Applied Economics Quarterly Vol. 61. N° 3 (2015)
Duncker & Humblot GmbH, 12165 Berlin

Explaining the Determinants of the Frequency of Exchange Rate Interventions in Peru Using Count Models

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Abstract

The determinants of the frequency of Central Bank interventions (purchases and sales) in the Peruvian exchange rate market are analyzed using weekly data for the period from January 2001 to December 2010 using count data models (Poisson, Negative Binomial and Zero Inflated). Findings show that the deviations of the logarithm of the exchange rate with respect to a long term trend, previous week's interventions (persistency), the Embig spread, the spread between interbank interest rates, and the spread of prime corporate interest rates are important determinants. In terms of the models used, the Zero Inflated models allow a better fit and performance in predicting the number of interventions (purchases and sales).

Keywords: Exchange Rate Intervention, Frequency of Intervention, Count Models, Exchange Rate, Interest Rate Spread

JEL Classification: C22, C32, C35, E52, F31

1. Introduction

The latest financial crisis showed that inflation is not the only concern of Central Banks. When policy interest rates reach their lower bound, Central Banks resort to other unconventional instruments like reserve requirements or interventions in the foreign exchange (Forex, hereafter) market.

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This paper is drawn from the Thesis of Edgar Ventura at the Department of Economics of the Pontificia Universidad Católica del Perú. We thank useful comments of Paul Castillo (BCRP), participants at the Degit XVIII, September 26–27, 2013, Lima, Peru, the Editor of the Journal and an anonymous Referee. We also thank Sebastián Guevara for translation and Patricia Lengua Lafosse for her assistance in the formatting of this document. Authors acknowlege financial support from the Department of Economics of the Pontificia Universidad Católica del Peru. All remaining errors are our own.

Intervention in the Forex market is a feature of the Peruvian exchange rate regime of intermediate or administered floating. Among the reasons for this are the high costs that frequent deviations in the exchange rate impose on trade and the real economy, especially in emerging economies like ours. In the last 6 years, there has been an increase in the frequency of foreign exchange interventions. For instance, there have been high volumes of intervention with levels reaching net daily purchases of US$ 493.5 million (on July 10, 2009) and net daily sales of US$ 443.8 million (on October 2, 2008).

The aim of this document is to analyze the main determinants of the frequency of interventions in the Forex market by the Peruvian Central Bank (BCRP hereafter) using count data models. According to BCRP's statements, Forex interventions have the goal of reducing exchange rate volatility. One of the purposes of this document is to demonstrate that there are other variables that determine the frequency of intervention in the Forex exchange market.

The economic issue to be discussed has empirical relevance, since this kind of analysis has not been performed in Peru previously. The contribution of this work resides in finding the main variables that explain the frequency of Forex interventions in a manner that is consistent with the stylized facts of the Peruvian economy and because the financial crisis has showed the importance of unconventional measures as instruments of monetary policy.

The document analyzes the number of weekly Forex interventions for the period covering January 2001 until December 2010. Among the set of explanatory variables are: a measure of the deviation of the exchange rate from its long term trend, the spread of interbank interest rates, the spread of prime corporate interest rates, and risk country measure like the Embig. Most of this data is obtained from the BCRP.

The dependent variable is the number of days that the Central Bank intervenes each week. Given the properties of the variable, the most adequate methodology is the use of count data models. These models assign a distribution function to the dependent variable as determined by the independent variables, which influence the number of expected interventions. This type of methodology, at least to our knowledge, is the first time that is applied (at least to emerging countries).

The present document is organized as follows. Section 2 presents a literature review which defines the concept of intervention and its potential determinants, as well as some empirical evidence found in other countries. Section 3 presents the methodology related to the so-called count data models like Poisson, Negative Binomial and Zero Inflated. Section 4 analyzes the results of the estimations and explains the behavior and determinants of exchange rate interventions. Section 5 presents the conclusions.

2. Literature Review

Intervention in the Forex market is a feature of an intermediate or administered floating exchange rate regime, as stated by Tapia and Tokman (2003). This policy consists of direct sales or purchases of foreign currency by the monetary authority in the Forex market. There are two types of exchange intervention, sterilized and non-sterilized. In the latter, any purchase or sale of foreign currency is not compensated by other monetary operations, which generates a change in the monetary base that in turn affects the interest rate. Hence, the new interest rate prompts the exchange rate to move to a new level determined by arbitrage. Alternatively, sterilized interventions involve buying and selling assets denominated in the home currency. In this case, the aim is to decouple the exchange rate and monetary policy by keeping the monetary base and the interest rate stable.

The literature suggests that there are three transmission mechanisms of sterilized intervention into the exchange rate. The first is through a shift in the relative supply of local and foreign assets, which has an effect on the equilibrium exchange rate; see Domínguez and Frankel (1993) and Evans and Lyon (2002).

The second mechanism is related to the signalling theory, according to which an intervention provides information on future monetary policy, which leads agents to adjust their positions in local and foreign currency (Mussa 1981). However, this mechanism depends on the credibility of the Central Bank, since otherwise agents may anticipate that the present decisions will not be consistent with future actions. In this case the equilibrium exchange rate is changed.

The third mechanism is a particular case of the previous one. Here, it is assumed that the market exchange rate may deviate from equilibrium due to the presence of speculators (Frankel and Rose 1995). In this case, intervention does not change the equilibrium exchange rate because there is only a transitory deviation.

Baillie and Osterberg (1997) analyze the motivations for an exchange rate intervention policy. According to their view, the goal of intervention is to establish a stable foreign exchange market and to let the dollar depreciate towards an equilibrium level. Additionally, these authors assert that a volatility target does not exist, but that authorities have an interest in calming unruly markets; see also Neely (2008).

On a different approach, Ito (2002) separates foreign exchange intervention into four types of policy. The first two are related with the "lean against the wind" mechanism: in one type the aim is to change the tendency, whereas on the other only a reduction in exchange rate volatility is attempted. The other two types of intervention are related with the "lean in the wind" mechanism. One has as an objective to make sure that the current tendency in the exchange rate continues, and the other seeks to accelerate the convergence towards an equilibrium level.

In this respect, Arena and Tuesta (1999) state that exchange rate intervention can be explained by the existence of " bandwagon effects" in the Forex market as a result of private speculation. In consequence, exchange rate intervention should counter this tendency. On the other hand, Calvo and Reinhart (2000), after analyzing 154 cases, provide evidence that there is a clear rejection of a completely free exchange rate. They attribute this fear of floating to the grave problems that a lack of credibility of the Central Bank could give rise to. If there is not confidence in the monetary authority, it has no power or leverage. In this case the market is dominated by speculators.

Ito (2002) proposes a function for intervention reaction by the Japanese monetary authority. In this case, results show that exchange rate intervention is a function of the daily variation in the yen-dollar exchange rate, among other indicators, and that intervention in the United States can prompt intervention in Japan on the following day.

In another study, using a Tobit model, Kamil (2008) uses a two-step method to estimate the dynamics of intervention for the case of Colombia. The author affirms that intervention is motivated by two factors: the daily percentage change in the exchange rate, and the percentage deviation from an equilibrium exchange rate. In a second stage, Kamil (2008) estimates a GARCH model for the peso-dollar exchange rate and finds that the exchange rate intervention has been efficient during certain periods of the sample.

On the other hand, Echevarra, Vásquez and Villamizar (2009) assess the determinants of currency purchases for the Colombian case in the 2000–2008 period. According to the results of Tobit estimations, the main determinants of intervention are daily revaluations, decreases in inflation pressure, and excessive trends in the exchange rate.

For the Peruvian case, Carranza, Cayo, and Galdón-Sánchez (2003) find evidence that exchange rate depreciations severely affect investment decisions by firms that maintain dollar-denominated debt. This is due to four reasons: the high degree of liability dollarization which creates a balance sheet effect in the economy, the strong bank lending channel that reinforces the balance sheet effect, a contraction in demand that severely affects the sales of the companies, and low diversification in the export sector. Therefore, the authors are interested in analyzing the way in which exchange rate volatility has an effect on the Peruvian economy by using financial statements from 164 firms for the 1994–2001 period. The results show evidence of a negative balance sheet effect, which leads them to focus on measures that the monetary authority can take to address this situation.

There are diverse authors that deal with determinants or behavior of the monetary interventions of the authorities in the Forex market. For example, Arena and Tuesta (1999) study the effect of monetary variables on the probability of intervention. Their results show, by using a logistical probability model, that BCRP does not subordinate monetary policy to an exchange rate target.

Finally, Humala and Rodriguez (2010) evaluate whether a reduction in exchange rate volatility in Peru is due to intervention or other explanatory variables. The chosen methodology is a Markov Switching autoregressive vector model, and the explanatory variables are exchange rate variations, net purchases by BCRP, deviations of the exchange rate from its long term trend, changes in BCRP's net international position, and variations in interest rate differentials. In a sample of monthly data covering the 1994–2007 period, two clearly differentiated regimes regarding net purchases and exchange rate volatility are identified.

A study related to the present paper is Hoshikawa (2008), which focuses on the relationship between the frequency of intervention and the volatility of the exchange rate. The interest arises from the fact that the Japanese case presents a distribution of exchange rate intervention that is high on the extremes and low in the middle for the 1991–2005 period. The results show that low frequency has an effect on the long term exchange rate, and that high frequency tends to reduce volatility. The author associates these results with the objectives of the monetary authority (either the level or the volatility of the exchange rate).

Other studies related to reaction functions of interventions and related to the present paper are Kears and Rigobon (2005), Ito and Yabu (2007), Fatum and Hutchison (2010), Kim and Sheen (2002), and Fry-McKibbin and Wanaguru (2013). Kears and Rigobon (2005) deals with efficiency of Central Bank interventions for Australia and Japan. The intervention is a function of first differences of exchange rate, a common shock, and an idiosincratic shock. They estimate a function of decision to intervene or not and also they use a theshold level of intervention. In their case, if the value of the exchange rate is larger than this threshold, it implies an intervention of the Central Bank.

In the case of Ito and Yabu (2007), the intervention function is analyzed using daily data from 1991 until 2002. They use an ordered probit model and they found evidence of regime changes from small scale frequent interventions to large scale infrequent interventions. One important issue in this study is that the Central Bank has a target for the exchange rate. They works with thresholds and consequently with bands for the exchange rate. Another important point in this paper is that most of their explanatory variales are first differences of the exchange rate using different moving averages calculations.

In the case of Fatum and Hutchison (2010), the authors deal with the effect of the official intervention in the Forex market. They use the propensity matching score method to construct conterfactuals exchange rate movements in the absence of intervention. They use a logit framework to estimate a regression where the dependent variabe is a dichotomic variable. The explanatory variables are the growth rate of exchange rate, deviations of the exchange rate from a target, a 21 moving average of the exchange rate, a one year moving average of the exchange rate and a vector of variables capturing the unexpected components of Japanese macroeconomics news, that is, when an oficial macroeconomic announcement differs from the market expectations. In this sense, the authors include output news, unemployment news, CPI news.

This document has several differences with the above mentioned related papers. In our case, at least explicitly, the Central Bank has not a target for the exchange rate; see Arena and Tuesta (1999). We use weekly data and we are interested in explaining the determinants of the frequency of interventions. Therefore, our dependent variable is not dichotomous. In our case our dependent variable is a count variable and also we estimate a type of models where firstly we estimate a binary equation before to estimate the frequency equation. Unfortunately, there are some interesting variables used in the above papers which we cannot use because they are not available, as for example, unexpected macroeconomic news. Given that BCRP has not a target for exchange rate, we cannot work with thresholds or bands. However, our methodology is novel in the application to the study of the frequencies of intervention in the Forex market. To our knowledge, it is a first study using this kind of methodology applied to this topic. We also analyze the levels (or scale) of interventions in the Forex market.

3. Methodology

The present paper estimates the probability of exchange rate intervention as a function of a set of explanatory variables, such as the deviation of the exchange rate from its long term trend, country risk, and the difference in interbank and prime corporate interest rates between domestic and foreign currency.

The dependent variable is the number of times (days) that BCRP intervenes in the Forex market each week by purchasing or selling dollars. Using information of intervention volumes, an observation can be classified as a purchase or a sale of foreign currency in the Forex market. Given the nature of the dependent variable, the most suitable models for this type of analysis are the so called count models. Among the frequently used models are the Poisson Regression (PR hereafter) model and the Negative Binomial Regression (NBR hereafter) model. These models assume an endogenous variable as the result of a Poisson or Negative Binomial probability function, respectively. Another utilized model is the so called Zero Inflated model (be it Poisson-ZIP; or Negative Binomial-ZINB), which is relevant when the dependent variable contains an elevated number of zeroes. In the present study the dependent variable shares this property, which justifies the utilization of this type of models. In all cases, the estimations are carried out by the method of maximum likelihood. The mentioned models are described in the following lines based on Cameron and Trivedi (2005, 2010), Greene (2003), Long (1997), Long and Freese (2006), and Winkelmann (2008), among others references.

3.1 The Poisson Regression Model

The Poisson distribution may be derived from a simple stochastic process known as Poisson process, where the outcome is the number of times that something has happened assuming that the events are independent.

Let y be a random variable indicating a number of times that an event has occurred during an interval of time. We say that y has a Poisson distribution with parameter $\mu > 0$ if $\Pr(y|\mu) = \frac{\exp(-\mu)\mu^y}{y!}$, for $y = 0, 1, 2 \ldots$; where the parameter μ can be thought as the expected count[1].

In the PR model, the number of events y has a Poisson distribution with a conditional mean which depends on a set of individuals characteristics ($\mathbf{X}_i$) according to the structural model: $\mu_i = E(y_i|\mathbf{x}_i) = \exp(\mathbf{x}_i\beta)$. Since y is a count, it can only have nonnegative integer values. Therefore, the probability of a count given $\mathbf{X}_i$ is given specifically by the following expression:

$$\Pr(y_i|\mathbf{x}_i) = \frac{\exp(-\mu_i)\mu_i^{y_i}}{y_i!}, \tag{1}$$

where the variable y_i, in our case, is the number of times (by week) that the BCRP intervenes in the Forex market. As in the Poisson distribution, in the PR model the mean and the variance are equal and it is known as equidispersion. In practice, count variables often have a variance greater than the mean which is known as overdispersion and many models have been developed in an attempt to account for it.

In order to estimate the PR model, the likelihood function is

$$L(\beta|y, \mathbf{x}_i) = \Pi_{i=1}^{N} \Pr(y_i|\mu_i), \tag{2}$$

$$= \Pi_{i=1}^{N} \frac{\exp(-\mu_i)\mu_i^{y_i}}{y_i!}, \tag{3}$$

where $\mu_i = \exp(\mathbf{x}_i\beta)$. After taking logarithms, numerical maximization may be used. The gradient and the Hessian of the likelihood are given in Maddala (1983). Since the likelihood is globally concave, if a maximum is found, it will be unique.

One way to interpret the results is to calculate the predicted probabilities which are based on the formula:

$$\widehat{\Pr}(y = m|\mathbf{x}) = \frac{\exp(-\widehat{\mu})\widehat{\mu}^m}{m!}. \tag{4}$$

[1] The parameter μ is known as the rate since it is the expected number of times that an event has ocurred per unit of time.

It is important to explain the interpretation of the estimator, since it is different in this context from the conventional one. The interpretation of the coefficients can be divided in two ways. One is related to the mean, and the other is associated to the probability of occurrence of the event being analyzed (exchange rate intervention); see Long and Freese (2006) for further details.

In the present paper, the interpretation of the coefficients is related to the percentage change in the mean. For ease of this, the coefficients will represent the percentage change in expected intervention when the independent variables have a change equal to their standard deviation.

Sometimes PR models do not fit well the observed data. One explanation for this failure is that the rate μ differs across individuals. This is known as heterogeneity. Failure to account for it in the rate results in overdispersion in the marginal distributions of the count. One possible solution is to introduce heterogeneity based on observed characteristics. Another solution is the so named negative regression models.

3.2 The Negative Binomial Regression Model

Since in most applications, the conditional variance is greater than the conditional mean, the PR model rarely fits in practice. If the mean structure is correct, but there is overdispersion, Gourieroux et al. (1984) show that the estimates of the PR model are consistent but inefficient. Furthermore, Cameron and Trivedi (1986) argue that the standard errors are biased downwards, resulting in spuriously large z-values.

The NBR model may be obtained from different perspectives. Here, we follow the arguments of Long (1997) who introduces this model in terms of unobserved heterogeneity. Unlike the PR model, where the mean is known, in the NBR model, the mean μ is replaced with the random variable $\widetilde{\mu} = \exp(\mathbf{x}_i\beta + \epsilon_i)$, where ϵ is a random error which is assumed to be uncorrelated with $\mathbf{x}$. In terms of Gourieroux et al. (1984), we may think in ϵ as the combined effects of unobserved variables that have been omitted from the model. It may be thought as another source of randomness. In the PR model, variation in μ is introduced trough observed heterogeneity. In the NBR model, variation in $\widetilde{\mu}$ is due both to variation in $\mathbf{x}$ among individuals but also to unobserved heterogeneity introduced by ϵ. Therefore, for a given combination of values for the independent variables, there is a distribution of $\widetilde{\mu}'$s rather than a single μ.

The relationship between $\widetilde{\mu}$ and the original μ follows from $\widetilde{\mu}_i = \exp(\mathbf{x}_i\beta)\times \exp(\epsilon_i) = \mu_i \exp(\epsilon_i) = \mu_i\delta_i$, where $\delta_i = \exp(\epsilon_i)$. An assumption in the NBR model is that $E(\delta_i) = 1$ which implies that the expected count after adding the new source of variation is the same as in the PR model, that is, $E(\widetilde{\mu}) = E(\mu_i\delta_i) = \mu_i E(\delta_i) = \mu_i$.

Following above arguments, the distribution of observations given $\mathbf{x}$ and δ is still Poisson:

$$\Pr(y_i|\mathbf{x}_i, \delta_i) = \frac{\exp(-\widetilde{\mu}_i)\widetilde{\mu}_i^{y_i}}{y_i!}, \tag{5}$$

$$= \frac{\exp(-\mu_i\delta_i)(\mu_i\delta_i)^{y_i}}{y_i!}. \tag{6}$$

We need to compute the distribution of y given only $\mathbf{x}$, that is, $\Pr(y_i|\mathbf{x}_i)$ $\int_0^\infty [\Pr(y_i|\mathbf{x}_i, \delta_i) \times g(\delta_i)]d\delta_i$. However, in order to solve it, we must specify the form of the density for δ. The most common assumption is that δ_i has a Gamma distribution with parameter v_i: $g(\delta_i) = \frac{v_i^{v_i}}{\Gamma(v_i)}\delta_i^{v_i-1}\exp(-\delta_i v_i)$, for $v_i > 0$, and where the Gamma function is defined as $\Gamma(v) = \int_0^\infty t^{v-1}e^{-t}dt$.[2] Following Cameron and Trivedi (1986), the equation for the NBR model is

$$\Pr(y_i|\mathbf{x}_i) = \frac{\Gamma(y_i + v_i)}{y_i!\Gamma(v_i)}\left(\frac{v_i}{v_i + \mu_i}\right)^{v_i}\left(\frac{\mu_i}{v_i + \mu_i}\right)^{y_i}. \tag{7}$$

The expected value of y for the NBR model is the same as in the PR model but the variance differs:

$$var(y_i|\mathbf{x}) = \mu_i\left(1 + \frac{\mu_i}{v_i}\right), \tag{8}$$

$$= \exp(\mathbf{x}_i\beta)\left(1 + \frac{\exp(\mathbf{x}_i\beta)}{v_i}\right), \tag{9}$$

where, since μ and v are positive, the conditional variance of y in the NBR model must exceed the conditional mean $\exp(\mathbf{x}_i\beta)$. The literature shows that increasing variance in the NBR model allows to have better fit in comparison with the PR model. However the variance in (9) is not identified and the problem is that v varies with the individuals. In order to simplify notation and calculation, the literature has adopted the assumption that v is the same for all individuals doing that $v_i = \alpha^{-1}$, for $\alpha > 0$, which implies that the variance of δ is constant. The parameter α is known as the parameter of overdispersion and increasing α we increase the conditional variance of y. Therefore, replacing $v = \alpha^{-1}$ in (9), we have that

$$var(y_i|\mathbf{x}) = \mu_i\left(1 + \frac{\mu_i}{v_i}\right), \tag{10}$$

$$= \mu_i(1 + \alpha\mu_i), \tag{11}$$

$$= \mu_i + \alpha\mu_i^2, \tag{12}$$

where we may note that if $\alpha = 0$, variance is equal to mean and we return to the PR model[3].

2 Johnson et al. (1994) show that in this case, $E(\delta_i) = 1$ and $var(\delta_i) = 1/v_i$.

The NBR model may be estimated by maximum likelihood. The likelihood function is

$$L(\beta|y,\mathbf{x}) = \Pi_{i=1}^{N} \Pr(y_i|\mathbf{x}_i), \tag{13}$$

$$= \Pi_{i=1}^{N} \frac{\Gamma(y_i+\alpha^{-1})}{y_i!\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu_i}\right)^{\alpha^{-1}}\left(\frac{\mu_i}{\alpha^{-1}+\mu_i}\right)^{y_i}, \tag{14}$$

where $\mu = \exp(\mathbf{x}_i\beta)$. After taking logarithms, the log likelihood can be maximized with numerical methods.

As before, one way to interpret the results is to calculate the predicted probabilities which are based on the formula:

$$\widehat{\Pr}(y=m|\mathbf{x}) = \frac{\Gamma(m+\widehat{\alpha}^{-1})}{m!\Gamma(\widehat{\alpha}^{-1})}\left(\frac{\widehat{\alpha}^{-1}}{\widehat{\alpha}^{-1}+\widehat{\mu}}\right)^{\alpha^{-1}}\left(\frac{\widehat{\mu}}{\widehat{\alpha}^{-1}+\widehat{\mu}}\right)^{m}. \tag{15}$$

3.3 The Zero Inflated Regression Models

One issue in count models is the number of zeros in the count (dependent) variable which is modeled. For example in the PR model, as the parameter μ increases, the prediction of zeroes decreases. The NBR model responds to this underprediction of zeroes by increasing the conditional variance without changing the conditional mean. The zero modified count models change the mean structure to explicitly model the production of zero counts. This is performed by assuming that zeroes can be generated by a different process that positive counts. In our case, the PR model and the NBR model assume that Central Bank has a positive probability of intervention in the Forex market any given number of times. The probability differs across interventions according to some characteristics but in all cases the Central Bank risk of not intervene and in all cases Central Bank might intervent. But it may be unrealistic because in some cases Central Bank may be forced (or something like) of no intervent.

In order to fix these issues, Mullahy (1986) assumes that the population has two groups. An individual is in group 1 with probability ψ and is in group 2 with probability $1-\psi$. The first group consists of observations where always have zero counts. For example, there may be some observations where there is no intervention because some characteristics influenced or determined to the Central Bank to act like this. We do not know whether some observations with zero interventions are in

3 Under the specification of (12), the conditional variance is quadratic in the mean. It has led Cameron and Trivedi (1986) to call this model the Negative Binominal Regression Model 2 (NBRM-2).

the first or second group[4]. In the second group, counts are governed by a PR model or a NBR model.

Lambert (1992) and Greene (1994) extend the model described above to allow ψ to be determined by characteristics of the individuals (in our case, Central Bank and/or macroeconomic conditions). Using the PR model, both zero and positive counts can be generated by a Poisson process like (1). In addition, zeroes arise with probability ψ from a second process. In this process, ψ is a function of characteristics $\mathbf{x}_i$. In the Zero Inflated Poisson (ZIP) model, ψ is determined by either a logit or probit models: $\psi = F(\mathbf{z}_i\gamma)$, where F is the Normal or the Logistic cumulative density function, respectively. The $\mathbf{z}_i$ variables may the same as the $\mathbf{x}_i$ variables and it is our case[5].

Combining the Poisson count model and the binary process for the ZIP model, we have

$$\Pr[y_i = 0|\mathbf{x}_i] = \psi_i + (1-\psi_i)\exp(-\mu_i), \tag{16}$$

$$\Pr[y_i|\mathbf{x}_i] = (1-\psi_i)\frac{\exp(-\mu_i)\mu^{y_i}}{y_i}, \mathrm{y} > 0. \tag{17}$$

The Zero Inflated Negative Binomial Regression Model (ZINB) is created using (7) and the corresponding adjustments.

Greene (1994) shows that $E[y_i|\mathbf{x}_i, \mathbf{z}_i] = (0 \times \psi_i) + [\mu_i \times (1-\psi_i)] = \mu_i - \mu_i\psi_i$. It is clear that the the conditional mean of the model has been changed lowering the expected count by $\mu\psi$. The conditional variance is also changed. For the ZIP model: $var(y_i|\mathbf{x}_i, \mathbf{z}_i) = \mu_i \times (1-\psi_i)(1+\mu_i\psi_i)$ and for the ZINB: $var(y_i|\mathbf{x}_i, \mathbf{z}_i) = \mu_i(1-\psi_i)[1+\mu_i(\psi_i+\alpha)]$. If $\psi = 0$ we retrieve the standard PR model. Otherwise, the variance exceeds the mean. For $\psi > 0$, the dispersion is greater than for the standard NBR model.

The likelihood function is $L(\beta, \gamma|y, x, z) = \sum_{i=1}^{N} \Pr[y_i, x_i, z_i]$. The β parameters are interpreted in the same way as the parameters in the PR model and the NBR model, and the γ parameters are interpreted in the same way as the parameters in a probit or logit models. A positive coefficient in the binary process increases the probability of being in the group where the probability of a zero count is one. Regarding the predicted probabilities, for the ZIP model, they are: $\widehat{\Pr}(y = 0|\mathbf{x}) = \widehat{\psi} + (1-\widehat{\psi})\exp(\widehat{\mu})$, where $\widehat{\mu} = \exp(\mathbf{x}\widehat{\beta})$ and $\widehat{\psi} = f(\mathbf{z}\widehat{\gamma})$. Therefore, $\widehat{\Pr}(y = m|\mathbf{x}) = (1-\widehat{\psi})$ times (4). In the case of the ZINB model: $\widehat{\Pr}(y = 0|\mathbf{x}) = \widehat{\psi} + (1-\widehat{\psi})\left(\frac{\widehat{\alpha}^{-1}}{\widehat{\alpha}^{-1}+\widehat{\mu}_i}\right)^{\widehat{\alpha}^{-1}}$ and the $\widehat{\Pr}(y = m|\mathbf{x}) = (1-\widehat{\psi})$ times (15).

[4] The distinction between both groups is a form of discrete unobserved heterogeneity; see Long (1997).

[5] The parameters in the binary model are assumed to be a scalar multiple of the parameters in the count model.

4. Empirical Evidence

This section describes the data used as well as the results of the estimations obtained using the models described in the previous section.

4.1 Data Analysis

Peru suffered from a hyperinflation process by the end of the 1980s, but it successfully stabilized its economy by mid-1990s.[6] A number of structural economic reforms were introduced during the first part of the 1990's, namely financial system liberalization (including a pension fund reform), trade openness, reinsertion in the international financial system, tax-system reform, sound and prudent monetary and fiscal policies, investments promotion and, in general, more market-oriented policies throughout the economy. Building upon new trends in macroeconomic variables by the late 1990's, Peru started to use money-aggregates targeting with explicit (but not yet binding) preferred inflation rates in 1994. By 2002, Peru formally adopted a fully-fledged inflation-targeting regime.

The data in this study has a weekly frequency and spans the period from the first week of January 2001 to the last week of 2010. We provide a brief description of the behavior of the following variables: the number of interventions per period (which is the dependent variable), the exchange rate's deviation or cycle, the Embig spread, and the spread between currencies in prime corporate and interbank interest rates[7]. We selected weakly frequency given the fact that the Directory of the BCRP has one meeting by week in which many decisions are taken and in particular, decisions of movements in the interest rate and intervention in the Forex market are taken into account. It is a principal reason why weakly frequency has been selected[8].

Table 1 shows the number of interventions of the BCRP in the Forex market both in purchases as in sales. Observing the purchases, the number of no interventions

6 For an account of inflation dynamics in Peru see Castillo, Humala, and Tuesta (2006).

7 We also used the variance of the exchange rate as an explanatory variable in the regressions. However, it is an explicit announced goal of the intervention policy of the BCRP. Given it, simultaneous or endogenous bias may be present in the estimations. Findings shown that including this variable affects the significance and sign of the other variables. We decided to exclude from the regressions.

8 Other frequency may be used, for example, bi-weekly, monthly. Of course, data intervention frequency also changes. We performed estimations for other frequencies of data and the results are very similar. We prefer keep weekly frequency for two reasons: first, the dependent variable is well bounded between 0 and 5 interventions by week; and second, because the BCRP has weekly meetings where decisions about monetary policy are taken. It is true that decisions about interventions in the Forex market are taken daily but many explanatory variables are not available at this frequency in Peru and also because daily data reduces analysis to a probit or logit analysis because in this case the dependent variable is binary. We think the present methodology is an advance in this way. Binary and frequency equations will be estimated jointly when we will use the named Zero Inflated regression models.

(zero interventions) by the BCRP are around the half of the total number of observations ($T = 522$). The other half of observations is increasingly divided in the range of interventions from 1 to 5. We observe that the BCRP has acted in the Forex market in a increasing way. While the number of one or two interventions by week is around 6%, interventions of higher magnitude (4 or 5) have been done in around 12%–15% of the sample. It implies an active role in the Forex market purchasing foreign currency at least in what is concerned with the half of the total of observations. In the case of sales, the numbers of Table 1 indicate an opposite panorama. The BCRP has not intervened in the Forex market in almost 93% of the sample size, that is, it is around 484 weeks where the BCRP did not intervene in the Forex market in terms of selling foreign currency. When the BCRP decided to intervene, these interventions were very small, around 2%. The values presented in the Table 1 are not surprising given that in the sample we are analyzing, the BCRP was confronted with situations related to purchases more than sales of foreign currency. Furthermore, the evidence is important because it indicates the importance of the number of zeros in the sample, that is, the number of no interventions by the BCRP in both cases. It is more obvious, of course, in the case of sales of the foreign currency. However, we think, that the high presence of zero values will imply the importance of the estimation of the named Zero Inflated Regression (ZIR, hereafter) models (see below).

Table 1

Intervention in the Forex Market: Purchases and Sales by Week

Number of Interventions by Week	Purchases		Sales	
	(absolute)	(%)	(absolute)	(%)
0	274	52.49	484	92.72
1	27	5.17	7	1.34
2	33	6.32	9	1.72
3	48	9.20	11	2.11
4	62	11.88	10	1.92
5	78	14.94	1	0.92

The behavior of the log of the exchange rate and of exchange rate interventions throughout the analyzed period clearly indicates that intervention ceases to be sporadic and becomes a frequently used instrument. This reinforces the idea of intervention in the Forex market as an instrument of monetary policy. The highest incidence of intervention is around the year 2005. It appears that interventions have become more common as the exchange rate has undergone appreciation.

It is clear that during the financial crisis the economic agents needed dollars to cover their positions. Facing this excess demand, BCRP decided to provide dollars to the banking system that was having difficulties in renewing its credit lines. In this way, dollar sales increased and the exchange rate fell. A different scenario took place in the previous period, where BCRP purchased dollars in order to hinder the entrance of speculators that were pushing the exchange rate lower.

Figure 1 illustrates the values presented in Table 1. It indicates that the purchases intervention (solid line) occurs frequently, whereas the sales intervention (dotted line) seldom takes place. Currency sales have taken place in only four periods: April 2001, September 2002, late 2005 to early 2006, and finally during the financial crisis of mid-2008. On the other hand, currency purchases encompass longer periods ranging from 2003 to late 2005, and from mid-2006 to right before the financial crisis. Since early 2009 purchases begin to recover and reach a higher frequency in 2010.

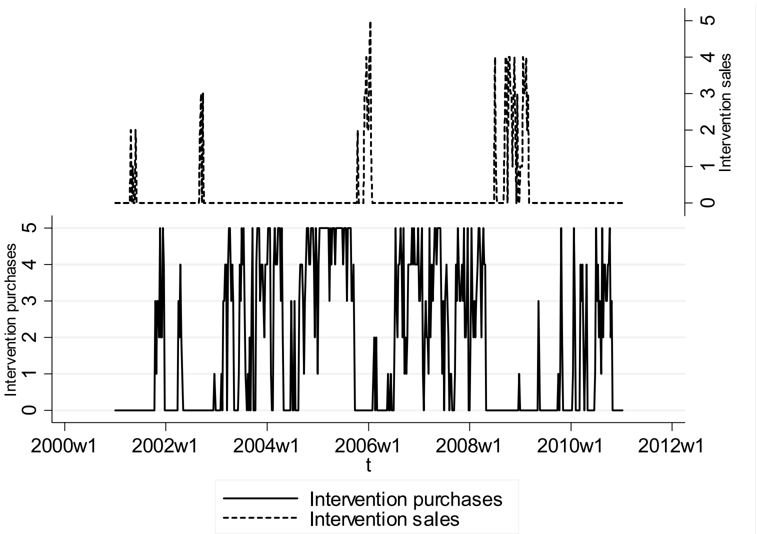

Figure 1: Weekly Interventions in the Forex Market

We now may describe briefly some of the our explanatory variables. The deviations of the logarithm of the exchange rate with respect to its long term trend have been calculated assuming a linear trend. Positive deviations indicate that the exchange rate is having a higher value than average depreciation (long term trend), which would prompt BCRP to react with foreign exchange sales. In the opposite scenario, BCRP intervenes in the Forex market by purchasing foreign currency. Deviations from the log of the exchange rate have also been calculated by using the filter proposed by Hodrick and Prescott (1997) in order to assess for sensitivity to this variable. Results do not show different results.

The Embig spread is a country risk indicator, which can determine an inflow or outflow of dollars. For instance, if Embig increases, an outflow of dollars occurs which leads to an increase in the exchange rate. In this case, BCRP will engage in foreign currency sales in order to stem this depreciation. Moreover, it is frequent for this indicator to rise during electoral periods. In this sense, it is proposed that an increase in Embig will have a positive effect on foreign exchange sales and a negative effect on foreign exchange purchases.

The spread of prime corporate indicates inflows or outflows of short-term foreign capitals. If domestic short-term interest rate is larger than foreign short-term interest rate, it implies an inflow of external capitals which implies that the price of foreign currency decreases. It indicates that number of purchases should increase. In other words, if the spread of prime corporate increases, then purchases also do it.

Regarding the spread of interbank interest rates, it provides an indicator of devaluation expectations. The difference between the interest rate in domestic and foreign currency will be covered by expected devaluation. Thus, an increase in the spread is an indicator of a possible increase in devaluation expectations. This results in an increase in the expected foreign exchange sales or decrease of purchases. Therefore, increases in spread of interbank interest rates implies a decrease of purchases of foreign currency.

We also include the purchasing amount (current and lagged) as an explanatory variable. It is important because big amount of purchases one day of the week may imply smaller amounts of purchases the next day of intervention. The viceversa situation may occur too.

It is worth to note that other explanatory variables would be useful. For example, authorities could have been focused on maintaining a robust reserve buffer against contingences that may emerge from external shocks. An interesting variable may be the difference between net international reserves froms its precautionary level. The "optimal" reserve amount could be calculated using some of the recommendations of Jeanne and Ranciere (2006). This variable is not available in the desired frequency. Furthermore, Peruvian economy, given the amount of purchases during the sample analyzed argues in favor of an accumulation of reserves implying a high level of reserves[9]. Another interesting variable could be something named "inflation surprises", given by the difference betwen inflation in a given month and what the market was expecting or deviation of inflation from a target. This variable is not available in a wekly frequency.

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9 It is worth to mention that the level of dollarization in the Peruvian financial system for our sample period has decreased from around 70% in 2010 until 37% in 2010. Therefore, we consider that level of dollarization of the Peruvian economy is not longer a big issue.

4.2 Estimations

In the following lines, the analysis of the determinants of purchases and sales of foreign currency is presented separately. First, we analyze the determinants of the respective frequencies of intervention (purchases and sales). Second, a brief analysis of the levels of intervention is also provided. In the following Tables the coefficients are provided with their respective p-values shown in parentheses.

4.2.1 Foreign Exchange Purchases

Table 2 shows the results of the estimations of the PR and NBR models for the number of Forex purchases. Two models are estimated for each one of them and the difference is the inclusion or exclusion of the constant term which is not statistically significant, except for the NBR (III) model. The models are denoted by I and II for the PR models and III and IV for the NBR models, respectively. The NBR models presents similar although slightly higher coefficients (in absolute value) in comparison with the PR models. Although the dispersion parameter is not very high, it is statistically significant and consequently overdispersion test suggests statistical validation of the NBR models.

Both models give results according to the theoretical expectations or according to what economic theory suggests and the findings support our initial assertions with respect to the effect of explanatory variables. Both models show that lagged purchases affect current purchases with a coefficient indicating around a 37%–40% of persistence indicating short memory. The Embig spread affects negatively the frequency of the foreign exchange purchases. Same type of effect is shown by the spread interbank interest rates. If the country risk is higher, it acts as an indicator of capital flights which press to an increase in the foreign exchange rate. Therefore, frequency of purchases of foreign exchange rate must decrease or reduce in order to avoid a devaluation of the domestic currency. On the other hand, (assuming) that the spread prime corporate implies that foreign investment are more profitable, it mays induce an entering of foreign capitals creating an excess of foreign currency on the market. In order to avoid a decrease in the price of the foreign currency, the frequency of purchase interventions should increase.

Another significant explanatory variable is the deviations of the foreign exchange rate from its long-run trend. This variable has a negative impact indicating that when cycle is positive, that is, foreign exchange rate is above its long-run trend, the number of frequencies to intervene purchasing in the Forex market decreases to avoid that the value of the foreign currency continues to increase.

In order to note the relationship between the frequencies of purchasing and the amount of purchasing, this last variable has also been included as explanatory variable. We include current and past values of this variable. The coefficient of the current and past purchasing amount is very small but statistically significant in both cases and for all models. The lagged or past purchasing amount has a negative

Table 2

Regression of Foreign Exchanges Purchases

Variable	PR		NBR	
	Model I	Model II	Model III	Model IV
First lagged purchases	0.372	0.387	0.384	0.399
	(0.000)	(0.000)	(0.000)	(0.000)
EMBIG spread	–0.143	–0.184	–0.145	–0.194
	(0.001)	(0.000)	(0.003)	(0.000)
Spreads of prime corporate	0.168	0.182	0.181	0.191
	(0.000)	(0.000)	(0.001)	(0.001)
Spread interbank interest rates	–0.129	–0.224	–0.151	–0.242
	(0.001)	(0.000)	(0.001)	(0.000)
Purchasing amount for negotiation	0.001		0.001	
	(0.000)		(0.000)	
First lagged Purchasing amount		–0.001		–0.001
		(0.001)		(0.003)
Foreign exchange rate's cycle	–12.747	–20.881	–14.973	–22.565
	(0.006)	(0.000)	(0.009)	(0.000)
Constant	–0.238	0.105	–0.285	0.098
	(0.101)	(0.452)	(0.078)	(0.521)
α			0.092	0.100
LR test of $\alpha = 0$ (p-value)			0.016	0.022

impact in the current foreign exchange purchases. It indicates that big amounts of purchasing in the previous week implies a reduction in the number or frequency of interventions of purchasing foreign exchange currency in the current period. At the same time, current amount of purchasing in the same period has a positive impact indicating an increase in the frequency of interventions, perhaps suggesting that decision to purchase big amounts should be done in various days and not in only one. It is worth noting that both impacts are very small but statistically significant. Their signs are opposite suggesting a cancellation in the total effect of both variables on the frequency of purchasing foreign exchange currency.

Table 3 shows the results of three selected Zero Inflated Regression (ZIR hereafter) models. As previously described, the ZIR method allows the calculation of an event's occurrence as the result of two processes: a binary process (Logit) that calculates whether an intervention takes place or not, and another process (count) that calculates the number of interventions. Initially, the ZIR regression is run including all explanatory variables, in order to discern which ones are related to the decision to intervene and which ones to the number of interventions.

A first glance at the results reveals that the exchange rate cycle, the spread interbank interest rates, and the lagged purchases are significant in the Logit process. This means that the decision to intervene is influenced by these three variables. On the other hand, the decision to intervene is very seldom influenced by the other variables. In general, as foreign exchange purchases are more frequent, the decision of the magnitude of intervention could be more complex than the decision of whether to intervene.

Table 3

Regression of Foreign Exchanges Purchases: Zero Inflated Regression Models

Variable	Model V	Model VI	Model VII
First lagged purchases	0.111 (0.000)	0.113 (0.000)	0.118 (0.000)
EMBIG spread	–0.063 (0.238)	–0.069 (0.170)	
Spreads of prime corporate	0.151 (0.044)	0.124 (0.011)	0.078 (0.013)
Spread interbank interest rates	–0.037 (0.508)		
Purchasing amount for negotiation	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)
Foreign exchange rate's cycle	–5.493 (0.340)		
Constant	0.804 (0.000)	0.823 (0.000)	0.645 (0.000)
Binary Equation: Probability of no Intervention			
First lagged purchases	–1.276 (0.000)	–1.279 (0.000)	–1.272 (0.000)
EMBIG spread	0.305 (0.085)		0.188 (0.082)
Spreads of prime corporate	–0.202 (0.315)		
Spread interbank interest rates	0.580 (0.003)	0.591 (0.000)	0.488 (0.005)
Foreign exchange rate's cycle	84.117 (0.007)	90.522 (0.004)	90.736 (0.005)
Constant	0.183 (0.724)	0.966 (0.001)	0.429 (0.329)

A positive coefficient in the count (regression) process means that the associated variable increases the expected number of purchase interventions. On the other hand, a positive coefficient in the Logit estimation means that the variable increases the probability of zero interventions (no interventions). Therefore, we expect coefficients with opposite signs in each process.

Figure 2a shows the fitted frequencies values for the PR, NBR and ZIR models, respectively[10]. The PR and NBR models appear to give similar predictions respect to the number of expected frequencies of intervention. What we observe is that both models fit well when the monetary authority intervenes three times in the week, and there also are good performance for 2 and 4 number of interventions. The major discrepancy in the estimations is when there are 0, 1 and 5 interventions by week. Both models underestimate the number of interventions when there are 0 and 5 interventions by week. For example, for zero interventions, the observed data indicates around a 50% of the times while the estimated models predict around 40%. When the Central Bank intervenes five times in the week, it does it in around 12% while the estimated models predict around 15%. On the other side, both models overestimate the number of frequencies when there is one intervention by week. The best performance is given by the ZIR models. The prediction of counts is very close to the observed counts with slightly differences when there are 5 interventions by week.

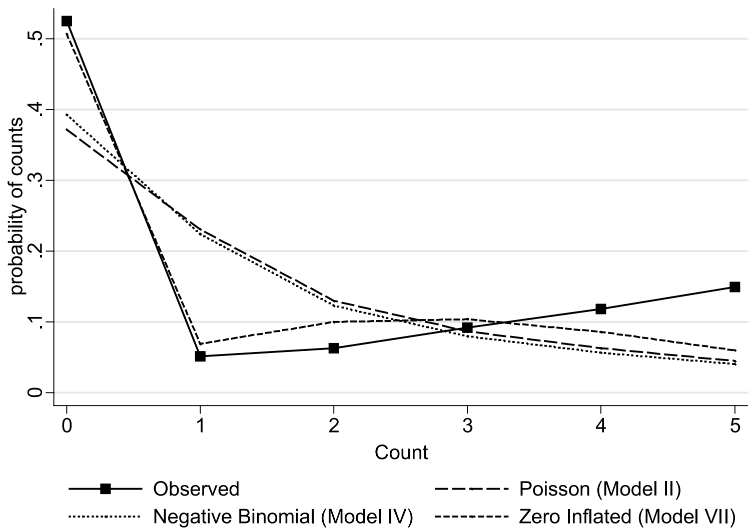

Figure 2a: Probability of Counts of Intervention in the Forex Market Purchases: Observed, Poisson, Negative Binomial and Zero Inflated Regression Models

[10] We estimated two PR models, two NBR models and three ZIR models. However, given similar performance between each type of models (an in order to be clear in the Figures), we only present one of each type of models.

Figure 2b shows similar information but given in the form of difference between the observed frequency value and the respective estimated or expected frequency given for each model. In general, observing Figure 2b, the PR and the NBR models have bad predictions in around 10% to 18% (in absolute value). Notice that in both cases these values are not high and consequently we may affirm that both models do a good job in the prediction of the expected value of the frequencies of intervention in the foreign exchange rate purchases. However, the performance of the ZIR models is the best. In Figure 2b, we observe that the differences between observed frequency of purchase intervention and the expected or estimated respective frequency are the smallest compared to the PR and NBR models. This indicates a better performance of these models. For zero interventions, the model predicts almost same probability: 50%. The largest difference is when there are five interventions but the value is small. For two interventions the error is around 3% while that for 4 or 5 interventions, it is around 4% and 8%, respectively.

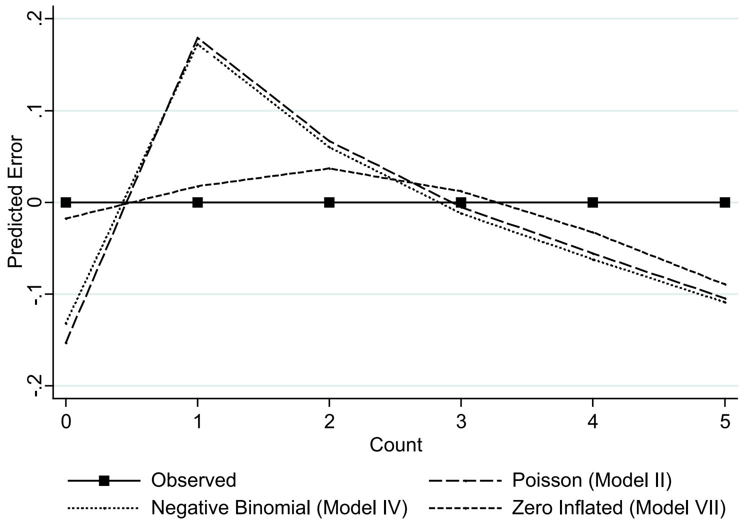

Figure 2b: Difference in Probability of Counts of Interventions in the Forex Market Purchases: Poisson, Negative Binominal and Zero Inflated Models

As previously mentioned, the coefficients obtained in the preceding regressions cannot be interpreted in the conventional way. Table 4 indicates that each coefficient is to be understood as the percentage change that would arise in the expected intervention if an explanatory variable increases by an amount equal to its standard deviation[11]. A standard deviation was chosen as the variation level, since this allows

[11] Other variations or ways to interpret the coefficients are possible, of course.

to know which effect would usually arise in interventions. Furthermore, it allows for comparisons between the effects of different variables in order to establish which is higher.

Table 4 makes clear that the main determinant of changes in intervention is the first lag of the number of purchases. Spreads have lower but still considerable effects. Thus, the Embig spread has a standard deviation of 1.96%, slightly lower than the spreads of prime corporate and interbank interest rates (2.28% and 2.26%, respectively) and it implies that the frequency of purchasing foreign exchange currency decreases in the range of 24% until 32%, according to which model we are

Table 4

Interpretation of the Regression Coeficients of the Number of Foreign Exchanges Purchases

Variable	PR		NBR		ZIR	
	Model I	Model II	Model III	Model IV	Model VI	Model VII
First lagged purchases	111.60%	118.00%	116.70%	123.80%	25.70%	27.00%
	(2.016)	(2.016)	(2.016)	(2.016)	(2.016)	(2.016)
EMBIG spread	–24.50%	–30.40%	–24.80%	–31.70%	–12.70%	
	(1.961)	(1.961)	(1.961)	(1.961)	(1.961)	
Spreads of prime corp orate	46.90%	51.40%	51.20%	54.80%	32.80%	19.50%
	(2.280)	(2.280)	(2.280)	(2.280)	(2.280)	(2.280)
Spread interbank interest rates	–25.30%	–39.80%	–28.90%	–42.20%		
	(2.264)	(2.264)	(2.264)	(2.264)		
Purchasing amount	19.50%		22.40%		13.40%	14.20%
	(167.628)		(167.628)		(167.628)	(167.628)
First lagged Purchasing amount		–10.90%		–11.00%		
		(167.574)		(167.574)		
Foreign exchange rate's cycle	–9.90%	–15.70%	–11.50%	–16.80%		
	(0.008)	(0.008)	(0.008)	(0.008)		
Binary Equation: Probability of no Intervention						
First lagged purchases					–92.40%	–92.30%
					(2.016)	(2.016)
EMBIG spread						44.70%
						(1.961)
Spread interbank interest rates					281.00%	201.70%
					(2.264)	(2.264)
Foreign exchange rate's cycle					109.30%	109.60%
					(0.008)	(0.008)
α			0.092	0.100		
LR test of $\alpha = 0$ (p-value)			0.016	0.022		

observing. In the case of the spread of interbank interest rates, an increase of one standard deviation (2.264) implies a decreasing of between 25% until 42% in the expected number of purchases. In the case of the purchased amount in the previous week, it indicates that if it increases by one standard deviation (167.28), then the expected number of purchases the next week will be decreased in around 11%. If the purchased amount increases in the current period, then the expected number of purchases increases in around 20%.

In the case of the ZIR models, the existence of two processes implies a more complex interpretation. For example, if lagged frequency of purchases increase in 2.016, it has two effects. The first effect is that the probability of no intervention decreases in around 92%, that is, the BCRP is more tempted to intervene in the Forex market. At the same time, the increase of the standard deviation implies an increase of around 25%–27% in the expected number of purchases, that is the expected number of intervention increases by these values. Another example is using the spread of the interbank interest rates. Increases in standard deviation of this variable implies an increase of around 200%–280% in the probability of no intervention in the Forex market. It is consistent because if standard deviation of the spread of interbank interest rate increases it means that there are more inflow of foreign capitals and foreign currency has less value and the BCRP should intervene. It is the reason why the probability of no intervention increases a lot. However, this variable is not significant to explain the (positive) number of interventions. On another hand, if the standard deviation of the cycle of the foreign currency increases, it means that price of foreign currency is higher than its long-run value which implies an increases of around 110% of the probability of no intervention by the BCRP. In other words, there is almost not doubt (as in the previous case) that the BCRP will intervene in the Forex market to stabilize this situation. This variable, however, is not statistically significant to explain the (positive) number or frequency of purchases in the Forex market.

4.2.2 Foreign Exchange Sales

In the analysis of the frequency of sales in the Forex market, we follow a similar path to the performed for the purchases. Table 5 shows estimates of two models for the PR model and two models for the NBR model. A first insight from this Table is the fact that the coefficient of adversion is larger than in the cases of purchases and highly statistically significant. Both models suggest coefficients with similar magnitude. The first lagged sales indicates a level of persistence between 53% to 69%. It is interesting because the memory measure for sales is larger than for purchases even when our sample is characterized for a scarce number of sales compare to purchases. It indicates that when the Central Bank sales dollars it does it more persistently. The variables Embig and the spread of interbank interest rates present a positive sign in agreement with expectations or economic theory. Both measures are indicators of risk country. Given more risk country there are an ouflow of capitals which press to an increase in the price of the foreign currency. Central Bank should be enter to the Forex market to sale to decrease the velocity at which the price of the dollar is increasing. The spread prime corporate of interest rates show a negative sign. High value of this variable suggests an increase in the expectations of devaluation of the foreign currency. Against it, the Central Bank enters to the Forex market to sale to avoid a devaluation of the foreign currency.

As in the case of purchases, we have introduced the amount of sale as an explanatory variable. Either if this variable enter in the current or past period, its sign is positive indicating that if the monetary authority, for example, sales a big amount of foreign currency, then the frequency of sales intervention in the same period or next period will be increased. However the magnitude is close to the case of purchases, that is, it is very smaller.

Finally, the cycle of the foreign currency shows a strong value with positive sign statistically significant. It means that when the foreign currency value is above its potential value, Central Bank should enter selling in the Forex market to avoid that price still increase.

Table 5

Regression of Foreign Exchanges Sales

Variable	PR		NBR	
	Model I	Model II	Model III	Model IV
First lagged sales	0.525 (0.000)	0.679 (0.000)	0.539 (0.000)	0.690 (0.000)
EMBIG spread	0.139 (0.130)	0.292 (0.000)	0.356 (0.012)	0.360 (0.022)
Spreads of prime corporate	–0.295 (0.003)	–0.465 (0.000)	–0.279 (0.059)	–0.533 (0.001)
Spread interbank interest rates	0.241 (0.000)	0.272 (0.000)	0.179 (0.055)	0.470 (0.000)
Sales amount for negotiation	0.001 (0.003)		0.006 (0.000)	
First lagged Sales amount		0.001 (0.036)		
Foreign exchange rate's cycle	33.011 (0.001)	42.962 (0.000)	99.343 (0.000)	91.885 (0.001)
Constant	–2.902 (0.000)	–3.361 (0.000)	–4.526 (0.000)	–4.302 (0.000)
α			3.909	5.747
LR test of $\alpha = 0$ (p-value)			0.000	0.000

Table 6 shows same model of the previous Tables but in the form of ZIR models. Given that in our sample period, most of interventions had been purchases, there are few sales interventions determining a big number of zeros. In this case, according to the literature, a ZIR model should be more appropriate.

Let it to analyze firstly the binary equation. All variables are statistically significant. We estimated three variants of this models according to the significance in the

Table 6

Regression of Foreign Exchanges Sales: Zero Inflated Regression Models

Variable	Model V	Model VI	Model VII
First lagged sales	–0.038		
	(0.578)		
EMBIG spread	0.004		
	(0.965)		
Spreads o prime corporate	–0.126	–0.099	–0.124
	(0.176)	(0.020)	(0.002)
Spread interbank interest rates	0.023		
	(0.638)		
Foreign exchange rate's cycle	7.035		
	(0.418)		
Sales amount or negotiation	0.001	0.001	
	(0.003)	(0.001)	
First Lagged Sales amount			0.000
			(0.512)
Constant		0.720	0.955
		(0.000)	(0.000)
Binary Equation: Probability o no Intervention			
First lagged sales	–2.850	–2.753	–2.710
	(0.001)	(0.001)	(0.000)
EMBIG spread	–0.583	–0.567	–0.581
	(0.019)	(0.023)	(0.017)
Spreads o prime corporate	0.554	0.578	0 567
	(0.030)	(0.029)	(0.025)
Spread interbank interest rates	–0.844	–0.889	–0.861
	(0.000)	(0.000)	(0.000)
Foreign exchange rate's cycle	–112.15	–128.99	–118.04
	(0.030)	(0.033)	(0.021)
Constant	6.853	6.865	6.930
	(0.000)	(0.000)	(0.000)

next step. The first lagged sales suggests that if the past week Central Bank intervenes in the Forex market, then, in the current period the probability to avoid to enter in the market decreases. Similar interpretations occur for the Embig and the spread interbank interest rates. If the risk of the country is higher in the previous week, the probability to no intervention (BCRP does not move) decreases which is consistent because the Central Bank should enter in the market to act. In relation with the spread of the prime corporate, the sign is positive. If expectation of devaluation increases, it suggest that investments are more profitable here and more foreign currency enter pressing to a decreasing of its price. The sign of the variable suggests that the probability to no intervene increase. That is, the Central Bank does not intervene. It suggests some type of asymmetry of the monetary authority. It is more probable to intervene when the price of the foreign currency is going up than when it is going down[12].

The effect of the cycle of the exchange rate is negative and statistically significant. It suggests that if the current price of dollar is above its current price, the probability to no intervene decrease, that is, the Central Bank probably intervene more. It could confirm the type of asymmetry mentioned above.

In the second step of the ZIR model, three models had been estimated but we eliminated not significant variables. After the monetary authority has decided to enter in the Forex market, the variables that appear to explain the number of interventions in sales are the spread of prime corporate and the amount of sales negotiated in the current or previous week. In the first case, the spread of prime corporate, the sign is negative, suggesting that if we have an inflow of foreign currency it press to its price to down and the Central Bank enters to equilibrate the market or to avoid a loss of value of the foreign currency. In the second case, even when the effect is very small, it indicates that the amount sold in the current period or the previous week implies an increase of the frequency of interventions in the same period or the next week. However the coefficient of the amount of intervention of the previous week is not significant.

Table 7 shows interpretation of coefficients similar as Table 4. In the case of the PR and NBR models, an increase of Embig by 1.961 (standard deviation) implies an increase of 31% to 100% in the number of frequencies of sales. This is because when risk country increases, it produces an outflow of foreign capitals pressing price of foreign currency up and Central Bank must enter to sale. It is worth to note the difference between the coefficients between both models. An increase of 2.28 standard deviation in the spread of the prime corporate implies that sales decrease in around 49% to 70% according to the model estimated. In the case of the spread of interbank interest rates the effect is opposite and the reaction of the frequency of sales is between 73% and 190%. The movements in the cycle of the exchange rate implies increases in sales of around 31% to 112%.

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12 It appears to be consistent with the stylized facts. The BCRP appears to intervene more to avoid an increase of the price of foreign currency.

Table 7

Interpretation of the Regression Coeficients of the Number of Foreign Exchanges Sales

Variable	PR		NBR		Zero Infiated	
	Model I	Model II	Model III	Model IV	Model VI	Model VII
First lagged sales	51.70% (0.794)	71.50% (0.794)	53.40% (0.794)	73.00% (0.794)		
EMBIG spread	31.30% (1.961)	77.20% (1.961)	100.10% (1.961)	102.60% (1.961)		
Spreads of prime corporate	–49.00% (2.280)	–65.30% (2.280)	–47.10% (2.280)	–70.40% (2.280)	–20.20% (2.280)	–24.60% (2.280)
Spread interbank interest rates	72.50% (2.263)	85.30% (2.263)	50.20% (2.263)	190.00% (2.263)		
Sales amount for negotiation	9.80% (94.881)		81.00% (94.881)		9.40% (94.881)	
First lagged Sales amount		–8.70% (94.881)				2.2% (94.881)
Foreign exchange rate's cycle	30.90% (0.008)	42.00% (0.008)	124.90% (0.008)	111.60% (0.008)		
Binary equation						
First lagged sales					–88.80% (0.794)	–88.40% (0.794)
EMBIG spread					–67.10% (1.961)	–68.00% (1.961)
Spreads of prime corporate					274.00% (2.280)	264.30% (2.280)
Spread interbank interest rates					–86.60% (2.264)	–85.80% (2.264)
Foreign exchange rate's cycle					–65.10% (0.008)	–61.80% (0.008)
α			3.909	5.948		
LR test of $\alpha = 0$ (p-value)			0.000	0.000		

In the ZIR models (see Table 7), all variables are significant to explain the binary equation. For example, if the cycle of the exchange rate increases, the probability of no interventions decreases, that is, BCRP intervenes more. Same situation happens for the spread of prime corporate. Finally, if Embig increases, the probability of no interventions decreases and therefore the BCRP enters more in the Forex market. In the second equation only the spread of prime corporate is important (decreases the number of frequencies of sales) and also the past and current amount of sales. In both cases it implies an increase in the number of frequencies of sales.

Figure 3a shows the expected or predicted frequency value for the PR, NBR and ZIR models. We observe that all models do a good job in predicting the value of the frequencies with a slight disadvantage of the PR models. The Figure 3b shows dif-

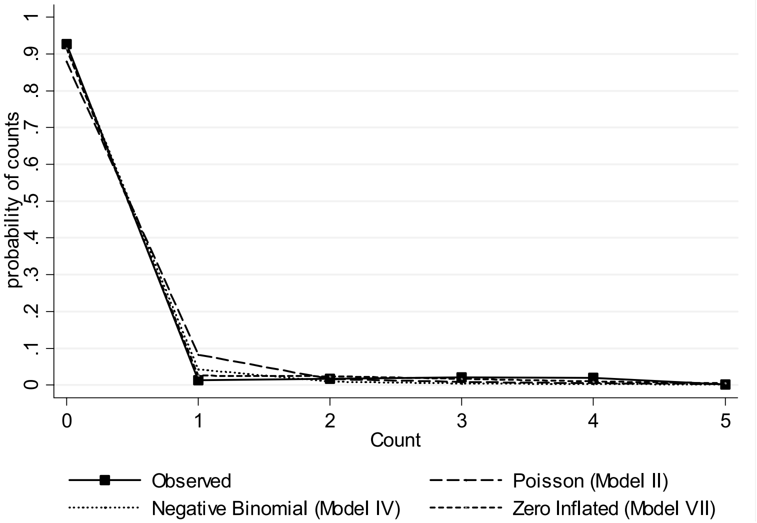

Figure 3a: Probability of Counts of Intervention in the Forex Market Sales: Observed, Poisson, Negative Binomial and Zero Inflated Regression Models

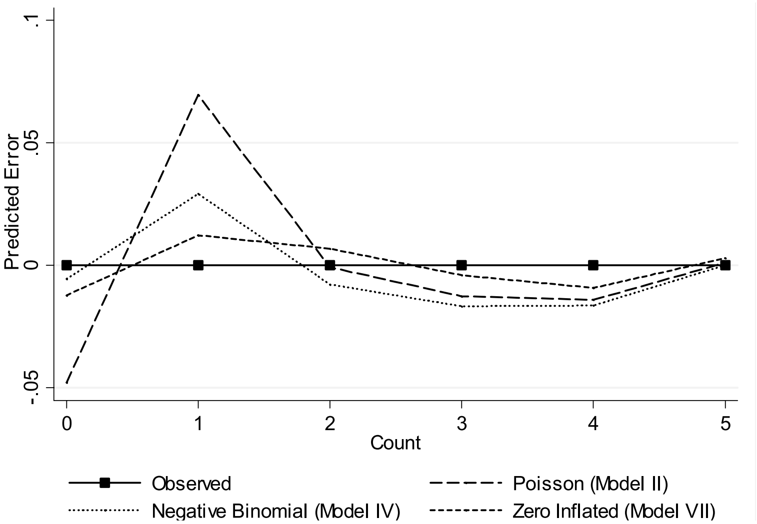

Figure 3b: Difference in Probability of Counts of Interventions in the Forex Market Sales: Poisson, Negative Binomial and Zero Inflated Regression Models

ferences between observed values and the fitted models. The NBR models do better job than PR models which predict relatively bad for zero and one interventions (around –5% and 8%, respectively). However, again, the performance of the ZIR model is the best. The results verify the excellent result of these models. Notice that the discrepancies between the observed data and the fitted values by the ZIR models is around 1% (in absolute value). It is fine because, as we argued before (and according to the literature), the ZIR models are more adequate when there are a big number of zero interventions which is the case for the Forex market sales.

4.3 Explaining the Levels of Purchases and Sales

We also performed regressions where dependent variable is the level (or amount) of purchases and sales, respectively. In order to save space, these results are not shown in the Tables but they are available upon request.

We use the same set of explanatory variables as in the previous analysis. In the case of the level of purchases of foreign currency the determinants are the same as in the case of the frequencies. The signs are consistent with the economic theory and their interpretation is similar as in the frequency analysis. We experimented introducing the frequency of interventions as an explanatory variables. In this case, the adjustment of the equation is notably high but the spread of the prime corporate and deviations of the exchange rate respect its long-run trend turn to be not significant. The frequency of interventions is highly significant, with a coefficient close to unity and this variable is the responsible for the increase in the R^2 of the regression. In summary, more level of purchases are closely related to more frequencies of intervention in the Forex market whic appear to be obvious. The frequency or count variable appears to absorbe a great percentage of the explanation of the level of purchases. Therefore, explaining frequency or number of purchases by week is very closely or likely to explain the levels of purchases by week. The coefficient close to unity indicates that if the number of intervention increases in one unity there is almost a proportional or equal response in the amount of purchases.

In the case of the level of sales, a very similar issue occurs. All explanatory variables used in the count models are also significant and with a consistent sign with economic theory. When number of sales (by week always) is introduced as a regressor, this variable allows that regression increases its R^2 from 30.7% to 91.9%, a similar result as in the case of purchases. However, the variable named cycle of the exchange rate loss significance. The coefficient of the number of interventions is positive indicating that more interventions by week, more level of sales which is also obvious. The magnitude of the coefficient, however, is larger than unity (around 1.49 with a interval of confidence of 1.44 – 1.54) indicating that if number of sales increases in one unity, the amount or level of sales increases in 1.5 times.

5. Conclusions

The latest financial crisis showed that inflation is not the only concern of Central Banks. When policy interest rates reach their lower bound, Central Banks resort to other unconventional instruments like reserve requirements or interventions in the Forex market.

Intervention in the Forex market is a feature of the Peruvian exchange rate regime of intermediate or administered floating. Among the reasons for this are the high costs that frequent deviations in the exchange rate impose on trade and the real economy, especially in emerging economies like ours. In the last 6 years, there has been an increase in the frequency of foreign exchange interventions.

The determinants of the frequency of Central Bank interventions (purchases and sales) in the Peruvian exchange rate market are analyzed using weekly data for the period from January 2001 to December 2010 using count data models. Three kind of models have been estimated: Poisson, Negative Binomial and Zero Inflated regression models, respectively.

Findings show that the deviations of the logarithm of the exchange rate with respect to a long term trend, previous week's interventions (persistency), the Embig spread, the spread between interbank interest rates, and the spread prime corporate interest rates are the principal determinants of the frequency of interventions in the Forex market.

Particularly, it has been shown that, although foreign exchange purchases and sales are related to each other, they may have differing behaviors. Additionally, explanatory variables do not have the same effect on them, neither in sign nor in magnitude. The performance of the three kind of models is good. However, given the number of zeroes in purchases (50%) and sales (93%), the ZIR models appear to be more appropriate. Findings show that this type of model presents a better fit of the predicted frequencies compared to the observed ones. The ZIR models are also more richer because they imply two decision process: first, a binary equation where the BCRP decides to intervene or not in the Forex market; second, the decision (given that BCRP decided to intervene) of the number of interventions in the Forex market.

A brief analysis of the level (scale) of interventions (purchases and sales) has been also provided. Of course, we find a close relationship between the level of interventions and the number of frequencies of intervention. Basically, the same variables that influence the number of interventions also determine the levels of intervention.

Other explanatory variables could be included in the analysis, as for example differences respect a target of reserves (even when the BCRP has not a target for the level of reserves), differences in expectation of inflation, among others. However, we select variables according to availability of information in the frequency analyzed. Further, we opted for using count models because they are appropriate in this case and also because, at least to our knowledge, this type of modelling has not been performed in the literature (at least for emerging countries or in particular Latin American countries).

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