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PALABRAS CLAVE: Intervención Cambiaria, Frecuencia de Intervención, Modelos de Conteo, Tipo de Cambio, Spread de Tasas de Interés.

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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. Results 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 of prime corporate and interbank interest rates, and the spread between interest rate in domestic and foreign currency are important determinants.

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

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

Resumen

En este documento se analizan los determinantes de la frecuencia de intervención del Banco Central de Reserva en el mercado cambiario Peruano (compras y ventas). Se usan datos en frecuencia semanal para el periodo Enero 2001 hasta Diciembre 2010 usando la metodología de modelos de conteo. Los resultados muestran que las desviaciones del logaritmo del tipo de cambio respecto de su tendencia de largo plazo, las intervenciones del periodo anterior (persistencia), el spread medido por el Embig, el spread entre las tasas de interés bancarias, y el spread entre las tasas de interés doméstica y foránea son importantes determinantes.

Palabras Claves: Intervención Cambiaria, Frecuencia de Intervención, Modelos de Conteo, Tipo de Cambio, Spread de Tasas de Interés.

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

Explaining the Determinants of the Frequency of Exchange Rate Interventions in Peru using Count Models[1]

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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 market.

Intervention in the foreign exchange 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 the 10th, 2009) and net daily sales of US$ 443.8 million (on October the 2nd, 2008).

The aim of this document is to analyze the main determinants of the frequency of interventions in the foreign exchange market by the Peruvian Central Bank (BCRP) using count data models. According to BCRP's statements, foreign exchange 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 foreign exchange market.

The economic issue to be discussed has empirical relevance, since this kind of analysis has not been performed in Peru previously. The contri-

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bution of this work resides in finding the main variables that explain the frequency of foreign exchange 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 non conventional measures as instruments of monetary policy.

The document analyzes the number of weekly foreign exchange interventions for the period covering January 2001 until December 2010. Among the set of explanatory variables are: exchange rate volatility, a measure of the deviation of the exchange rate from its long term trend, interest rate spreads (as a measure of risk), and other indicators of foreign exchange market conditions. 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.

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 foreign exchange 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 foreign exchange 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.

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.

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).

In this respect, Arena and Tuesta (1999) state that exchange rate intervention can be explained by the existence of "bandwagon effects" in the foreign exchange 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.

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 exchange rate 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.

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.

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).

On the other hand, Echevarría, 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.

Finally, Humala and Rodríguez (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.

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, exchange rate volatility, 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 foreign exchange 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 currency in the exchange 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 Model (PRM) and the Negative Binomial Regression Model (NBRM). 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 Possion 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 assumming that the events are independent.

Let y be a random variable indicating a number of times that an event has ocurred 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 $y = 0, 1, 2...$; where the parameter μ can be thought as the expected count[3].

In the PRM, 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 variavle y, in our case, is the number of times (by week) that the BCRP intervens in the exchange rate market. As in the Poisson distribution, in the PRM 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 this model, the likelihood function is

$$\begin{aligned} L(\beta|y, \mathbf{x}_i) &= \Pi_{i=1}^N \Pr(y_i|\mu_i) \\ &= \Pi_{i=1}^N \frac{\exp(-\mu_i)\mu_i^{y_i}}{y_i!}, \end{aligned} \tag{2}$$

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 predited probabilities which are based on the formula:

$$\widehat{\Pr}(y = m|\mathbf{x}) = \frac{\exp(-\widehat{\mu})\widehat{\mu}^m}{m!}. \tag{3}$$

[3]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 interpretation. 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 interpretation, the coefficients will represent the percentage change in expected intervention when the independent variables have a change equal to their standard deviation.

One explanation for the failure of the Poisson distribution to fit the observed data 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 PRM rarely fits in practice. If the mean structure is correct, but there is overdisperssion, Gourieroux et al. (1984) show that the estimates of the PRM are consistent but inefficient. Furthermore, Cameron and Trivedi (1986) argue that the standard errors are biased downwards, resulting in spuriosly large z-values.

The NBRM 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 PRM, where the mean is known, in the NBRM, 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 thougth as another source of randomness. In the PRM, variation in μ is introduced trough observed heterogeneity. In the NBRM, 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 $\widetilde{\mu}_i = \exp(\mathbf{x}_i\beta)$ $\exp(\epsilon_i) = \mu_i \exp(\epsilon_i) = \mu_i\delta_i$, where $\delta_i = \exp(\epsilon_i)$. An assumption in the

NBRM 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 PRM, that is, $E(\widetilde{\mu}) = E(\mu_i \delta_i) = \mu_i E(\delta_i) = \mu_i$.

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

$$\begin{aligned} \Pr(y_i|\mathbf{x}_i, \delta_i) &= \frac{\exp(-\widetilde{\mu}_i)\widetilde{\mu}_i^{yi}}{yi!}, \\ &= \frac{\exp(-\mu_i\delta_i)(\widetilde{\mu}_i\delta_i)^{yi}}{y!}. \end{aligned} \tag{4}$$

We need to compute the distribution of y given only $\mathbf{x}$, that is, $\Pr(y_i|\mathbf{x}_i) = \int\limits_0^\infty [\Pr(y_i|\mathbf{x}_i, \delta_i) \times g(\delta_i)] d\delta_i$. 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 $\Gamma(v) = \int_0^\infty t^{v-1} e^{-t} dt$.[4] Following Cameron and Trivedi (1986), the equation for the NBRM is

$$\Pr(y_i|\mathbf{x}_i) = \frac{\Gamma(y_i + v_i)}{y_i!\Gamma(v_i)} \left(\frac{v_i}{v_i + \mu_i}\right)^{v_i} \left(\frac{\mu_i}{v_i + \mu_i}\right)^{y_i}. \tag{5}$$

The expected value of y for NBRM is the same as in the PRM but the variance differs:

$$\begin{aligned} var(y_i|\mathbf{x}) &= \mu_i \left(1 + \frac{\mu_i}{v_i}\right), \\ &= \exp(\mathbf{x}_i\boldsymbol{\beta}) \left(1 + \frac{\exp(\mathbf{x}_i\boldsymbol{\beta})}{v_i}\right), \end{aligned} \tag{6}$$

where since μ and v are positive, the conditional variance of y in the NBRM must exceed the conditional mean $\exp(\mathbf{x}_i\boldsymbol{\beta})$. The literature shows that increasing variance in the NBRM allows to have better fit in comparison with the PRM. However the variance in (6) is not identified and the problem is that is v varies with the individuals. In order to simplify notation and calculation, the literature has adopted the asumption 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 incresing α we increase the conditional variance of y. Therefore,

[4] Johnson et al. (1994) show that in this case, $E(\delta_i) = 1$ y $var(\delta_i) = 1/v_i$.

subtituting $v = \alpha^{-1}$ in (6), we have that

$$\begin{aligned} var(y_i|\mathbf{x}) &= \mu_i \left(1 + \frac{\mu_i}{v_i}\right), \\ &= \mu_i(1 + \alpha\mu_i), \\ &= \mu_i + \alpha\mu_i^2, \end{aligned} \tag{7}$$

where we may note that if $\alpha = 0$, variance is equal to mean and we return to the PRM[5].

The NBRM may be estimated by maximum likelihood. The likelihood function is

$$\begin{aligned} L(\beta|y, \mathbf{x}) &= \Pi_{i=1}^{N} \Pr(y_i|\mathbf{x}_i), \\ &= \Pi_{i=1}^{N} \frac{\Gamma(y_i + \alpha^{-1})}{y_i!\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{\alpha^{-1}} \left(\frac{\mu_i}{\alpha^{-1} + \mu_i}\right)^{y_i}, \end{aligned} \tag{8}$$

where $\mu = \exp(\mathbf{x}_i\boldsymbol{\beta})$. 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:

$$\widehat{\Pr}(y = m|\mathbf{x}) = \frac{\Gamma(m + \widehat{\alpha}^{-1})}{m!\Gamma(\widehat{\alpha}^{-1})} \left(\frac{\widehat{\alpha}^{-1}}{\widehat{\alpha}^{-1} + \widehat{\mu}}\right)^{\alpha^{-1}} \left(\frac{\widehat{\mu}}{\widehat{\alpha}^{-1} + \widehat{\mu}}\right)^{m}. \tag{9}$$

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 PRM, as the parameter μ increases, the prediction of zeroes decreases. The NBRM responds to this underprediction of zeroes by increasing the conditional varianza 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 PRM and the NBRM assume that Central Bank has a positive probability of intervention in the exchange market any given number of times. The probability differs accross interventions according to some characteristics but in all cases the Central Bank risk of

[5] Under the specification of (7), the conditional variance is quadratic in the mean. It has led Cameron and Trivedi (1986) to call this model the Negative Binominal Regression Model (NBRM) 2.

not intervent and in all cases Central Bank migth 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 the first or second group[6]. In the second group, counts are governed by a PRM or a NBRM.

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 Poisson 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 cummulative density function, respectively. The $\mathbf{z}_i$ variables may the same as the $\mathbf{x}_i$ variables and it is our case[7].

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

$$\begin{aligned} \Pr[y_i &= 0|\mathbf{x}_i] = \psi_i + (1-\psi_i)\exp(-\mu_i), \qquad (10) \\ \Pr[y_i|\mathbf{x}_i] &= (1-\psi_i)\frac{\exp(-\mu_i)\mu^{y_i}}{y_i}, \; y>0. \qquad (11) \end{aligned}$$

The Zero Inflated Negative Binominal Regression Model (ZINB) is created using (5) 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 varianza 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 PRM. Otherwhise, the varianza exceeds the mean. For $\psi > 0$, the dispersion is greater than for the standard NBRM.

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

[7] The parameters in the binary model are assumed to be a scalar multiple of the parameters in te count 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 PRM and the NBRM, 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 (3). In the case of the ZINB model: $\widehat{\Pr}(y=0|\mathbf{x}) = \widehat{\psi} + (1-\widehat{\psi})(\frac{\widehat{\alpha}^{-1}}{\widehat{\alpha}^{-1}+\widehat{\mu}_i})^{\widehat{\alpha}^{-1}}$ and the $\widehat{\Pr}(y=m|\mathbf{x}) = (1-\widehat{\psi})$ times (9).

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.[8] 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 exchange rate's variance, the EMBIG spread, and the spread between currencies in prime corporate and interbank interest rates.

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

The deviations of the logarithm of the exchange rate with respect to its long term trend have been calculated assuming a linear trend[9]. Positive deviations indicate that the exchange rate is having a higher than average depreciation (long term trend), which would prompt BCRP to react with foreign exchange sales. In the opposite scenario, BCRP intervenes in the market by purchasing foreign exchange. Deviations from the log of the exchange rate have also been calculated by using the filter proposed by Hodrick-Prescott (1997) in order to assess for sensitivity to this variable.

The variance of the log of the exchange rate is an indicator of disequilibria in the exchange market. However, this variable does not discriminate between appreciation and depreciation pressures, which could be a problem. An interesting result is that periods with higher volatility are related to foreign exchange sales, which are rather sporadic. Besides, there is a possibility that the variance is itself determined by intervention, which would give rise to an endogeneity problem. In this case an intervention would generate a reduction in volatility as represented by variance.

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 exchange 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.

Finally, the spreads of prime corporate and interbank interest rates provide 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.

The behavior of the log of the exchange rate and of exchange rate intervention 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 foreign exchange rate 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.

Figure 1 shows purchases and sales of foreign currency separately. The

[9] Of course, other kind of calculations are possible; see below.

information provides clear evidence of the frequency of each type of intervention. The first relevant feature is the difference between purchases and sales. The first type of intervention occurs frequently, whereas the latter 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.

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.

4.2 Estimations

In the following lines, the analysis of the determinants of purchases and sales of foreign currency is presented separately. In the following Tables the coefficients are provided with their respective p-values shown in parentheses.

4.2.1 Foreign Exchange Purchases

Table 1 shows the results of the estimations of the Poisson and Negative Binomial models for the number of foreign exchange 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. The models are denoted by I and II for the PRM and III and IV for the NBRM, respectively. The NBRM presents similar although higher coefficients (in absolute value) in comparison with the PRM. The overdispersion test suggests the validation of the NBRM, although the dispersion parameter is not very high.

Both models show that lagged purchases affect current purchases with a coefficient indicating around a 37%-38% of persistence. The Embig spread affects negatively the foreign exchange purchases. Same type of effect is shown by the spread interbank interest rates and the deviations of the exchange rate from its long-run trend (cycle of the exchange rate). Finally, the spread of the prime corporate affects positively the foreign exchange purchases. The results of both models support our initial assertions with respect to the effect of explanatory variables.

Table 2 shows the results of three selected ZIP regression models. As previously described, the ZIP method allows the calculation of an event's occurrence as the result of two processes: a process (Logit) that calculates whether an intervention takes place or not, and another process (count) that calculates the number of interventions. Initially, the ZIP 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.

A positive coefficient in the count (regression) process means that the associated variable increases the expected number of interventions (in purchases in the present case). On the other hand, a positive coefficient in the Logit estimation means that the variable increases the probability of zero interventions. Therefore, we expect coefficients with opposite signs in each process.

Figure 2 allows the evaluation of the Poisson (model II), Negative Binomial (model IV) and the Zero Inflated Poisson (model VII) regression models based on the estimated probability to obtain a given number of counts (or interventions in our case). The solid line shows the observed distribution of BCRP's purchases in the foreign exchange market, whereas the others show the estimated distributions of the same variable using the above mentioned models. A characteristic is that the Poisson and the Negative Binomial models show the same distribution. The results allow one to compare distributions and to take notice of possible problems that the models may have in representing reality. The estimations show some difficulties to capture the probability of four to five interventions each week. The probability of a null intervention is close to 50%, then it decreases to 7% for one intervention, and shows a slight increase to 15% for a value of five interventions.

Figure 3 shows the difference between the distribution observed and predicted for each regression model. This allow for a more precise assessment of which regression model fit better the observed data. As we saw in Table 1, neither of these models have a constant in the regression equation. Despite the fact that both models are apart from zero, the ZIP model presents a better behavior. It is natural that purchases are difficult to estimate, as they are very frequent, volatile, and it is possible that decisions depend on variables that are not being taken into account[10].

As previously mentioned, the coefficients obtained in the preceding regressions cannot be interpreted in the conventional way. Table 3 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. A standard deviation was chosen as the variation level, since this allows 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 3 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. The standard deviation of the EMBIG spread is 196.113 because this variable's unit is represented as percentage basis points, where 100 equals 1%. Thus, the EMBIG spread has a standard deviation of (1.96%), lower than the spreads of prime corporate and interbank interest rates (2.28% and 2.26%, respectively). In the case of the ZIP models, the existence of two processes implies a more complex interpretation. For example, if lagged purchases increase in 2.016, it has two effects. The first effect means an increase of the expected number of purchases in 20.30% and the second effect indicates a reduction in the probability of a null intervention almost completely which is consistent with the high number of purchases of the Peruvian monetary authority. Another example is using the spread of interest rates. Higher spread of interest rates increases probability of zero (purchases) interventions in more than 100.0%. It is consistent observing the distribution of the purchases in the foreign exchange market which shows that the probability of null intervention is rare. It is also consistent with the behavior of the BCRP when foreign capitals entered to the country: they react purchasing foreign currency to avoid a depreciation with consequent effects in domestic inflation. A possible interpretation of these results could suggest that BCRP's decisions are more influenced by those determinants that show higher volatility. The deviations of the exchange rate from its long-run trend are also important. Furthermore, this variable and the lagged purchases are the principal variables determining the decision to intervene or not in the foreign exchange rate market (see binary equation).

[10] For this reason, this work represents a first approximation and contribution to this kind of issue and the way as it is analyzed. Further research is in progress.

4.2.2 Foreign Exchange Sales

Foreign exchange sales are estimated separately because they evidence a different behavior, which suggests that their determinants could be relatively different. Table 4 shows the results for the Poisson and Negative Binomial regressions.

Models I and III include the variance of the logarithm of the exchange rate as a determinant of foreign exchange sales. This yields as a result that all variables with the exception of the variance are significant. Besides, they have a sign that is consistent with economic intuition. The potential problem with the variance is that it poses an endogeneity problem. The coefficient indicates that an increase in the variance reduces the number of foreign exchange sales. However, in reality the relationship is negative because an increase in intervention should reduce variance of the foreign currency. Because of this endogeneity problem, the variance is removed from the model as an explanatory variable. Although both regressions (Poisson as well as Binomial) are similar, the latter presents higher coefficients (in absolute values). The likelihood ratio statistic for overdispersion confirms that the mean is not equal to the variance implying a rejection of the PRM.

In contrast with the foreign exchange purchases presented in the previous section, in this case a Zero Inflated regression model appears to be more relevant due to the higher proportion of null interventions in the foreign exchange sales. The results based on the ZIP regression models are presented in Table 5. It appears that the decision of whether to intervene is more important than the decision on the magnitude of intervention. A possible explanation could be that BCRP is more reticent to engage in sales of dollars denominated assets that diminish the amount of international reserves.

In contrast with the ZIP estimation for foreign exchange purchases, in this case most of the explanatory variables are statistically significant for the binary process. Only the prime corporate interest rate is significant in the count process. Notice that the persistence is now very small and statistically not significant which is consistent with the rare occurrences of sales of foreign exchange currency.

Model V runs the regression with all explanatory variables in both processes. This provides an idea of the significance of the determinants. Model VI undertakes a first selection to determine which explanatory variables correspond to each process. However, the problem with the variance variable arises as the coefficient has a positive sign potentially due to endogeneity. We may recall that the coefficients of the binary process explain the relation between explanatory variables and the probability of null intervention; thus it is usual that the coefficients show opposite signs in each process. For example, the positive sign for the spread of the the prime corporate coefficient indicates that an increase of this variable increases the probability that the intervention is null. Whereas in the count process a negative sign would indicate that the expected number of intervention decreases with this variable.

Model VII presents the final explanatory variables. In this case the first lag of foreign exchange sales is not included because their sporadic nature precludes from assuming any sort of inertia or persistency in this type of intervention. All coefficients are statistically significant and according to the economic interpretation.

Figure 4 shows the estimated distribution of foreign exchange sales compared with the observed distribution. The results are more encouraging than in the case of foreign exchange purchases, as both distributions are close to each other. The distribution shows a 90% probability for null interventions, and the rest is spread in a proportionate fashion. In other words, interventions of 1 to 5 times have a probability of approximately 5%.

Figure 5 allows a more precise assessment as to which model shows a better fit with the data. The estimation's distribution will be closer to the observed one, the closer this difference nears zero. Thus, it is clear that the ZIP model is the most adequate, followed by the Negative Binomial model which shows some difficulties in capturing the probability of one intervention. On the other hand, the Poisson model fails in capturing the probability for 0 and 1 interventions, but shows a slight improvement in probabilities for 2, 3 and 4 interventions when compared to the Negative Binomial model.

Table 6 shows the interpretation of the coefficients in foreign exchange sales is provided. In this case, the Poisson and Negative Binomial regressions are comparable with each other. However, they cannot be directly compared with the ZIP regression model, due to the fact that the explanatory variables of the ZIP model are mostly significant only for the binary process.

The proper way to interpret the effect is, in the case of model VI, as follows: a change in the interbank interest rate spread equal to the standard deviation (2.28) prompts a decrease of -22.7% in the expected number of foreign exchange sales. In the case of the binary process, the spread of the prime corporate increases the probability of a null intervention in around 392.0%.

In models VI and VII we see that the main determinants of foreign exchange sales are the interbank interest rate spread, the cycle of the exchange rate's logarithm, and the prime corporate interest rate spread.

5 Conclusions

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. Results 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 between domestic and foreign exchange rates are important determinants.

Particularly, it has been shown that, although foreign exchange purchases and sales are related to each other, they have differing behaviors. Additionally, explanatory variables do not have the same effect on them, neither in sign nor in magnitude.

On the other hand, estimations manage to predict more accurately the foreign exchange sales, whereas foreign exchange purchases are less precise. This seems to indicate that foreign exchange purchases have other determinants that could not taken into account. This is logical, since decisions to buy, apart from reducing exchange rate volatility, also have the aim of cumulating international reserves from a precautionary motive and in order to ensure that the monetary authority has the necessary means to keep macroeconomic stability. Further research about these issues is in progress.

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Table 1. Regression of foreign exchanges purchases

Variable	Poisson Regresion		Negative Binomial Regression	
	Model I	Model II	Model III	Model IV
First lagged purchases	0.370	0.372	0.385	0.386
	(0.000)	(0.000)	(0.000)	(0.000)
EMBIG spread	-0.002	-0.002	-0.002	-0.002
	(0.001)	(0.000)	(0.000)	(0.000)
Spreads of prime corporate	0.173	0.170	0.192	0.189
	(0.000)	(0.000)	(0.001)	(0.000)
Spread interbank interest rates	-0.182	-0.181	-0.213	-0.212
	(0.000)	(0.000)	(0.000)	(0.000)
Foreign exchange rate's cycle	-16.227	-16.164	-19.892	-19.846
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.0160		0.0154	
	(0.907)		(0.920)	
α			0.135	0.135
LR test of $\alpha = 0$ (p-value)			0.003	0.003

Table 2. Regression of foreign exchanges purchases: ZIP Regression Models

Variable	Model V	Model VI	Model VII
First lagged purchases	0.093	0.096	0.124
	(0.000)	(0.000)	(0.000)
EMBIG spread	-0.001	-0.001	-0.001
	(0.108)	(0.090)	(0.015)
Spreads of prime corporate	0.127	0.082	0.127
	(0.116)	(0.109)	(0.008)
Spread interbank interest rates	-0.052		
	(0.369)		
Foreign exchange rate's cycle	-7.438		
	(0.208)		
Constant	1.086	1.097	1.046
	(0.000)	(0.000)	(0.000)
Binary equation			
First lagged purchases	-1.218	-1.228	-0.987
	(0.000)	(0.000)	(0.000)
EMBIG spread	0.003		
	(0.076)		
Spreads of prime corporate	-0.240		
	(0.210)		
Spread interbank interest rates	0.552	0.515	1.001
	(0.002)	(0.000)	(0.000)
Foreign exchange rate's cycle	74.282	78.728	136.985
	(0.004)	(0.004)	(0.000)
Constant	0.327	1.102	
	(0.505)	(0.000)	

Table 3. Interpretation of the regression coeficients of the number of foreign exchanges purchases

Variable	Poisson Regression		Negative Binomial Regression		ZIP Models	
	Model I	Model II	Model III	Model IV	Model VI	Model VII
First lagged purchases	110.90%	111.70%	117.30%	118.00%	21.40%	28.50%
	(2.016)	(2.016)	(2.016)	(2.016)	(2.016)	(2.016)
EMBIG spread	-28.50%	-27.90%	-30.60%	-30.00%	-16.00%	-21.90%
	(196.113)	(196.113)	(196.113)	(196.113)	(196.113)	(196.113)
Spreads of prime corporate	47.30%	47.40%	54.90%	54.00%	20.50%	33.90%
	(2.280)	(2.280)	(2.280)	(2.280)	(2.280)	(2.280)
Spread interbank interest rates	-33.70%	-33.70%	-38.20%	-38.10%		
	(2.264)	(2.264)	(2.264)	(2.264)		
Foreign exchange rate's cycle	-12.40%	-12.40%	-15.00%	-14.90%		
	(0.008)	(0.008)	(0.008)	(0.008)		
Binary ecuation: probability of no intervention						
First lagged purchases					-91.60%	-86.20%
					(2.016)	(2..016)
Spread interbank interest rates					220.60%	863.20%
					(2.264)	(2.264)
Foreign exchange rate's cycle					90.10%	205.70%
					(0.008)	(0.008)
α			0.135	0.135		
LR test of $\alpha = 0$ (p-value)			0.003	0.003		

Table 4. Regression of foreign exchanges sales

Variable	Poisson		Negative Binomial	
	Model I	Model II	Model III	Model IV
First lagged sales	0.536	0.583	0.666	0.690
	(0.000)	(0.000)	(0.000)	(0.000)
EMBIG spread	0.002	0.002	0.004	0.004
	(0.007)	(0.005)	(0.016)	(0.022)
Spreads of prime corporate	-0.395	-0.379	-0.517	-0.533
	(0.000)	(0.000)	(0.002)	(0.001)
Spread interbank interest rates	0.262	0.246	0.446	0.470
	(0.000)	(0.000)	(0.000)	(0.000)
Foreign exchange rate's cycle	44.017	43.955	93.682	91.885
	(0.000)	(0.000)	(0.001)	(0.001)
Variance of the logaritmic exchanges rate	-41.649		-42.401	
	(0.077)		(0.346)	
Constant	-2.903	-3.148	-4.108	-4.302
	(0.000)	(0.000)	(0.000)	(0.000)
α			3.125	3.219
LR test of $\alpha = 0$ (p-value)			0.000	0.000

Table 5. Regression of foreign exchanges sales: ZIP Regression Models

Variable	Model V	Model VI	Model VII
First lagged sales	0.021		
	(0.759)		
EMBIG spread	0.000		
	(0.794)		
Spreads of prime corporate	-0.195	0.113	-0.125
	(0.053)	(0.012)	(0.002)
Spread interbank interest rates	0.049		
	(0.347)		
Foreign exchange rate's cycle	0.148		
	(0.988)		
variance of the logaritmic exchanges rate	13.398		
	(0.667)		
Constant	0.738	1.010	1,005
	(0.065)	(0.000)	(0.000)
Binary equation			
First lagged purchases	-1.600	-1.541	-2.711
	(0.000)	(0.000)	(0.000)
EMBIG spread	-0.007	-0.007	-0.006
	(0.018)	(0.012)	(0.015)
Spreads of prime corporate	0.613	0.699	0,569
	(0.041)	(0.019)	(0.024)
Spread interbank interest rates	-0.823	-0.847	-0.857
	(0.000)	(0.000)	(0.000)
Foreign exchange rate's cycle	-234.20	-226.39	-115.76
	(0.000)	(0.001)	(0.019)
variance of the logaritmic exchanges rate	222.73	203.76	
	(0.080)	(0.087)	
Constant	6.361	6.408	6.944
	(0.000)	(0.000)	(0.000)

Table 6. interpretation of the regression coeficients of the number of foreign exchanges sales

Variable	Poisson Regression		Negative Binomial Regression		ZIP Models	
	Model I	Model II	Model III	Model IV	Model VI	Model VII
First lagged sales	53.10%	58.80%	69.70%	73.00%		
	(0.794)	(0.794)	(0.794)	(0.794)		
EMBIG spread	56.60%	55.90%	112.00%	102.60%		
	(196.113)	(196.113)	(196.113)	(196.113)		
Spreads of prime corporate	-59.40%	-57.90%	-69.20%	-70.40%	-22.70%	-24.90%
	(2.280)	(2.280)	(2.280)	(2.280)	(2.280)	(2.280)
Spread interbank interest rates	80.80%	74.40%	174.20%	190.00%		
	(2.263)	(2.263)	(2.263)	(2.263)		
Foreign exchange rate's cycle	43.20%	43.10%	114.70%	111.60%		
	(0.008)	(0.008)	(0.008)	(0.008)		
Variance of the logaritmic exchanges rate	-22.90%		-23.20%			
	(0.006)		(0.006)			
Binary equation						
First lagged sales					-70.6%	-88.4%
					(0.794)	(0.794)
EMBIG spread					-76.8	-68.2%
					(196.113)	(196.113)
Spreads of prime corporate					392.2	266.2%
					(0.022)	(0.022)
Spread interbank interest rates					-85.3	-85.6%
					(2.264)	(2.264)
Foreign exchange rate's cycle					-84.2	-61.10%
					(0.008)	(0.008)
Variance of the logaritmic exchanges rate					256.4	
					(0.006)	
α			3.125	3.219		
LR test of $\alpha = 0$ (p-value)			0.000	0.000		

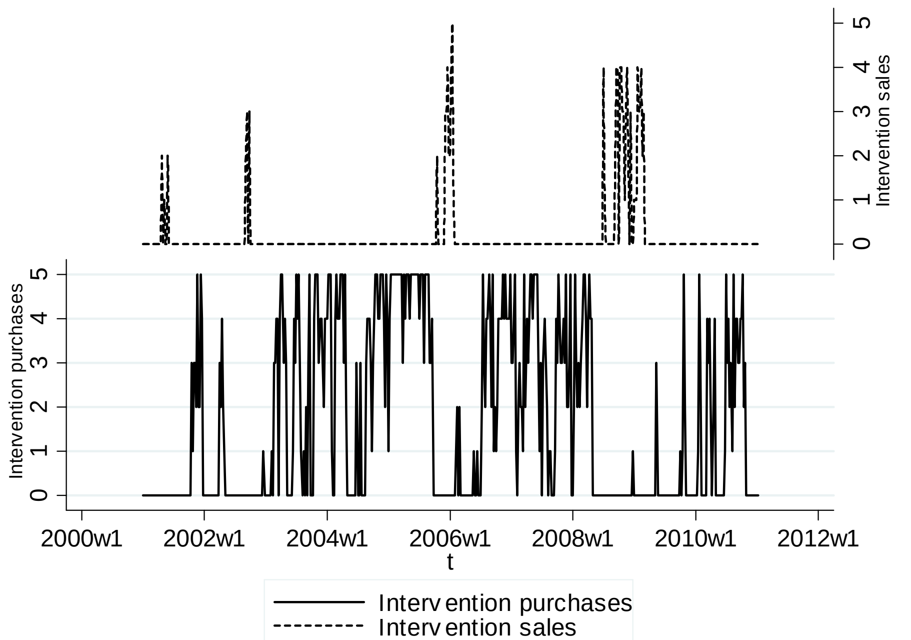

Figure 1. Intervention in Doreign Exchange Rate Purchases and Sales

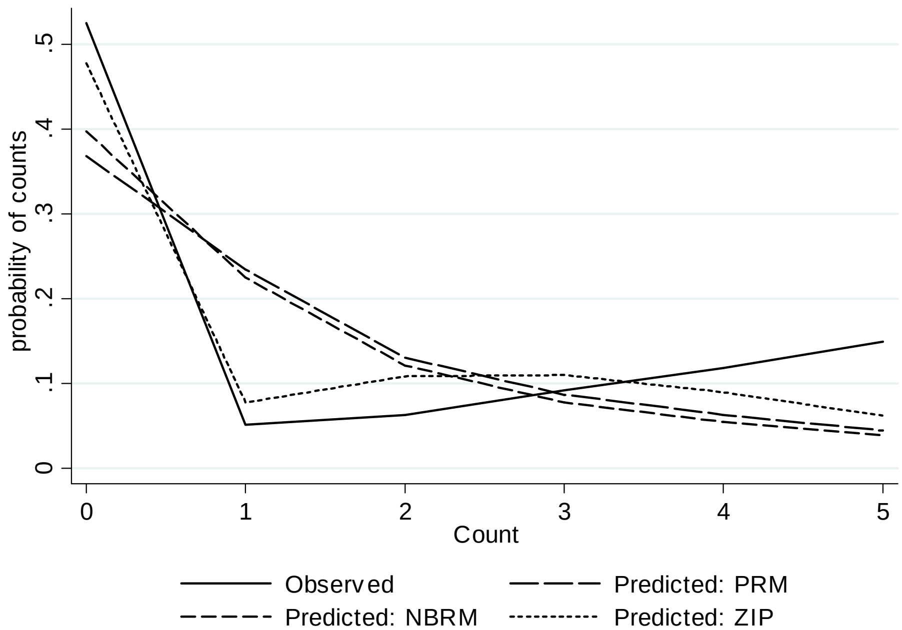

Figure 2. Probability of Counts of Interventions in the foreign Exchange Rate Purchases: Observed, Poissson Negative Binomial and Zero Inflated Poisson Regression Models

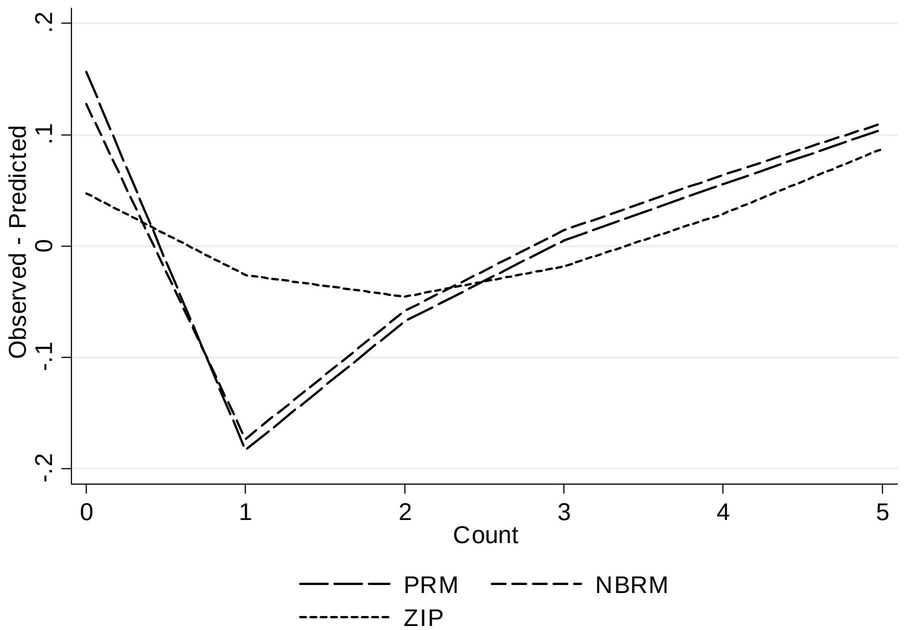

Figure 3. Difference in Probability of Counts of Interventions in the foreign Exchange Rate Purchases: Poissson Negative Binomial and Zero Inflated Poisson Regression Models

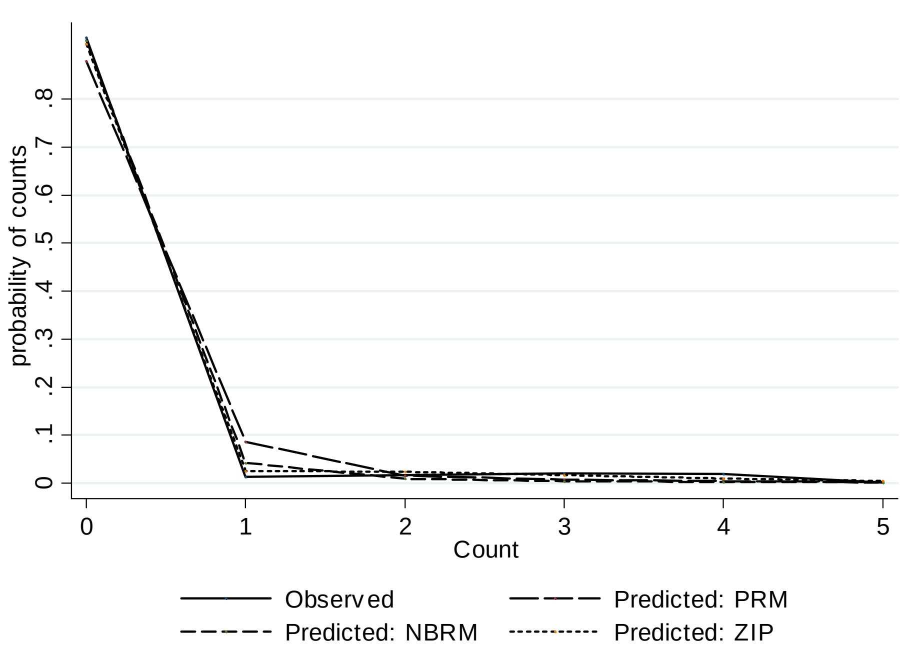

Figure 4. Probability of Counts of Interventions in the foreign Exchange Rate Sales: Observed, Poissson Negative Binomial and Zero Inflated Poisson Regression Models

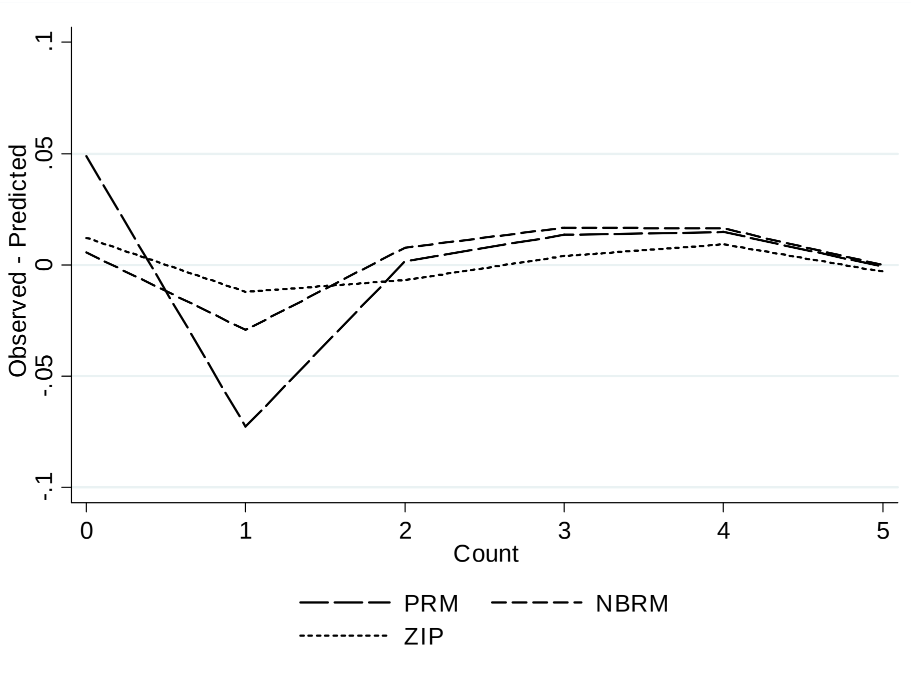

Figure 5. Difference in Probability of Counts of Interventions in the foreign Exchange Rate Sales: Poissson Negative Binomial and Zero Inflated Poisson Regression Models

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