Interventions and expected exchange rates in emerging market economies[1]

Santiago García-Verdú[2] and Manuel Ramos-Francia[3]

Abstract

We study variations in the distributions of the expected exchange rates in Brazil, Chile, Colombia, Mexico, and Peru due to interventions implemented in these countries. To this end, we first estimate the risk-neutral densities of the exchange rates based on derivatives market data, for one-day and one-week horizons. Second, using a linear regression model, we assess potential effects on the distributions of the expected exchange rate given these interventions. We find little evidence of an effect on the expected exchange rates' means, volatilities, skewness, kurtoses, and risk premiums. In the few cases for which we do find statistical evidence of a possible effect, it tends to be short-lived or not economically significant.

Keywords: interventions, expected exchange rate, emerging market economies, risk-neutral density

JEL classification: E5, F31, G12

[1] The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Banco de México.

[2] Adviser to the Board, Banco de México.

[3] Deputy Governor, Banco de México.

Introduction

As part of the recent global financial crisis's aftermath, the unprecedented monetary policy stances in advanced countries have provided leeway for significant surges in capital flows. At the same time, significant variations in risk appetite and global financial volatility have impacted the rate with which capital flows enter and exit emerging market economies. Although capital flows undoubtedly provide benefits to the recipient countries, eg more financing, improved risk-return profiles, and a lower cost of capital, they surely entail potential costs, eg sudden stops, abrupt currency depreciation, and loss of competitiveness, asset price bubbles, and risk mispricing. In this context, some policy makers have responded by intervening in their exchange rate markets with different specific aims, along with implementing other policy measures.

Central to interventions in the exchange rate markets is their effectiveness, a topic that has been a matter of debate. To assess their effect, a plethora of methods has been used (see, for example, Sarno and Taylor (2001)). Yet, comparisons are generally burdensome, as interventions are seldom analyzed together. It thus seems fitting to assess interventions in various emerging countries under a common methodology. Doing so presents some challenges but also has some key advantages, such as being able to make comparisons.

Against this backdrop, we assess the potential effects on the expected exchange rates in Brazil, Chile, Colombia, Mexico, and Peru due to interventions implemented by these countries. To this end, we proceed as follows. First, we obtain the risk-neutral densities from options data on the individual exchange rates. Second, we estimate key statistics based on these densities. Third, using a linear regression model, we analyze how these statistics might have changed as a result of the implementation of interventions in the respective exchange rate markets.

Literature review

We divide our abridged literature review into three parts. In the first, we recap a selected number of topics in the interventions literature germane to our paper. In the second, we cite relevant papers that extract the risk-neutral densities from options prices aiming to analyze how such distributions might have been affected by various economic events. In the last one, we briefly compare our paper to Miyajima and Montoro (2013), which is part of this volume.

First, whether an intervention is sterilized or not is crucial to its potential effects. On the one hand, provided there is no sterilization, the effects of an intervention are similar to those of an open market operation, as the monetary base is in effect changed. The key difference is that in an unsterilized intervention a central bank only uses foreign assets, while in an open market operation it only uses domestic assets.

On the other hand, for sterilized interventions, the literature has considered mainly two possible channels through which interventions might have an effect on the exchange rate. It is worth mentioning that all of the interventions we consider in this paper are in principle sterilized. The mentioned two possible channels are the portfolio balance and expectations or signaling channel, as we now explain.

In the portfolio balance channel, as an intervention takes place, e.g. when financial institutions buy dollars from the central bank, in the sterilization process the central bank buys domestic bonds from the public. Thus, the relative supply of domestic to foreign bonds decreases. If domestic and foreign bonds are imperfect substitutes then their relative price changes, thus leading, in our example, to an appreciation of the exchange rate. The converse effect takes place when financial institutions sell dollars to the central bank.

The expectations (or signaling) channel has an effect if participants perceive the intervention as signaling the central bank's intentions with regard to its future policy, for example, monetary stance (for example, see Mussa (1981)). For this channel to be operative, it is irrelevant whether domestic and foreign bonds are substitutes or not.

Another related issue is whether an intervention should be public, rules-based, and transparent, or discretionary and private. On the one hand, paraphrasing Kenen (1988), the rules of the exchange rate market need to be as transparent as possible to maintain credibility. Thus, the authorities have an incentive to convey their intentions to render the expectations channel more effective. On the other hand, Dominguez and Frankel (1993) have considered whether the authorities might have the incentive to minimize the effects of an intervention under some circumstances and, if such is the case, make it private and discretionary. We leave these issues aside and consider an intervention of the same type irrespective of whether it is rules-based or discretionary.

Second, extracting the risk-neutral distribution from options prices to see how it is affected by economic events is an interesting application of asset pricing. For example, Figlewski and Birru (2010) study how the risk-neutral distribution of the S&P 500 index changed through the fall of 2008. Abarca et al. (2012a) analyze how the risk-neutral distribution for the peso/dollar exchange rate changes with monetary policy announcements, while Abarca et al. (2012b) consider how the implementation of capital controls and banking regulations affect the risk-neutral distribution of the exchange rate in a group of emerging market economies.[4]

Gnabo and Teiletche (2008) and Roger and Siklos (2001) analyze the expected exchange rate using methods similar to those we use. The former paper studies how announcements impact the US dollar/Japanese Yen exchange rate risk-neutral density. The latter paper considers the interventions of the Bank of Canada and the Reserve Bank of Australia in their respective exchange rate markets. Here, volatility is measured using the implied volatility, and uncertainty is approximated with the kurtosis of the risk-neutral probability density function.

Finally, our paper is similar to Miyajima and Montoro's (2013), since both analyze the effects of interventions on exchange rate expectations. Yet ours differs in some key aspects. First, while they consider survey expectations, we consider market-based expectations. Second, we have access to daily data and densities for short-term horizons. In contrast, surveys typically entail data with lower frequencies

[4] Bayoumi and Saborowski (2012) have recently underscored the importance of analyzing interventions and capital controls together to adequately measure the effectiveness of interventions. Thus, a natural step in our study would be to consider how interventions and capital controls together (and perhaps with other macroprudential policies) might have affected the expected distribution of exchange rates. This is a topic where our paper and that of Abarca et al. (2012b) intersect. We leave this important exercise for future research.

and densities for longer horizons. Third, in a survey there is the issue of when exactly a piece of data was collected from each forecaster, which is not necessarily the same date as when the survey was published. Our data do not have this problem.

Interventions

Although different countries have different aims when intervening, common ones have been, among others, to reduce the volatility of the exchange rate and to provide liquidity to the exchange rate market. We leave the countries' stated aims aside and, as mentioned, study the effects on the expected exchange rate distribution by analyzing the possible effects on the risk-neutral density. This provides a way of examining an aspect of the expectations or signaling channel, possibly as an unintended effect.

Our sample includes five countries, Brazil, Colombia, Chile, Mexico, and Peru. The following country-specific descriptions refer to our database. Brazil is probably one of the most active countries in terms of intervening in the exchange rate market. We specifically consider those interventions implemented in the spot market (i.e. *Intervenção do Banco Central: mercado pronto*). Nonetheless, Brazil in addition intervenes actively in other markets, for example in the swap exchange rate market. To account for this fact, we estimate a regression controlling for three interventions not implemented in the spot market (i.e. *Intervenção do Banco Central: mercado a Termo, Leilões do Banco Central de swap cambial,* and *Leilões do Banco Central de swap cambial reverso*). The sample of interventions in the spot market is from 1999 1Q to 2012 2Q.

Chile has been relatively active intervening in the exchange rate market. We consider those Chilean interventions involving the selling and buying of US dollars through auctions (i.e. *compra y venta de dólares por licitación*). The recent Chilean intervention activity can be characterized by three periods, an initial buying period from 2008 2Q to 2008 3Q; second, a selling period from the middle of 2009 1Q to the middle of 2009 4Q; and finally, a buying period from 2011 1Q to 2011 4Q.

Colombia has also intervened in the exchange rate market in recent years. They have done so for the most part buying dollars through auctions (i.e. *subastas de compra directa de dólares*). We consider those interventions which started around 2008 3Q and have also taken place more recently.

For the case of Mexico, we similarly consider all of the interventions implemented in the spot market in recent years, except for one for which detailed data are not publicly available.[5] More specifically, our database has interventions from 1997 4Q to part of 2013 1Q. It is worth mentioning that Mexico has mostly implemented interventions involving the sale of US dollars through auctions. The

[5] This type of intervention took place on September 10, 1998, and in a second period on February 4, 5, 6, 20, 23, and 27, 2009.

one exception is the intervention aiming to increase the rate of reserves accumulation, which involves the sale to banks of US dollar put options.[6]

Finally, Peru has intervened in the exchange rate market at least since 2003 1Q. It typically has sold and bought dollars in the spot market. The case of Peru stands out for the fact that its exchange rate market's turnover is small relative to its international reserves, which can be considered an advantage in terms of its interventions' potential.

In addition, central to our study are two common characteristics of these economies. First, they are small open economies. Thus, for each country, the exchange rate is a fundamental price in its economy. Second, they all essentially have floating exchange rate regimes, which implies that (at least, in some cases, nominally) none of these countries targets its exchange rate.

In sum, we are only considering broadly similar interventions, in the sense that they are all implemented in the spot market. This is so, mainly to make the comparison as direct as possible. In addition, in emerging market economies the most common place in which interventions take place is typically the spot market, with Brazil being an exception.

Data and methodology

Data

Some preliminary comments are in order. The theoretical price of an option is a function of several parameters, including the volatility of the underlying asset's return. All of the parameters are observable except for this volatility. The implied volatility is such that the option's theoretical price equals its observed market price, having plugged all of the other parameters into the formula. Similarly, some options' characteristics such as the delta, defined as the partial derivative of the option's value with respect to the underlying asset, are a function of a set of parameters including the volatility. It is customary for options data to be provided in terms of the implied volatilities of specific positions on derivatives' deltas.

More specifically, we use daily data on the implied volatility of 10 and 25 risk reversals (RR), 10 and 25 butterflies (BF), and at-the-money (ATM) options. For example, the 10 risk reversal implied volatility (denoted by V) is the difference between the 10 Delta Call and the 10 Delta Put implied volatilities.

$$V(RR\ 10) = V(10\ Delta\ Call) - V(10\ Delta\ Put)$$

where the 10 refers to the value of the delta (0.1) of the associated call or put. In this case the underlying is the exchange rate (local currency per US dollar). The 10 butterfly is defined as:

$$V(BF\ 10) = (V(10\ Delta\ Call) + V(10\ Delta\ Put))/2 - V(ATM)$$

[6] There were two episodes in which such interventions were active: first, from August 1996 to June 2001, and then from February 2010 to November 2011. Since these interventions were not implemented in the spot market they are not considered as part of our data base, as explained in the main text.

Likewise, for the 25 risk reversals, 25 butterfly, and ATM option we have:

V(RR 25) = V(25 Delta Call) – V(25 Delta Put)

V(BF 25) = (V(25 Delta Call) + V(25 Delta Put)) /2 – V(ATM)

This set of equations indicates that, in terms of implied volatilities, we have the following relationships:

V(25 Put) = V(BF 25) + V(ATM) – V(25 RR)/2

V(10 Put) = V(BF 10) + V(ATM) – V(10 RR)/2

V(10 Call) = V(BF 10) + V(ATM) + V(10 RR)/2

V(25 Call) = V(BF 25) + V(ATM) + V(25 RR)/2

where the implied volatility for a call (or a put) at-the-money gives us the implied volatility associated to a delta close to 50 (i.e. 0.5). This set of equations provides us with five (delta, implied volatility) data points for each day.

We use daily data on: the exchange rates, each country's one-month risk-free rate, and the one-month risk-free rate of the US. Since one of our aims is to compare the effects across countries, we chose comparable rates across them. We found that comparable risk-free rates with shorter horizons are not available for some countries in our sample. Also, interest rates with small differences in horizons (i.e. close to a month) have very high correlations. The risk-free rate from the US is needed for the options pricing.[7] Thus, the rates we use are representative of short-term horizon rates.[8]

Data description

Table 1

Data Description

	Interventions		Options		Interest Rates		Exchange Rates	
	Start	End	Start	End	Start	End	Start	End
Brazil	27-Oct-99	15-Feb-15	5-Jan-06	28-Feb-13	28-Mar-07	28-Feb-13	4-Jan-00	28-Feb-13
Chile	5-Jan-08	16-Dec-11	11-Sep-06	28-Feb-13	30-Sep-05	28-Feb-13	4-Jan-00	28-Feb-13
Colombia	29-Feb-00	31-Jan-13	11-Sep-06	28-Feb-13	1-May-06	28-Feb-13	4-Jan-00	28-Feb-13
Mexico	27-Oct-97	28-Feb-13	5-Jan-06	28-Feb-13	11-Aug-03	28-Feb-13	4-Jan-00	28-Feb-13
Peru	3-Jan-03	28-Feb-13	17-Jun-08	28-Feb-13	16-Jul-98	28-Feb-13	4-Jan-00	28-Feb-13
US	-	-	-	-	31-Jul-01	28-Feb-13	-	-

Sources: The interventions data are from the respective Central Banks' websites, except for Peru, for which they were obtained directly from the Bank. Options, Interest Rates, and FX Data are from Bloomberg.

7 It is analogous to considering the dividend (rate) of a stock of a company when pricing an option.

8 We could have also used target rates that are generally available across countries. Yet, these commonly do not include the markets' high frequency information.

A dummy variable is constructed based on the intervention data, as we explain in more detail below. Our country sample is in Table 1 with the periods for each data category. We could have considered other countries, but as mentioned, we were unable to obtain access to all the necessary data to perform a complete analysis.[9]

One would like to consider the complete periods where interventions take place. However, the linear regressions we estimate have a common component that involves data from all the countries in the sample. This is one of the reasons we were forced to leave some countries out of our study. In short, the time series' dates have to coincide.

In addition, one can presuppose a potential break point as part of the recent financial global crisis, with respect to a number of parameters in any model considered. Thus, bearing in mind both elements, the specific period we use for our estimation goes from January 1, 2009 to February 28, 2013. The idea in choosing this initial date is that agents at the time had gained "full" knowledge of the crisis's full force and implications. In other words, a "new normal" regime had been generally assimilated.

We consider two horizons in the options data, one-day and one-week. This allows for examining the effects of the interventions for various horizons. Although there are options data available for longer horizons, we thought it was unlikely that there would be an effect on longer horizons. This is in line with what we later found in our estimations: as will be seen in the estimated models below, any possible effect fades away rather swiftly.

Methodology

Derivatives are typically priced based on their associated so-called risk-neutral density. Its use greatly simplifies many asset-pricing problems, although the name can be considered a misnomer, as no agent is risk-neutral in the option pricing model. Its interpretation should be conducted with some caution. For example, an increase in the risk-neutral probability must be due either to an increase in the real probability of the underlying asset having a set of values, or to an increase in the marginal utility of the representative agent in the states of nature associated to the referred set of values of the underlying asset.[10]

We obtain the implied volatilities on several derivatives on the exchange rate for various horizons, as explained. These implied volatilities are typically reported as a function of the deltas and as a function of the option that is at-the-money, i.e. the current price of the underlying asset equals the strike price. Next, we directly obtain the implied volatilities as a function of the strike prices. Then we use spline interpolation to obtain a denser set of strike prices, each one being associated to a

[9] We would be grateful if any of our readers would call our attention to data sets available with a daily frequency, specifically any including options market data and interventions.

[10] Technically, we have assumed that the real probability distribution and the risk-neutral distribution are absolutely continuous measures with respect to each other. Intuitively, this means that if one distribution assigns zero probability to an event, the other one does as well. Then, as a result of the Girsanov Theorem, these densities differ only in their means. What is relevant to us is that we are generally able to take the risk neutral distribution's moments as bona fide moments, except for the first one.

level of implied volatility. In turn, we find the prices of various calls and puts based on strike prices and their implied volatilities. Finally, we make use of the formula due to Breeden and Litzenberger (1978) to extract the risk-neutral density as a function of the calls' and puts' values second partial derivatives with respect to the underlying asset.

In what follows we describe our method in more detail. To this end, we consider a fixed horizon, for example one week. Thus, for every period t, we proceed with the following steps.

1. From the data in terms of the 10 and 25 risk reversals, the 10 and 25 butterflies, and the at-the-money option, we calculate the implied volatilities associated with 10 call and put, 25 call and put, and the at-the-money call, as a function of the associated deltas, i.e. data points in the (deltas, implied volatilities) space.
2. Then, we estimate the implied volatilities as a function of the strike prices, i.e. data points in the (strike prices, implied volatilities) space.
3. We obtain a denser set of strike prices using spline interpolation. The interval was initially constructed considering the historical behavior of the exchange rates, and revised to completely include the densities' supports.[11]
4. Using Breeden and Litzenberger (1978) formulae, we then obtain the probability density function of the underlying asset, in this case the exchange rates:

   $$f(K) = \exp(rT)\frac{\partial^2 C}{\partial K^2} = \exp(rT)\frac{\partial^2 P}{\partial K^2}$$

   where C and P are the value of the call and the put, respectively. Their discrete counterparts are used to approximate the partial derivatives. It is worth mentioning that we only consider options that are either in the money or at-the-money.
5. Finally, from the risk-neutral density function, *f*(K), we estimate five key statistics: the mean, the volatility, the skewness, the kurtosis, and the risk premium.

The formula proposed by Breeden and Litzenberger (1978) is quite general. In particular, it does not assume the same volatility for different strike prices; thus, the so-called volatility surface as observed in the data is accounted for. This is key to our results, as strictly assuming the Black and Scholes framework would remove much flexibility from our analysis. Otherwise, the spot exchange rate and the implied volatility would be sufficient statistics to obtain the complete risk-neutral density.

This approach has the clear advantage of being based on market information and not merely on expectations, as can be the case when using surveys. Although there is a reputational aspect to surveys, market information is based on prices that agents use to make buying and selling decisions. Centrally, using market-based expectations allows for daily frequency data and short horizons, which is considered a key aspect in the analysis of interventions.[12]

[11] A probability density's support is the set in its domain for which it is strictly positive.

[12] One could also consider expectations based on surveys, but the frequency in the data would probably be fortnightly or, perhaps, lower.

Thus, we specifically estimate the following linear model:

$s_{t,c,i} = \beta_{0,c,i} + \beta_{1,c,i} I_{t-1,c} + \beta_{2,c,i} CF_{t,-c,i} + \beta_{3,c,i} s_{t-1,c,i} + e_{t,c,i}$

where t is the time period (day), c is the country (c = Brazil, Chile, Colombia, Mexico, or Peru), and i is the type of statistic estimated based on the risk-neutral density. Thus, $s_{t,c,i}$ is the statistic i (i = mean, volatility, skewness, kurtosis, or risk premium) of the risk-neutral distribution on day t, for country c.

$I_{t-1,c}$ is the intervention dummy variable, which equals one if there is an intervention that involves buying dollars on day t-1 in country c, minus one if the intervention involves the sale of dollars, and zero in any other case.

We use intervention in period t-1 to mitigate potential simultaneity in our regressions. In this context simultaneity might be an issue, as the variable $I_{t,c}$ might depend on $s_{t,c,i}$. Thus, the information used to decide whether to intervene (in the discrete case) or the information used by the triggering rule (in the rules-based case) in t-1 occurs before the data to price the option is determined in t.

$CF_{t,-c,i}$ is a common factor or component. Following Abarca et al. (2012b), this factor is defined as the average of the percentage changes in $s_{t,-c,i}$ for all the countries in the sample except for c, hence the notation –c. Specifically, $CF_{t,-c,i} = (\Delta\% \, s_{t,1,i} + \ldots + \Delta\% \, s_{t,c-1,i} + \Delta\% \, s_{t,c+1,I} + \ldots + \Delta\% \, s_{t,N,i})/(N-1)$, where Δ%x denotes the percentage change of x, and N is the number of countries in our sample. Thus, this factor controls for various macroeconomic and financial effects that could be affecting the exchange rates markets jointly.

The lagged term $s_{t-1,c,i}$ accounts for the possible presence of autocorrelation in the error term of the same regression but without such term. Recall that the data frequency is daily. Thus, the presence of autocorrelation in the error term is very likely. Finally, $e_{t,c,i}$ is the error term associated with time period t, country c, and statistic i.

A common way of defining a risk premium is to consider the percentage change of the real probability density's mean against the risk-neutral density's mean. Although this would be an ideal situation, it is statistically difficult to accurately estimate the (real) probability density of the exchange rate. Thus, we approximate this risk premium with the realized value of the exchange rate, as follows:

$\text{Risk Premium} = (\mathbf{E}_t(S_T) - \mathbf{E}_t^*(S_T)) \,/\, \mathbf{E}_t^*(S_T) \cong (S_T - \mathbf{E}_t^*(S_T)) \,/\, \mathbf{E}_t^*(S_T)$

where * denotes that this expected value is taken with respect to the risk-neutral probability, S_T is the value of the exchange rate at time T, and $\mathbf{E}_t(S_T)$ is the expected value of the exchange rate at time T taken with respect to the real probability at time t, where it is assumed that t<T.

Results

To set the stage, consider the average of the five statistics we are analyzing for the countries in our sample (Table 2), and the coefficient of variation (defined as the ratio of the volatility over the mean). Several comments are in order. First, the means reflect the averages of the exchange rates. Recall that their expected growth rate through time is adjusted under the risk-neutral distribution. Second, as the horizon increases, the volatility increases, as one would expect to observe.

Average statistics for the expected distribution of the exchange rates Table 2

	Mean	Volatility	Coefficient of variation	Skewness	Kurtosis	Risk Premium
Horizon One day						
Brazil	1.86379	0.01871	0.01004	0.02892	2.99581	-0.00589
	[0.193]	[0.0092]		[0.0197]	[0.0158]	[0.0093]
Chile	509.50393	4.89185	0.00960	0.04385	3.00391	-0.00272
	[38.6303]	[2.418]		[0.0339]	[0.0074]	[0.0067]
Colombia	1924.18072	17.41341	0.00905	0.02857	3.00120	-0.00304
	[176.1797]	[7.4563]		[0.0149]	[0.004]	[0.0067]
Mexico	12.96482	0.12341	0.00952	0.03406	3.00270	-0.00310
	[0.6879]	[0.0568]		[0.0237]	[0.0053]	[0.0082]
Peru	2.80703	0.01456	0.00519	0.01604	2.95523	-0.00386
	[0.1552]	[0.0102]		[0.0394]	[0.1695]	[0.0026]
Horizon One week						
Brazil	1.86625	0.03868	0.02073	0.08221	3.01558	-0.00752
	[0.1933]	[0.0186]		[0.0368]	[0.0161]	[0.0186]
Chile	509.29340	9.80394	0.01925	0.10303	2.99994	-0.00339
	[37.5895]	[5.0021]		[0.1525]	[0.085]	[0.0162]
				-0.00169		
Colombia	1923.14999	35.50612	0.01846	0.09209	2.99826	-0.00326
	[172.1936]	[16.6277]		[0.1458]	[0.0951]	[0.0172]
Mexico	12.98162	0.25556	0.01969	0.07793	3.01212	-0.00446
	[0.6878]	[0.1096]		[0.0402]	[0.0154]	[0.0172]
Peru	2.80814	0.02752	0.00980	0.04607	3.00101	-0.00494
	[0.1555]	[0.0221]		[0.0241]	[0.0111]	[0.0055]

The mean and volatility are in local currency per USD. The risk premium is in percentage for the respective time period. Standard deviations are in brackets.

Since the mean and volatility are not comparable across countries, the coefficient of variation is included. Its value is very similar across countries, and it visibly increases as the horizon rises.

As for the skewness, which captures the degree of asymmetry in the density function, all five countries share the same two properties. Namely, they are positive and increase with the horizon. This means that these exchange rates have a right tail that is slightly fatter, indicating proportionally a greater probability of potential depreciations. Also, as the horizon increases, the densities deviate further from a normal distribution.

With respect to the kurtosis, the exchange rates seem to behave similarly. In effect, all values are around three, close to a normal distribution in this respect, and have a similar value as the horizon increases.

As for the average risk premium, all of the estimates are close to zero. The largest absolute values are associated with Brazil, regardless of the horizon. These are followed by Colombia, which is, in turn, closely followed by Chile and Mexico. A negative risk premium entails an appreciation of the local currency or a higher local short-term rate compared to the one in the US.

In addition, these statistics are useful to get an idea of the statistics' magnitudes for the different horizons considered. More specifically, the standard deviations provide a yardstick to assess the economic significance of the expected exchange rates' variations due to the interventions, which will be useful when we comment on the estimations of the linear model.

Moving on to our main results, we now consider the estimates of the different variants of our linear model. In our tables, the statistic being considered is constant; what changes along the rows are the countries. The one-day and one-week horizons are included in that same order. Starting with the mean and the one day-horizon (Table 3), several comments are in order. In terms of the intervention, there seems to be no statistically significant effect for any of the countries. Note that under the risk-neutral distribution the expected growth rate of the exchange rate is the domestic risk-free rate minus the US risk-free rate. Thus, one would expect not to observe economically significant effects, as these interventions are sterilized. On the other hand, the common factor certainly plays a role with respect to the determination of the expected exchange rate. For all the countries, the associated coefficients are statistically significant. This underscores the relevance of the common factors determining the exchange rate dynamics.

Second, considering the volatilities and a one-day horizon (Table 4), the interventions seem to have an effect in the Mexican and the Peruvian cases. In these cases, an intervention entailing a sale of dollars (a negative intervention dummy) seems to imply a slight increase in volatility. Moreover, the coefficients are only 10% and 1% of the standard deviations (Table 2) of the respective volatilities, not economically significant effects. As for the one-week horizon, no country seems to show a statistically significant variation in its exchange rate volatility due to an intervention. Similarly, for both horizons the common factor is significant for most cases. This bespeaks the important role played by the common factors in determining the exchange rate volatility.

Third, considering the one-day horizon skewness (Table 5), Brazil, Mexico and Peru show statistically significant effects. A dollar sale is associated with a decrease of 0.00154 in the Brazilian case, and with increases of 0.0033 and 0.00985, in the Mexican and Peruvian cases, respectively, as regards the exchange rate distributions' skewness. For Brazil, it implies a slight decrease in the probability of an abrupt depreciation, while for Mexico and Peru it implies a marginal increase in the probability of an abrupt depreciation. Moreover, these stand for changes near 7%, 13% and 24% in terms of the respective standard deviations of their skewness (Table 2), hardly economically significant. As for the one-week horizon, only Chile has a statistically significant coefficient associated with an intervention. Yet, it is only 1% of the standard deviation of the skewness for a one-week horizon, and thus of no economic significance. With respect to variations in skewness, one should also consider the following. For example, an increase in skewness implies an increase in the probability of an abrupt depreciation, but in tandem the probability mass of the distribution tends to move towards the left of the median, thus assigning greater probability to a small appreciation.

With respect to the kurtosis for a one-day horizon (Table 6), three countries seem to show a potential effect, namely, Chile, Mexico, and Peru. For all three cases, the kurtoses increase when selling dollars as part of an intervention. The associated changes are barely economically significant, representing 26%, 18%, and 31% of their respective standard deviations (Table 2). An increase in the kurtosis, reflecting fatter tails, means an increase in the probability of an extreme appreciation or depreciation. Moreover, for the one-week horizon no estimation seems to reflect a statistically significant effect.

Fifth, as for the risk premium (Table 7), for the two horizons and five countries considered there seem to be no statistically significant effects at all. As a caveat, one should take the estimates for the one-day horizon with caution, as in this case the R^2's are low.

Some comments on two additional extensions to our model are as follows. First, if one considers a two-week horizon (estimates not reported), the results are similar, which is not surprising. In the cases for which the coefficients associated with the interventions that are statistically significant, they are not economically significant.

Second, hitherto we have not considered the fact that Brazil actively intervenes in other markets besides the spot market. To account for this difference we estimate the following model: $s_{t,c,i} = \beta_{0,c,i} + \beta_{1,c,i}I_{t-1,c} + \beta_{2,c,i}CV_{t-1,c} + \beta_{3,c,i}CF_{t,-c,i} + \beta_{4,c,i}s_{t-1,c,i} + e_{t,c,i}$, where all the variables are defined as usual, and in addition $CV_{t-1,c}$ is a control variable which equals one if an intervention in one of the three markets other than the spot market has taken place at time t-1 and it is zero in other cases. For these three markets only one dummy is used since it is only very rarely that interventions in these markets take place on the same day, and since we are mainly interested in understanding interventions in the spot exchange rate markets. Similarly, the estimation is done for two horizons and for the five statistics we have thus far considered. Interestingly enough, it is only for the one-day horizon and skewness (Table 8 in the appendix) that the intervention dummy is now statistically significant. It stands out that the control dummy, which involves those interventions in associated markets, is generally not statistically significant.

All in all, although there were some minor differences in the more general regressions for the Brazilian case, our results for the most part stand. Effects on the expected exchange rate, when statistically significant, are generally economically not significant or short-lived.

Estimated linear model for the mean

Table 3

	Mean				
	Constant	Int. Dummy	Common Comp.	Lagged variable	R-squared/F-stat.
Horizon	**One day**				
Brazil	0.01049 *	0.00037	0.62033 *	0.99452 *	0.99463
	(0.00568)	(0.00103)	(0.02388)	(0.00285)	66624.88462
	(0.00511)	(0.00090)	(0.03655)	(0.00265)	
Chile	3.64132 *	-0.16850	79.18348 *	0.99266 *	0.99370
	(1.44581)	(0.18034)	(4.42433)	(0.00282)	56777.53113
	(1.76473)	(0.22898)	(6.32834)	(0.00349)	
Colombia	2.51260	0.37866	338.76077 *	0.99847 *	0.99537
	(5.12064)	(0.88754)	(17.56114)	(0.00250)	77363.65492
	(9.34354)	(0.90523)	(27.74882)	(0.00483)	
Mexico	0.11317 *	-0.00908	3.73233 *	0.99131 *	0.98505
	(0.05079)	(0.00773)	(0.13645)	(0.00394)	23724.20935
	(0.05743)	(0.01179)	(0.23985)	(0.00453)	
Peru	0.00518	-0.00022	0.13751 *	0.99802 *	0.99807
	(0.00442)	(0.00047)	(0.00874)	(0.00155)	186489.59065
	(0.00574)	(0.00037)	(0.01746)	(0.00206)	
Horizon	**One week**				
Brazil	0.01187 *	0.00056	0.59960 *	0.99381 *	0.99427
	(0.00587)	(0.00107)	(0.02518)	(0.00294)	62519.22684
	(0.00567)	(0.00090)	(0.03554)	(0.00294)	
Chile	2.58067	-0.08958	72.27480 *	0.99477 *	0.99340
	(1.49427)	(0.18150)	(4.47064)	(0.00291)	54162.23043
	(1.76956)	(0.22879)	(7.48654)	(0.00350)	
Colombia	3.74109	0.39571	303.16306 *	0.99781 *	0.99456
	(5.56903)	(0.94482)	(18.84352)	(0.00273)	65867.24622
	(9.54990)	(0.91190)	(29.74545)	(0.00494)	
Mexico	0.12079 *	-0.01104	3.79713 *	0.99070 *	0.98511
	(0.05076)	(0.00772)	(0.13983)	(0.00393)	23819.80557
	(0.05606)	(0.01138)	(0.23891)	(0.00441)	
Peru	0.00565	-0.00026	0.13865 *	0.99786 *	0.99806
	(0.00444)	(0.00047)	(0.00897)	(0.00155)	185221.17805
	(0.00596)	(0.00038)	(0.01770)	(0.00214)	

The model is: $s_{t,c,i} = \beta_{0,c,i} + \beta_{1,c,i}I_{t-1,c} + \beta_{2,c,i}CF_{t,-c,i} + \beta_{3,c,i}s_{t-1,c,i} + e_{t,c,i}$. The dependent variable is the mean. The first column indicates the country considered in the regression. The second column corresponds to the estimate of $\beta_{0,c,i}$, the third to the estimate of $\beta_{1,c,i}$, and so forth. Below each estimate the ordinary standard errors are in parentheses. Further below, the HAC standard errors are in parentheses. An asterisk next to the estimate indicates that one fails to reject the null hypothesis that it is equal to zero with 95% confidence, based on the HAC standard error.

Estimated model for the volatility

Table 4

	Volatility								
	Constant		Int. Dummy		Common Comp.		Lagged variable		R-squared/F-stat.
Horizon	**One day**								
Brazil	0.00130	*	0.00005		0.00656	*	0.91871	*	0.853
	(0.00030)		(0.00021)		(0.00033)		(0.01219)		2095.388
	(0.00030)		(0.00020)		(0.00050)		(0.01433)		
Chile	0.11067	*	-0.03960		0.13562	*	0.97474	*	0.962
	(0.03548)		(0.02580)		(0.02957)		(0.00645)		9127.598
	(0.04519)		(0.02401)		(0.03702)		(0.01035)		
Colombia	0.43043	*	-0.10743		1.16846	*	0.97349	*	0.955
	(0.18736)		(0.11683)		(0.10308)		(0.00781)		7697.733
	(0.21631)		(0.10909)		(0.22776)		(0.01078)		
Mexico	0.00801	*	-0.00620	*	0.04827	*	0.91493	*	0.866
	(0.00156)		(0.00195)		(0.00202)		(0.01219)		2319.466
	(0.00157)		(0.00175)		(0.00330)		(0.01480)		
Peru	0.00009		-0.00007	*	0.00007		0.99314	*	0.995
	(0.00005)		(0.00005)		(0.00004)		(0.00242)		68431.811
	(0.00005)		(0.00003)		(0.00005)		(0.00347)		
Horizon	**One week**								
Brazil	0.00065	*	-0.00006		0.00777	*	0.97955	*	0.978
	(0.00024)		(0.00016)		(0.00043)		(0.00469)		16234.707
	(0.00032)		(0.00015)		(0.00275)		(0.00869)		
Chile	0.28980		-0.07801		0.93984	*	0.96792	*	0.961
	(0.07138)		(0.05343)		(0.14109)		(0.00645)		8839.313
	(0.17076)		(0.06421)		(0.34224)		(0.01858)		
Colombia	2.51068		-0.84739		4.96217	*	0.94041	*	0.910
	(0.53765)		(0.35926)		(0.74971)		(0.01077)		3632.707
	(1.99066)		(0.75768)		(2.02030)		(0.04611)		
Mexico	0.00555	*	-0.00171		0.05258	*	0.97514	*	0.967
	(0.00154)		(0.00182)		(0.00314)		(0.00582)		10655.462
	(0.00147)		(0.00212)		(0.01912)		(0.00670)		
Peru	0.00075		-0.00011		0.00051	*	0.97157	*	0.952
	(0.00029)		(0.00032)		(0.00074)		(0.00731)		7152.588
	(0.00064)		(0.00020)		(0.00024)		(0.02336)		

The model is: $s_{t,c,i} = \beta_{0,c,i} + \beta_{1,c,i} I_{t-1,c} + \beta_{2,c,i} CF_{t,-c,i} + \beta_{3,c,i} s_{t-1,c,i} + e_{t,c,i}$. The dependent variable is the volatility. The first column indicates the country considered in the regression. The second column corresponds to the estimate of $\beta_{0,c,i}$, the third to the estimate of $\beta_{1,c,i}$, and so forth. Below each estimate the ordinary standard errors are in parentheses. Further below, the HAC standard errors are in parentheses. An asterisk next to the estimate indicates that one fails to reject the null hypothesis that it is equal to zero with 95% confidence, based on the HAC standard error.

Estimated model for skewness

Table 5

	Skewness				
	Constant	Int. Dummy	Common Comp.	Lagged variable	R-squared/F-stat.
Horizon	**One day**				
Brazil	0.00570 *	0.00154 *	9.54E-05	0.82782 *	0.715
	(0.00073)	(0.00063)	(8.20E-05)	(0.01687)	903.996
	(0.00085)	(0.00064)	(7.84E-05)	(0.02125)	
Chile	0.01308	-0.00713	5.76E-06	0.70275 *	0.743
	(0.00084)	(0.00086)	(1.12E-05)	(0.01523)	1041.577
	(0.00707)	(0.00398)	(3.69E-06)	(0.15994)	
Colombia	0.01232 *	-0.00240	7.21E-06 *	0.61315 *	0.412
	(0.00093)	(0.00071)	(8.29E-06)	(0.02389)	252.167
	(0.00525)	(0.00144)	(1.44E-06)	(0.15638)	
Mexico	0.00482 *	-0.00330 *	-8.74E-07	0.84148 *	0.761
	(0.00062)	(0.00112)	(8.39E-06)	(0.01654)	1147.372
	(0.00090)	(0.00135)	(1.16E-06)	(0.02732)	
Peru	0.01288 *	-0.00985 *	1.14E-06	0.36984 *	0.168
	(0.00137)	(0.00216)	(2.64E-05)	(0.02810)	72.912
	(0.00240)	(0.00299)	(2.23E-06)	(0.10155)	
Horizon	**One week**				
Brazil	0.00152 *	-0.00016	0.00064	0.97829 *	0.971
	(0.00053)	(0.00036)	(0.00020)	(0.00520)	12266.000
	(0.00047)	(0.00032)	(0.00036)	(0.00609)	
Chile	0.01065 *	-0.00169 *	0.00207	0.88621 *	0.834
	(0.00224)	(0.00305)	(0.00231)	(0.01207)	1808.278
	(0.00379)	(0.00080)	(0.00196)	(0.04510)	
Colombia	0.00972	-0.00488	0.00222	0.92264 *	0.860
	(0.00291)	(0.00343)	(0.00185)	(0.01172)	2207.438
	(0.00561)	(0.00296)	(0.00182)	(0.05743)	
Mexico	0.01047	0.00039	0.00173	0.86450 *	0.755
	(0.00132)	(0.00177)	(0.00065)	(0.01547)	1110.463
	(0.00616)	(0.00160)	(0.00121)	(0.07957)	
Peru	0.00128	-0.00013	0.00014	0.97105 *	0.949
	(0.00043)	(0.00035)	(0.00027)	(0.00747)	6752.135
	(0.00092)	(0.00021)	(0.00008)	(0.02017)	

The model is: $s_{t,c,i} = \beta_{0,c,i} + \beta_{1,c,i}I_{t-1,c} + \beta_{2,c,i}CF_{t,-c,i} + \beta_{3,c,i}s_{t-1,c,i} + e_{t,c,i}$. The dependent variable is the skewness. The first column indicates the country considered in the regression. The second column corresponds to the estimate of $\beta_{0,c,i}$, the third to the estimate of $\beta_{1,c,i}$, and so forth. Below each estimate the ordinary standard errors are in parentheses. Further below, the HAC standard errors are in parentheses. An asterisk next to the estimate indicates that one fails to reject the null hypothesis that it is equal to zero with 95% confidence, based on the HAC standard error.

Estimated model for the kurtosis | Table 6

	Kurtosis				
	Constant	Int. Dummy	Common Comp.	Lagged variable	R-squared/F-stat.
Horizon	**One day**				
Brazil	1.64746 *	-0.00096	-0.00064	0.44991 *	0.203
	(0.08132)	(0.00081)	(0.00545)	(0.02714)	91.897
	(0.21498)	(0.00116)	(0.00429)	(0.07183)	
Chile	1.36122 *	-0.00196 *	-0.00008	0.54694 *	0.556
	(0.05421)	(0.00022)	(0.00158)	(0.01805)	451.300
	(0.48799)	(0.00077)	(0.00051)	(0.16242)	
Colombia	1.52742 *	-0.00045	0.00034	0.49114 *	0.253
	(0.07925)	(0.00021)	(0.00134)	(0.02640)	121.928
	(0.45270)	(0.00028)	(0.00027)	(0.15081)	
Mexico	0.76456 *	-0.00096 *	0.00106	0.74532 *	0.614
	(0.06089)	(0.00031)	(0.00126)	(0.02028)	573.143
	(0.19243)	(0.00037)	(0.00059)	(0.06409)	
Peru	2.11601 *	-0.05266 *	-0.41310	0.28905 *	0.124
	(0.08583)	(0.00954)	(0.73612)	(0.02884)	50.738
	(0.39934)	(0.01262)	(0.63069)	(0.13410)	
Horizon	**One week**				
Brazil	0.09241 *	0.00004	-0.00955 *	0.96933 *	0.964
	(0.01812)	(0.00018)	(0.00251)	(0.00600)	9504.085
	(0.03014)	(0.00015)	(0.00422)	(0.01001)	
Chile	0.61981 *	-0.00055	0.35437	0.79373 *	0.762
	(0.04062)	(0.00191)	(0.04169)	(0.01354)	1155.621
	(0.15215)	(0.00051)	(0.23649)	(0.05055)	
Colombia	0.45212	0.00355	0.67345	0.84841 *	0.712
	(0.04941)	(0.00313)	(0.07897)	(0.01651)	891.609
	(0.27614)	(0.00286)	(0.52800)	(0.09157)	
Mexico	0.44755 *	-0.00237	0.06363 *	0.85126 *	0.758
	(0.04503)	(0.00066)	(0.00638)	(0.01495)	1128.102
	(0.20762)	(0.00146)	(0.02631)	(0.06899)	
Peru	0.07865	-0.00009	0.00040	0.97379 *	0.955
	(0.02173)	(0.00016)	(0.00195)	(0.00723)	7631.919
	(0.05793)	(0.00016)	(0.00036)	(0.01929)	

The model is: $s_{t,c,i} = \beta_{0,c,i} + \beta_{1,c,i} I_{t-1,c} + \beta_{2,c,i} CF_{t,-c,i} + \beta_{3,c,i} s_{t-1,c,i} + e_{t,c,i}$. The dependent variable is the kurtosis. The first column indicates the country considered in the regression. The second column corresponds to the estimate of $\beta_{0,c,i}$, the third to the estimate of $\beta_{1,c,i}$ and so forth. Below each estimate the ordinary standard errors are in parentheses. Further below, the HAC standard errors are in parentheses. An asterisk next to the estimate indicates that one fails to reject the null hypothesis that it is equal to zero with 95% confidence, based on the HAC standard error.

Estimated Linear model for Risk Premium

Table 7

	Risk Premium								
	Constant		Int. Dummy	Common Comp.		Lagged variable		R-squared/F-stat.
Horizon	**One day**							
Brazil	-0.00611	*	0.00035	-2.66E-07		-0.06738		0.005
	(0.00043)		(0.00053)	(2.45E-06)		(0.03041)		1.744
	(0.00043)		(0.00047)	(2.02E-06)		(0.03513)		
Chile	-0.00242	*	0.00016	-8.88E-07		0.11755	*	0.014
	(0.00022)		(0.00033)	(2.11E-06)		(0.03022)		5.225
	(0.00024)		(0.00034)	(8.81E-07)		(0.03408)		
Colombia	-0.00303	*	0.00063	-4.53E-06		0.12405	*	0.021
	(0.00032)		(0.00041)	(2.42E-06)		(0.03014)		7.810
	(0.00042)		(0.00044)	(3.19E-06)		(0.04206)		
Mexico	-0.00329	*	0.00053	-2.37E-06		-0.08179		0.009
	(0.00029)		(0.00071)	(2.15E-06)		(0.03034)		3.148
	(0.00029)		(0.00100)	(2.12E-06)		(0.04790)		
Peru	-0.00431	*	-0.00016	-8.30E-07	*	-0.12584		0.017
	(0.00014)		(0.00015)	(6.53E-07)		(0.03039)		6.376
	(0.00034)		(0.00014)	(4.13E-07)		(0.07884)		
Horizon	**One week**							
Brazil	-0.00184	*	0.00008	3.30E-06		0.75021	*	0.564
	(0.00054)		(0.00071)	(8.40E-06)		(0.02022)		462.628
	(0.00059)		(0.00067)	(5.29E-06)		(0.02334)		
Chile	-0.00060	*	0.00021	-2.20E-06		0.82899	*	0.688
	(0.00029)		(0.00046)	(6.21E-06)		(0.01712)		792.165
	(0.00030)		(0.00048)	(5.40E-06)		(0.01872)		
Colombia	-0.00083		0.00059	-1.47E-05	*	0.84005	*	0.709
	(0.00043)		(0.00057)	(1.10E-05)		(0.01649)		873.576
	(0.00061)		(0.00065)	(6.51E-06)		(0.01925)		
Mexico	-0.00113	*	-0.00023	-1.83E-06		0.75472	*	0.569
	(0.00038)		(0.00098)	(8.00E-06)		(0.02002)		473.924
	(0.00037)		(0.00134)	(9.29E-06)		(0.02596)		
Peru	-0.00113	*	-0.00002	-2.17E-06		0.77170	*	0.597
	(0.00015)		(0.00021)	(2.64E-06)		(0.01965)		529.914
	(0.00022)		(0.00020)	(1.62E-06)		(0.04070)		

The model is: $s_{t,c,i} = \beta_{0,c,i} + \beta_{1,c,i}I_{t-1,c} + \beta_{2,c,i}CF_{t,-c,i} + \beta_{3,c,i}s_{t-1,c,i} + e_{t,c,i}$. The dependent variable is the risk premium. The first column indicates the country considered in the regression. The second column corresponds to the estimate of $\beta_{0,c,i}$, the third to the estimate of $\beta_{1,c,i}$ and so forth. Below each estimate the ordinary standard errors are in parentheses. Further below, the HAC standard errors are in parentheses. An asterisk next to the estimate indicates that one fails to reject the null hypothesis that it is equal to zero with 95% confidence, based on the HAC standard error.

Final remarks

We have analyzed potential variations in the expected exchange rates of Brazil, Chile, Colombia, Mexico, and Peru given interventions implemented in these countries. The expected exchange rate distributions have been obtained implicitly from data on the derivatives market. These represent an advantage in terms of frequency, availability, and the fact that they are based on prices.

The leitmotif in our paper is clear; we find little statistical evidence of an effect on the exchange rates risk-neutral density given an intervention, and when we do, it tends to be short-lived or not economically significant

We believe that our results add to the evidence that the effects of interventions on the expected exchange rate are, if any, short-lived and economically not significant. In addition, it is clear that as the horizon increases the possibility of any effect swiftly vanishes. Moreover, in the cases of the mean and the volatility, to a great extent the common factor explains changes in the corresponding statistics, reflecting the relevance of economic fundamentals for the determination of the expected exchange rate. This poses in general a dilemma with respect to interventions in terms of their costs and benefits. In effect, if they are costly and at the same time have short-lived effects, then their use should be warranted only under truly exceptional circumstances.

Although our results seem robust in general, some caveats are in order. First, it seems worthwhile to incorporate more countries, something we will do as we gain access to more data. Second, the interventions analyzed have been in a sense considered as the same type, except that we have distinguished between selling and buying dollars. Third, there may be some limitations to the tools we have used to measure the interventions' effects. Fourth, in some cases, the fact that there is an existing rule that triggers the intervention might create a more significant effect in the expected exchange rate than does the actual intervention itself. Fifth, the benefits of interventions might be assessed considering other dimensions. Further research is warranted.

Appendix

Estimated linear model for Brazil with controls

Table 8

Brazil	Constant	Int. Dummy	Control	Common Factor	Lagged	R-squared /F-stat.
Mean	0.01047 *	0.00037	0.00012	0.62031 *	0.99452 *	0.9946
One Day	(0.00569)	(0.00104)	(0.00229)	(0.02390)	(0.00286)	49922.51
	(0.00511)	(0.00091)	(0.00277)	(0.03672)	(0.00265)	
Mean	0.01186 *	0.00056	0.00012	0.59957 *	0.99382 *	0.9943
One Week	(0.00588)	(0.00107)	(0.00237)	(0.02520)	(0.00295)	46846.12
	(0.00567)	(0.00091)	(0.00277)	(0.03573)	(0.00294)	
Volatility	0.00130 *	0.00004	-0.00043	0.00658 *	0.91894 *	0.8535
One Day	(0.00030)	(0.00021)	(0.00057)	(0.00033)	(0.01220)	1571.07
	(0.00030)	(0.00020)	(0.00045)	(0.00050)	(0.01421)	
Volatility	0.00066 *	-0.00009	-0.00072	0.00778 *	0.97963 *	0.9784
One Week	(0.00024)	(0.00016)	(0.00044)	(0.00043)	(0.00469)	12195.35
	(0.00031)	(0.00016)	(0.00043)	(0.00275)	(0.00841)	
Skewness	0.00571 *	0.00152 *	-0.00061	0.00010	0.82797 *	0.7152
One Day	(0.00073)	(0.00063)	(0.00170)	(0.00008)	(0.01688)	677.48
	(0.00085)	(0.00063)	(0.00082)	(0.00008)	(0.02125)	
Skewness	0.00153 *	-0.00017	-0.00030	0.00064	0.97829 *	0.9715
One Week	(0.00053)	(0.00036)	(0.00100)	(0.00020)	(0.00520)	9191.76
	(0.00047)	(0.00032)	(0.00088)	(0.00036)	(0.00606)	
Kurtosis	1.65054 *	-0.00100	-0.00153	-0.00043	0.44889 *	0.2037
One Day	(0.08147)	(0.00081)	(0.00230)	(0.00546)	(0.02719)	69.00
	(0.21550)	(0.00118)	(0.00203)	(0.00434)	(0.07200)	
Kurtosis	0.09234 *	0.00004	-0.00004	-0.00955 *	0.96936 *	0.9635
One Week	(0.01815)	(0.00018)	(0.00049)	(0.00251)	(0.00601)	7121.51
	(0.03008)	(0.00016)	(0.00043)	(0.00422)	(0.00999)	
Risk Premium	-0.00613 *	0.00037	0.00063	-2.85E-07	-0.06748	0.0050
One Day	(0.00043	(0.00053)	(0.00151)	(2.45E-06)	(0.03043)	1.35
	(0.00043	(0.00047)	(0.00136	(2.02E-06)	(0.03516)	
Risk Premium	-0.00183 *	0.00007	-0.00047	3.23E-06	0.75016 *	0.5635
One Week	(0.00054)	(0.00071)	(0.00199)	(8.41E-06)	(0.02023)	346.68
	(0.00059)	(0.00067)	(0.00152)	(5.27E-06)	(0.02333)	

The model is: $s_{t,c,i} = \beta_{0,c,i} + \beta_{1,c,i} I_{t-1,c} + \beta_{2,c,i} CV_{t-1,c} + \beta_{3,c,i} CF_{t,-c,i} + \beta_{4,c,i} s_{t-1,c,i} + e_{t,c,i}$.

The dependent variables are indicated above. The first column indicates the statistic and horizon considered in each regression. The second column corresponds to the estimate of $\beta_{0,c,i}$, the third to the estimate of $\beta_{1,c,i}$ and so forth. Below each estimate the ordinary standard errors are in parentheses. Further below, the HAC standard errors are in parentheses. An asterisk next to the estimate indicates that one fails to reject the null hypothesis that it is equal to zero with 95% confidence, based on the HAC standard error.

References

Abarca, G.L., G. Benavides, and J.G. Rangel, (2012a). "Exchange Rate Market Expectations and Central Bank Policy: The case of the Mexican Peso-US Dollar from 2005-2009." The Journal of Derivatives, Vol. 19, No. 4 pp. 70–90.

Abarca, G.L., C. Ramirez, and J.G. Rangel, (2012b). "Capital Controls and Exchange Rate Expectations in Emerging Markets." Banco de Mexico Working Paper 2012–08.

Bayoumi, T. and C. Saborowski (2012). "Accounting for Reserves." IMF Working paper WP/12/302.

BIS (2010). "Triennial Central Bank Survey: Report on global foreign exchange market activity in 2010." Monetary and Economic Department. December 2010.

Breeden, D., and R. Litzenberger (1978). "Prices of State-Contingent Claims Implied in Option Prices." Journal of Business, 51, 621–651.

Clews R., N. Panigirtzoglou and J. Proudman (2000). "Recent Developments in Extracting Information from Option Markets." Bank of England, Quarterly Bulletin, February pp. 50-60.

Dominguez, K. and J.A. Frankel (1993). "Does Foreign Exchange Intervention Matter? The Portfolio Effect." American Economic Review 83, pp. 1356–1369.

Disyatat, P., and G. Galati (2007). "The Effectiveness of Foreign Exchange Market: Intervention in Emerging Market Countries: Evidence from the Czech Koruna." Journal of International Money and Finance, 26, 383–402.

Figlewski, S. (2009). "Estimating the Implied Risk-Neutral Density for the U.S. Market Portfolio." Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle.

Figlewski, Stephen and J. Pirru (2010). "Anatomy of a Metldown: The Risk Neutral Density for the S&P 500 in the Fall of 2008." Working Paper, Revised Feb 2010.

Gnabo, Jean-Yves and Teiletche, Jerome, (2008). "Foreign-Exchange Intervention Strategies and Market Expectations: Insights from Japan." May 2.

Kenen, Peter (1988). "Managing Exchange Rates." Chatham House Papers. London. Routledge.

Malz, A. M. (1997). "Estimating the Probability Distribution of the Future Exchange Rate from Option Prices. "Journal of Derivatives, 5, 18-36.

Miyajima, Ken and Carlos Montoro (2013). "Impact of FX interventions on exchange rate expectations." BIS Note.

Mussa, Michael. (1981). "The Role of Official Interventions." N.Y., Group of Thirty.

Neely, C. J. (2001). The Practice of Central Bank Intervention: Looking under the Hood. Federal Reserve Bank of St. Louis Review, 83(3):1–10.

Sarno and Taylor (2001). "Official Intervention in the Foreign Exchange Market: Is It Effective and, If So, How Does It Work?" Journal of Economic Literature, (September), pp. 839–868

Rogers, Jeff M. and Pierre L. Siklos (2001). "Foreign Exchange Market Intervention in Two Small Open Economies: The Canadian and Australian Experience." Journal of International Money and Finance, Volume 999, pages 393-416.