a sequence of blocks B of random length L : $B_{I_1, L_1}, B_{I_2, L_2}, \dots, B_{I_k, L_k}$.
5. Generate a pseudo-series X_i^* where the first L_1 observations are determined by the first sampled block, the next L_2 observations are determined by the second sampled block and so on. Stop when T observations of the pseudo series have been generated.
6. Calculate the statistic of interest using the pseudo series.

The main advantage of the described procedure is that the pseudo-series generated is stationary conditional on the original series. To address end corrections, we follow the same procedure as in the circular bootstrap (Politis and Romano, 1991).

It is easy to see that for the algorithm described above the expected length of the block is $\frac{1}{p}$. This feature makes the stationary bootstrap more robust to misspecification of the block size than the other types of block bootstrap. When bootstrapping, we construct the standard deviation using the robust scale estimator S_n as proposed by Rousseeuw and Croux (1993).

3 Simulations

This section analyzes the performance of the CLAD estimator in a time series setting through a simulation procedure. For each simulation study we consider 500 random samples of size 1000. The estimation problem is hence a censored regression with three regressors and an intercept.

The data generating process is described as:

$$y_t^* = \beta_0 + \beta_1 y_{t-1}^* + \beta_2 X_{1t} + \beta_3 X_{2t} + \epsilon_t \quad (6)$$

where $\beta_0 = 15, \beta_1 = 0.4, \beta_2 = 0.5$, and $\beta_3 = 1$. The initial values of the estimated coefficients were taken from a uniform distribution with mean 10 and variance 1. The first regressor (X_{1t}) follows a demeaned AR(2) process with $\phi_1 = 0.3, \phi_2 = 0.4$. The second regressor (X_{2t}) follows a demeaned AR(1) process with $\phi_1 = 0.5$. In both cases the error term is drawn from a normal distribution with mean 0 and variance (10, 20) respectively. Lastly, the third regressor is the lag of the latent variable.

3.1 Censoring Threshold

For the first simulation exercise we consider $\epsilon_t \sim N(0, 10)$, a 75% degree of censoring, and a censoring threshold given by $Quant_{0.75}(y^*)$.⁵ Following the results of Carson and Sun (2007) and Zuehlke (2010) we consider two cases: (i) a case in which we rescale the dependent variable to account for the non-zero threshold: $y_t^{corr} = y_t - \min_{\{t\}}\{y_t\}$ for which we refer to as Case I,⁶ and (ii) a case in which we wrongly (and intentionally) assume that the threshold is zero, without rescaling, for which we refer to as Case II.

The recording of a censoring value at zero rather than considering the actual censoring threshold is common in economic data mainly because of administrative recording practices (see Carson and Sun (2007)).⁷

Table 1: Estimation results for censoring threshold correction

	<i>Case I</i>			<i>Case II</i>		
	<i>Median</i>	<i>Sd</i>	<i>RMSE</i>	<i>Median</i>	<i>Sd</i>	<i>RMSE</i>
β_1	0.573	0.137	0.214	0.567	0.063	0.172
β_2	0.501	0.090	0.090	1.936	0.314	1.479
β_3	0.995	0.129	0.129	3.843	0.404	2.875

Authors' calculations. The table shows the CLAD estimation results when the censoring threshold is scaled (Case I) to account for the non-zero threshold and when it is not scaled and wrongly assumed to be zero (Case II). Note that the true data generating process corresponds to: $\beta_1 = 0.4, \beta_2 = 0.5$, and $\beta_3 = 1$. *RMSE* denotes the root mean squared error; *Sd* denotes the empirical standard deviation of the estimates.

Results suggest that the bias in the estimation (due to the incorrect specification of the censoring threshold) is severe for some of the coefficients. Namely, the bias in the estimation of β_2 and β_3 is over 100% and the standard deviation of the estimation is much larger. However, estimation results for the β_1 coefficient do not seem to change when the dependent variable is rescaled.

⁵The 75% threshold is similar to that of our data for Colombia and Turkey, and is in accord with the high degree of censoring of most of the foreign exchange intervention literature.

⁶In empirical applications where the censoring threshold differs from zero, the threshold can be estimated by $\min_{\{t\}}\{y_t\}$ as suggested in Carson and Sun (2007) and Zuehlke (2010).

⁷Moreover, some of the statistical software available defaults to a zero censoring threshold when estimating this type of regression models, so misspecification of the censoring threshold is liable to occur in empirical applications.

3.2 Degree of Censoring

For the second simulation exercise we consider $\epsilon_t \sim N(0, 10)$. In all cases the censoring threshold is $Quant_\theta(y^*)$ $\theta \in \{0.25, 0.5, 0.75\}$. Before the estimation procedure, the dependent variable is rescaled to account for the non-zero censoring threshold.

The degree of censoring in the sample is crucial to assess the efficiency of the proposed estimation method. In fact, Fitzenberger (1997) shows that all practical algorithms for the CLAD estimation perform poorly when there is a high percentage of censoring, which generally applies to foreign exchange intervention data.

Table 2: Estimation results for different censoring percentages

	25 %			50 %			75 %		
	<i>Median</i>	<i>Sd</i>	<i>RMSE</i>	<i>Median</i>	<i>Sd</i>	<i>RMSE</i>	<i>Median</i>	<i>Sd</i>	<i>RMSE</i>
β_1	0.442	0.021	0.048	0.495	0.030	0.099	0.565	0.055	0.176
β_2	0.495	0.039	0.039	0.502	0.053	0.053	0.502	0.084	0.084
β_3	0.997	0.036	0.036	0.997	0.051	0.051	1.001	0.104	0.103

Authors' calculations. The table shows the CLAD estimation results when the censoring percentage in the sample changes. Note that the true data generating process corresponds to: $\beta_1 = 0.4$, $\beta_2 = 0.5$, and $\beta_3 = 1$. *RMSE* denotes the root mean squared error; *Sd* denotes the empirical standard deviation of the estimates.

Table 2 shows the estimation results for different degrees of censoring. Estimations for the β_2 and β_3 coefficients do not change as the censoring percentage grows, but their corresponding standard deviation does. Results for β_1 suggest that, as the censoring percentage grows, the bias increases. This can be explained by noting that equation (6) depends on the lagged latent variable. Hence, the difference between the lagged latent and observed variable grows as the censoring in the sample increases.

3.3 Heteroskedastic behaviour

For the third simulation exercise we consider $\epsilon_t | \psi_{t-1} \sim N(0, \sigma_t^2)$ where $\sigma_t^2 = \gamma + 0.1\epsilon_{t-1}^2 + 0.8\sigma_{t-1}^2$ and γ is a number adapted to make the unconditional variance of the GARCH(1,1) process equal to 30 and 100, respectively. The censoring threshold is given by $Quant_{0.75}(y^*)$. Before the estimation procedure, the dependent variable is rescaled to account for the non-zero censoring threshold.

Table 3: Estimation results for GARCH(1,1)

	$\sigma^2 = 30$			$\sigma^2 = 100$		
	<i>Median</i>	<i>Sd</i>	<i>RMSE</i>	<i>Median</i>	<i>Sd</i>	<i>RMSE</i>
β_1	0.576	0.082	0.192	0.528	0.164	0.203
β_2	0.490	0.147	0.147	0.415	0.276	0.281
β_3	0.981	0.207	0.209	0.884	0.401	0.416

Authors' calculations. The table shows the CLAD estimation results when the error term follows a GARCH(1,1) process with different variances. Note that the true data generating process corresponds to: $\beta_1 = 0.4$, $\beta_2 = 0.5$, and $\beta_3 = 1$. *RMSE* denotes the root mean squared error; *Sd* denotes the empirical standard deviation of the estimates.

Table 3 shows the estimation results for the case of conditional heteroskedasticity. As expected, an increase in the unconditional variance of the GARCH(1,1) process leads to an increase in the standard deviation of the estimated coefficients.

3.4 Error Distribution

For the fourth simulation exercise we consider different distribution functions of the error term, including: Gaussian, t-student with 5 degrees of freedom, and t-student with 10 degrees of freedom. The latter two distributions capture the heavy tailed behavior of high frequency financial data. The censoring threshold is given by $Quant_{0.75}(y^*)$. Also, before the estimation procedure, the dependent variable is rescaled to account for the non-zero censoring threshold.

As can be seen in Table 4, the change in the distribution of the error term does not have any noticeable effect in the estimation results, which confirms the robustness of the method used in this particular aspect.

3.5 Multiple Thresholds

For the last simulation exercise, we consider multiple thresholds and $\epsilon_t \sim N(0, 10)$. In particular, we consider 10 sub-samples of equal length, each with a different threshold, according to two different rules. The type I censoring threshold is given by $Quant_{0.75}(y_i^*)$ where y_i denotes the i^{th} sub-sample, meanwhile the type II censoring threshold is given by $Quant_{\alpha}(y_i^*)$ where $\alpha = 0.25$ if i is even

Table 4: Estimation results for different error distributions

	<i>Normal</i>			t_5			t_{10}		
	<i>Median</i>	<i>Sd</i>	<i>RMSE</i>	<i>Median</i>	<i>Sd</i>	<i>RMSE</i>	<i>Median</i>	<i>Sd</i>	<i>RMSE</i>
β_1	0.570	0.103	0.196	0.549	0.098	0.171	0.553	0.097	0.183
β_2	0.486	0.186	0.186	0.483	0.160	0.160	0.472	0.177	0.178
β_3	0.974	0.251	0.252	0.973	0.219	0.220	0.973	0.248	0.250

Authors' calculations. The table shows the CLAD estimation results when the error term has different distributions. Note that the true data generating process corresponds to: $\beta_1 = 0.4, \beta_2 = 0.5$, and $\beta_3 = 1$. *RMSE* denotes the root mean squared error; *Sd* denotes the empirical standard deviation of the estimates.

and $\alpha = 0.75$ otherwise. Hence, the dependent variable is wrongly (and intentionally) rescaled by considering the minimum value of the whole sample, as described in the previous sections.⁸

In a foreign exchange intervention setting, the assumption of a unique censoring threshold across the entire sample is somewhat questionable given that the board of directors of a central bank is subject to the election of new members that can in turn react to different fundamentals. This brings to mind the possibility of several censoring thresholds during the time period considered.

Table 5: Estimation results for multiple thresholds

	<i>Type I</i>			<i>Type II</i>		
	<i>Median</i>	<i>Sd</i>	<i>RMSE</i>	<i>Median</i>	<i>Sd</i>	<i>RMSE</i>
β_1	0.592	0.062	0.198	0.770	0.045	0.371
β_2	0.473	0.097	0.101	0.378	0.081	0.149
β_3	0.972	0.137	0.141	0.798	0.073	0.215

Authors' calculations. The table shows the CLAD estimation results when there are multiple thresholds. The Type I censoring threshold is given by $Quant_{0.75}(y_i^*)$ where y_i denotes the i -th sub-sample, meanwhile the Type II censoring threshold is given by $Quant_{\alpha}(y_i^*)$ where $\alpha = 0.25$ if i is even and $\alpha = 0.75$ otherwise. Note that the true data generating process corresponds to: $\beta_1 = 0.4, \beta_2 = 0.5$, and $\beta_3 = 1$. *RMSE* denotes the root mean squared error; *Sd* denotes the empirical standard deviation of the estimates.

Table 5 shows the estimation results for two different types of censoring. The bias seems to appear in the estimation when the differences between the censoring thresholds of the sub-samples

⁸Note that these simulation exercises are misspecified since the CLAD estimations consider only one threshold.

and the value used to rescale the dependent variable are larger. This occurs in the type-II censoring threshold, mainly because the difference between the thresholds in the sub-sample is bigger than in the type-I censoring.

The simulation exercises suggest that the CLAD estimator used in a time series framework, is robust to both conditional heteroskedasticity (GARCH) and heavy tailed distributions in the error term. On the other hand, we find that misspecification of the censoring threshold as zero when it isn't (i.e non rescaling the dependent variable) leads to bias in the estimated coefficients. Another source of bias is found when there are multiple censoring thresholds and only one is taken into account in the estimation procedure.

Finally, it is important to note that increasing the degree of censoring, leads to bias in the lagged coefficient term along with an increase in the standard deviation of all the estimated coefficients.

4 Empirical Estimation

4.1 Data

Our data covers the period of January 2002 through May 2010 for the Turkish case and of December 1999 through October 2008 for the Colombian case. Prior to these dates, exchange rate bands and a fixed exchange rate regime were enacted for Colombia and Turkey, respectively. Also, following 2010 both countries adopted additional monetary instruments: a reserve option mechanism and an interest rate corridor in Turkey, and constant (daily) foreign exchange interventions in Colombia. Our selected sample thus poses a methodological advantage given that we avoid making further assumptions to model individual policies.

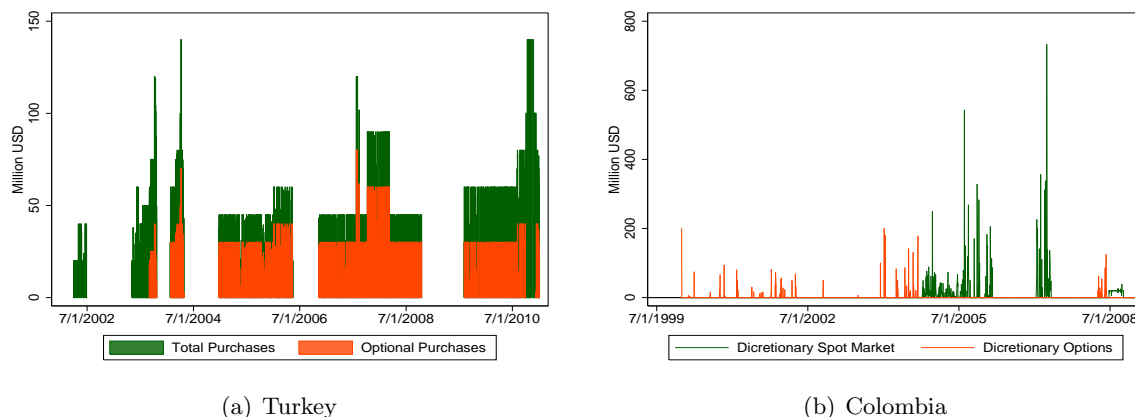
For the Colombian case, we use purchases of USD conducted in the spot market (22.8 billion) as well as discretionary interventions through foreign exchange rate options (3.3 billion). Alternatively, for the Turkish case, we use optional purchases (20.4 billion) which consisted of a discretionary amount of trading that took place during the day of an announced auction.⁹ These foreign exchange transactions are depicted in Figure 1.

Following Edison (1993) and Sarno and Taylor (2001), our explanatory variables include (i) exchange rate changes, (ii) a measure of exchange rate misalignments (i.e. deviations from a given target rate), and (iii) a set of economic factors that potentially influence official intervention.¹⁰

⁹We exclude unannounced purchases and sales for the Turkish case, due to the few observations available.

¹⁰This specification has been used by various works in the recent literature, which include: Guimaraes and Karacadag

Figure 1: Foreign Exchange Interventions for Colombia and Turkey 2000-2010



Namely, for the Colombian case we use the following variables as covariates:

- Lag of foreign exchange intervention (FXI_{t-1}).
- Exchange rate misalignments (ERM_t): Log-difference between the exchange rate and the average forecasted equilibrium value of seven in-house models used by the Central Bank of Colombia.
- Exchange rate volatility (Vol_t): Exchange rate returns with respect to its 20-day moving average
- Capital Controls (D_{Tax}): Period of capital controls implemented between May 2007 and October 2008.
- Net credit/debit position (D_{Net}): Dummy variable switched on whenever the the central bank was a net debtor with respect to the financial sector (i.e. excess liquidity).
- Year dummies (D_{year}).

Similarly, variables used as covariates used for the Turkish case include:

- Lag of foreign exchange intervention (FXI_{t-1}).
- Exchange rate misalignments (ERM_t): 20-day exchange rate change (log-difference).
- Inflation minus yearly target ($\pi_t - \pi^*$).
- Industrial output growth (ΔY_t).
- Year dummies (D_{year}).

All variables used were of a daily frequency, except for inflation and output which had a monthly frequency. Unit root tests are reported in Table 8 of Appendix A.

(2005), Herrera and Ozbay (2005), Akinci, Culha, Ozlale, and Sahinbeyoglu (2006), Huang (2007), Ito and Yabu (2007), Kamil (2008), Jun (2008), Bernal and Gnabo (2009), Rincón and Toro (2010), Humala and Rodríguez (2010), Echavarría, Melo, Téllez, and Villamizar (2013), Adler and Tovar (2014), Onder and Villamizar-Villegas (2015), and Villamizar-Villegas (2015).

4.2 Estimating Foreign Exchange Policy Functions

Tables 6 and 7 present results using the proposed CLAD methodology. For the case of Colombia, the central bank tried to depreciate domestic currency (by purchasing USD) whenever interventions were conducted the day before, when the exchange rate appreciated (relative to its forecasted equilibrium value), whenever the central bank was a net debtor with respect to the financial sector, and in lesser extent, when capital controls were enacted (see Table 6). Similarly, for the case of Turkey, the central bank tried to depreciate domestic currency whenever interventions were conducted the day before, when inflation was low (with respect to the yearly target), and whenever output increased (see Table 7).¹¹

While these results have the same expected sign as the ones found in Herrera and Ozbay (2005), Kamil (2008), Echavarría, Melo, Téllez, and Villamizar (2013), Onder and Villamizar-Villegas (2015), and Villamizar-Villegas (2015), the magnitude of the coefficients are significantly lower (in absolute terms). This result can have important policy implications in the sense that studies might be overstating the degree as to which monetary authorities react to fundamentals. Also, we find a significantly lower coefficient of lagged intervention. Namely, while most studies find a value of the coefficient close to unity, we find values of 0.2 and 0.5 for Colombia and Turkey, respectively. This shows a lower persistence when conducting foreign exchange interventions.

Finally, we analyzed whether changes in the composition of the board of directors within the Central Bank of Colombia had an effect over the estimated threshold.¹² In essence, we inquired whether Colombia exhibited multiple thresholds that, if ignored, would yield inconsistent estimates (see Section 3). Given the similarities between columns 2 and 4 reported in Table 6, we conclude that changes in the board did not alter the censoring threshold in the foreign exchange policy function.

¹¹We attribute the negative effect of inflation to a case of imperfect sterilization and the positive effect of output as a “leaning with the wind” policy.

¹²Due to lack of information we omitted this exercise for the Turkish case.

Table 6: Estimation results for Colombia

	<i>Fixed censoring threshold</i>		<i>Dynamic censoring threshold</i>	
	<i>Coefficient</i>	<i>S.d</i>	<i>Coefficient</i>	<i>S.d</i>
FXI_{t-1}	0.20***	0.07	0.21***	0.08
ERM_t	-0.71*	0.39	-0.70	0.53
Vol_t	9.55	7.72	10.70	6.79
D_{Tax}	-32.19***	13.41	-47.96***	16.68
D_{Net}	13.87**	6.69	13.60**	5.94
<i>Intercept</i>	-32.55***	11.02	-38.33***	12.81
D_{2004}	33.90**	14.72	38.67***	14.81
D_{2005}	36.06***	12.21	42.07***	14.15
D_{2006}	34.07***	13.70	41.16***	14.70
D_{2007}	73.33***	24.28	95.61***	24.68

Estimation results for Colombia with a fixed and dynamic censoring thresholds. FXI corresponds to foreign exchange interventions, ERM to exchange rate misalignments, Vol_t to exchange rate volatility, D_{Net} to the net credit/debit position of the central bank, and D_{Tax} to a period of capital controls. Sd denotes the standard deviation of the estimates. *, **, *** indicate significance at the 10%, 5 % and 1% level, respectively.

Table 7: Estimation results for Turkey

	<i>Fixed censoring threshold</i>	
	<i>Coefficient</i>	<i>S.d</i>
FXI_{t-1}	0.540***	0.117
$\pi_t - \pi^*$	-0.183***	0.000
ΔY_t	$1.43^{***} \times 10^{-4}$	4.15×10^{-5}
ERM_t	1.01×10^{-9}	4.18×10^{-9}
<i>Intercept</i>	-1.045***	0.002
D_{2004}	0.549***	0.002
D_{2008}	2.163***	0.019
D_{2009}	0.863***	0.011
D_{2010}	1.038***	0.008

Estimation results for Turkey for the fixed censoring threshold case. FXI corresponds to foreign exchange interventions, $\pi - \pi^*$ to inflation minus yearly target, ERM to exchange rate misalignments, and ΔY to industrial output growth. Sd denotes the standard deviation of the estimates. *, **, *** indicate significance at the 10%, 5 % and 1% level, respectively.

5 Conclusion

Specification issues arise in any model-based approach where a policy function needs to be empirically estimated. Such is the case of foreign exchange reaction functions in which the timing and magnitude of interventions are driven by market behavior in order to meet policy objectives.

To overcome this endogeneity problem and to control for heteroskedastic errors due to the high frequency of exchange rates, authors model foreign exchange policy through the use of a Generalized Autoregressive Conditional Heteroskedasticity process or through a Tobit type-I model in order to capture the marked asymmetries between purchases and sales of foreign currency.

In this paper we allow for a more flexible estimation by using quantile regressions; robust to heteroskedasticity and to any error distribution. Specifically, we estimate a Censored Least Absolute Deviation model (CLAD) applied to a time-series framework. First, through a simulation study, we analyze the small sample properties of the estimators and specific characteristics within our empirical context of foreign exchange intervention, such as: (i) when the degree of censoring varies, (ii) when errors are subject to conditional heteroskedasticity, (iii) when the distribution of the errors varies, and (iv) when there are multiple censoring thresholds. Second, we estimate foreign exchange policy functions for the Central Bank of Turkey and the Central Bank of Colombia during 2000-2010 using the CLAD methodology.

We find that the time-series extension of CLAD is robust to conditional heteroskedastic behavior and to different distributions in the error term. However, misspecification of the censoring threshold taken as single-valued when it is in fact multiple-valued leads to a bias in the estimation results. This does not seem to be the problem for the empirical case considered. Finally, we find that while our results have the same expected sign as most of those found in the literature, the magnitude of the coefficients are significantly lower (in absolute terms). This result can have important policy implications in the sense that studies might be overstating the degree as to which monetary authorities react to fundamentals.

6 Bibliography

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Appendix A

Table 8: Elliott-Rothenberg-Stock Test for Unit Root

Variable (up to 28 lags)	t-statistic	1% critical value	10% critical value
Turkey			
FXI_t	-3.791	-3.480	-2.570
$\pi_t - \pi^*$	-2.640	-3.480	-2.570
ERM_t	-6.336	-3.480	-2.570
ΔY_t	-3.070	-3.480	-2.570
Colombia			
FXI_t	-5.517	-3.480	-2.570
Vol_t	-8.413	-3.480	-2.570
ERM_t	-2.812	-3.480	-2.570
D_{Net}	-6.131	-3.480	-2.570
D_{Tax}	-7.599	-3.480	-2.570

FXI corresponds to foreign exchange interventions, $\pi - \pi^*$ to inflation minus yearly target, ERM to exchange rate misalignments, ΔY to industrial output growth, Vol_t to exchange rate volatility, D_{Net} to the net credit/debit position of the central bank, and D_{Tax} to a period of capital controls. The minimum lag is determined using the modified akaike's information criterion (MAIC). All variables reject the null hypothesis of a unit root at the 10% level, and most at the 1% level.

