Order Flow and the Real: Indirect Evidence of the Effectiveness of Sterilized Interventions

Emanuel Kohlscheen [*] [†]

Abstract

This study presents indirect evidence of the effectiveness of sterilized interventions in Brazil based on the complete records of daily customer order flow data reported by Brazilian dealers as well as foreign exchange intervention data over a time span of 10 years (2002-2011). We find that the effect of USD sales by end-users on the BRL/USD was much stronger on days in which the BCB did not intervene in the spot foreign exchange market. The regressions suggest that a 1% appreciation of the Real would have required the sale of 2.0 bn USD by final customers on days in which the Central Bank refrained from intervening. This compares to required sales of 5.5 bn USD on days in which the Central Bank was present in the market. This large effect, in spite of the fact that the median intervention amounted to only 140 mn USD, can be interpreted as evidence for the indirect *damping channel*. Furthermore, we find that order flows coming from outside of the financial sector have a (considerably) stronger effect on the BRL/USD exchange rate than those coming from financial customers. We argue that some studies may have failed to find significant effects of BCB interventions due to a problem of reverse causality, as in a regime of discretionary interventions the decision to intervene is often taken during trading hours.

[*]Research Department, Central Bank of Brazil. Setor Bancário Sul, Quadra 3, Bloco B, 70074-900 Brasília-DF, Brazil. *E-mail* address: emanuel.kohlscheen@bcb.gov.br

[†]I thank João B.R.B. Barroso, Marcos Chamon, Stefan Reitz and participants of the BIS CCA Working Group on Foreign Exchange Market Operations for very useful comments. The views expressed in this work are those of the author and do not necessarily reflect those of Banco Central do Brasil or its members.

1 Introduction

There is a great deal of controversy on whether exchange rate interventions that are sterilized have an effect on exchange rates in countries that operate under a floating exchange rate regime. While a consensus seems to have emerged that tick-by-tick data do show an effect at least at very high frequencies, the question is far from settled when one looks at horizons that go beyond the hour of the intervention (Sarno and Taylor (2001), Neely (2005), Menkhoff (2008)). Furthermore, most empirical studies have focused exclusively on the experiences of advanced economies. Works on emerging economies are much more scant, in part because their experience with floating exchange rate regimes is more recent. Some commentators have noted that intervention effects should be stronger in emerging markets, where liquidity and market turnover are typically smaller, and operations of the central bank are much larger when compared to the size of the foreign exchange market. Precise identification of the effects of exchange rate operations by the Central Bank at relevant horizons, however, is particularly challenging in countries where the decision to intervene is discretionary, rather than rules-based. Counter intuitive results are often obtained because the decision to intervene may be taken while the market is open, in reaction to ongoing market developments or disorderly conditions. In other words, rather than causing the daily exchange rate variation, the Central Bank could just be reacting to it, without necessarily reverting the sign of the variation. Hence, a study that simply looks at the relations between observed Central Bank actions and outcomes can easily lead to inaccurate conclusions. [1]

In light of the above, the approach we take in this paper is to make use of a uniquely comprehensive and long end-user order flow dataset to judge the effects of intervention under a discretionary regime indirectly. More specifically, we use the foreign exchange operations dataset of *Banco Central do Brasil*, which includes *all* transactions by authorized dealers in Brazil, to examine the effects of interventions on the relation between order flows and the BRL/USD exchange rate. [2] One advantage of the SISBACEN dataset that we use is that it allows us to focus on end-user flows (i.e. the primary market), rather than on the secondary inter-dealer market. [3] It has been noted elsewhere that, to the extent that private order flows carry information, exchange rates should be more sensitive to customer order flow than to interdealer flow (see Evans and Lyons (2005), Sager and Taylor (2006) and Reitz, Schmidt and Taylor (2011)). Theoretical market microstructure models such as that of Vitale (1999) and Killeen, Lyons and Moore (2006), have highlighted that sterilized interventions should affect the price impact of private trades. The study of Girardin and Lyons (2008), which was based on data obtained from *Citibank*, confirmed this hypothesis of an indirect

[1] This problem of reverse causality plagues for instance many popular GARCH estimations that are based on daily data.

[2] Broadly speaking, this study lies within the market microstructure literature of exchange rate determination pioneered by Lyons (2001), D'Souza (2001), Evans and Lyons (2002) and Dominguez (2003) among others.

[3] A related study by Wu (2010) used data from the same source for the period 1999-2003.

channel when they found that interventions changed the relation between order flow and the exchange rate for the Japanese Yen in a fundamental way. More recently, Marsh (2011) has used order flow data from the *Royal Bank of Scotland* to document that the link essentially disappears on days in which the Bank of Japan is present in the market. Our results for Brazil, which are based on a comprehensive dataset and a longer time series, [4] are broadly in line with the findings of these two studies for the Japanese Yen. More specifically, we find that the effect of USD sales by final customers on the BRL/USD was much stronger on days in which the BCB did not intervene in the spot foreign exchange market. On average, the correlations suggest that a 1% appreciation of the Real would have required the sale of 2.0 bn USD by final customers on days in which the Central Bank refrained from intervening. This compares to required sales of 5.5 bn USD on days in which the Central Bank was present in the market. The estimated difference is considerable if one takes into account that the median daily intervention in the spot market during the period, in absolute terms, was of only 140 mn USD. Moreover, the link appears to become weaker as the size of the intervention increases, though at a slow rate. Finally, we find that order flows coming from outside of the financial sector have a (considerably) stronger effect on the exchange rate than those coming from financial customers. Using the terminology of Girardin and Lyons (2008), intervention by the Brazilian

[4] We cover a period of 10 years of floating exchange rates (2002-2011), which is rather long for the standards of the microstructure literature.

monetary authority can therefore be considered effective as there is evidence that it "*damps the price impact of a given-sized private trade*". Our findings therefore corroborate the notion advanced by those authors that intervention may be working indirectly, by inducing changes in private pricing.

Outline. The paper proceeds as follows. Section 2 explains the unique dataset that is used in this paper. In Section 3, we analyze the effects of private order flows on the BRL/USD exchange rate for the full sample. Section 4 shows the strong dependence of this link on foreign exchange operations of the Central Bank. The paper closes with some concluding remarks, indicating possible directions for further research.

2 Data

Since January 1999 the Brazilian economy has been operating under a system of floating exchange rates. The Central Bank formally adopted and inflation target in July of that same year. Even though the exchange rate regime is characterized as a managed float, the volatility of the nominal exchange rate has been comparable to that seen in developed economies. [5] As in other inflation targeters, the open market desk of the Central Bank conducts monetary operations on a continuous basis to ensure that the SELIC interest rate remains on the target that is set by the Monetary Policy

[5] For more on nominal exchange rate volatilities of emerging markets vis-à-vis G-3 economies see Kohlscheen (2010).

Committe (COPOM) at pre-scheduled meetings. The monetary effects of exchange rate operations on the SELIC are therefore neutralized.

To assess how the relation between the exchange rate and order flow is affected by interventions of the Central Bank in the spot foreign exchange market, we use the complete records of private spot transactions of the electronic registry system of BCB (SISBACEN). Detailed order flow data is particularly interesting not only because it may provide real-time information about the evolving state of the economy (as suggested by Evans (2010)), but because order flow acts as a transmission mechanism of information to prices. In Brazil, recording of foreign exchange transactions at SISBACEN is mandatory, so that the system contains all transactions that are performed by authorized dealers. This unique database gives us the disaggregated flows of financial and non-financial customers on a daily basis over a ten year period (more precisely, from January 2nd, 2002 to November 30th, 2011). We have a total of 2,399 trading days. Our main variable of interest will be net order flows (i.e. purchases minus sales of US Dollars), from the perspective of foreign exchange dealers. This means that if one wants to interpret the coefficients from the perspective of an exporter or an importer, one has to switch the sign of the coefficients that we obtain. We abstract from interdealer flows, as our focus is on the primary (end-user) foreign exchange market.

In net terms, foreign exchange dealers acquired a total of \$ 369.4 bn from non-financial customers over the sample period and sold \$ 99.7 bn to their financial customers. This means that the net accumulated aggregate order flow over the period reached \$ 269.7 bn. [6] The central bank intervened in the spot market by either buying or selling USD in 1,345 days of the sample (i.e., 56% of the trading days). Net purchases of USD by the Central Bank during the period amounted to \$ 254.5 bn. Figure 1 shows the evolution of the BRL/USD exchange rate [7] from 2002 to 2011, as well as intervention activity by the BCB. [8]

We also use the SELIC base rate, the Fed Funds base rate, the VIX volatility index, [9] JP Morgan's EMBI spread for Brazil and the *Commodity Research Bureau*'s commodity price index as control variables. These variables are intended to proxy for changes in local and global monetary conditions, global risk aversion, country risk premia and international commodity prices. Interest rates were obtained from *Banco Central do Brasil* and the *Federal Reserve*, while exchange rates and data on the remaining control variables were obtained from *Bloomberg*.

[6] The average spot market turnover during the sampling period was \$991 mn for non-financial customers and \$1,927 mn for financial customers.

[7] At market close.

[8] Since September 2008, daily order flow as well as intervention data are made public on BCB's website during the following week.

[9] The VIX index is a measure of equity market volatility that is computed by the Chicago Board Options Exchange.

3 Full Sample Estimation

The matrix of correlations between the macroeconomic and financial variables is presented in Table 1. Note that there is a positive (and highly significant) correlation between total order flows and the BRL/USD rate (robust t-statistic=10.22). The disaggregated flows series show that this correlation is much stronger for non-financial order flows. [10]

We then proceed to estimate the simple relation

$$\Delta s_t = \alpha + \beta OF_t + \gamma \Delta Z_t + \varepsilon_t,$$

where Δs_t is (100 times) the log difference of the BRL/USD exchange rate, OF_t stands for net order flows (in million USD) and Z_t is a vector of macroeconomic and financial control variables. The hypothesis that the net order flow variables that we use have a unit root is clearly rejected by standard tests. [11] All other variables are in first differences. To obtain the t-statistics, we used the covariance estimator of Newey-West, that remains consistent in the presence of autocorrelation and heteroskedasticity.

The full sample estimation results are shown in Table 2, under six alternative specifications. What becomes clear from the table is that there is a strong link between order flows and exchange rate variations. In general, the point estimates of β suggest clear economic and statistical significance of the

[10] The robust t-statistic is 14.97 (p-value=0.0000) for non-financial customers order flows and 1.81 (p-value=0.0704) for financial customers order flows.

[11] The Augmented Dickey Fuller statistic is -38.48 for total flows, -24.21 for non-financial flows and -40.30 for financial flows.

order flow variables (with the exception of specification IV, that includes only financial customer order flow). Under (our preferred) specification III, a $ 1 bn USD sale by an end-user is associated with a 0.25% appreciation of the Real. This specification and those that follow include controls for changes in the interest rate differential, country risk premia, global uncertainty and global commodity prices. Throughout, the interest rate differential has no significant effect on the exchange rate, [12] while changes in the EMBI spread, the VIX and the CRB clearly do have an effect.

Note that, in principle, any of the four fundamentals that is used as a control variable in specifications III to VI could also be driving order flows. The correlations in Table 1 however suggest that this is not the case in our sample. The only correlation of the fundamentals in the four last lines of the table with order flows that attains the sign that would be predicted by theory is that of financial order flow vs. the interest rate differential. At 0.008, however, this correlation is far from statistically significant (p-value=0.6881). In the same fashion, the regression of each of the order flow variables on these fundamentals did not deliver a single instance of an explanatory variable that has the expected sign and is statistically significant at 10% at the same time. [13] It is still possible that order flow reacts to the *announcements* of macroeconomic variables. What is clear, however, is that daily order flows are not easily explained by the variation in the fundamentals that are used

[12] This result is in line with the event based study of Kohlscheen (2011).

[13] The regression results can be obtained from the author upon request.

here. [14]

One aspect that stands out from the estimation results is the stark difference that emerges between flows that are generated by financial and by non-financial customers. The latter clearly have a stronger and more significant effect on the exchange rate. When both flows are included separately, the effect of non-financial (i.e., mostly trade) flows is about five times as strong as that of financial customers. Note that when only order flows of financial customers are used, the strong link between order flows and exchange rate variations disappears. This observation is in stark contrast, for instance, with the case of Sweden, where Bjonnes, Rime and Solheim (2005) report that the coefficients for financial and non-financial customers are similar in absolute value, but have opposite signs. Obviously, one fundamental difference between the Brazilian and the Swedish exchange rate market is the strong market presence of the Brazilian Central Bank, that acquired a total of $ 254.5 bn over this 10-year period. The result is however consistent with the findings of the study by Wu (2010), that used Brazilian data between 1999 and 2003. Indeed, cointegration tests for our sample confirmed the existence of a significant long run relation between the accumulated net position of non-financial customers and the exchange rate, but not for financial

[14] Iwatsubo and Marsh (2011) also report a very poor fit in regressions aimed at explaining order flows. Their adjusted R2 for the EUR/USD is never above 0.01. Ostry, Ghosh and Chamon (2012) present a stylized model for emerging markets, with imperfect capital mobility, to show that the case for sterilized interventions within an inflation targeting framework becomes stronger when capital flows are insensitive to interest rates.

customers. [15]

Finally, it is interesting to note that the explanatory power of the variables is high by the standards of the exchange rate literature: order flow variables explain up to 10% of the exchange rate variation when no controls are included. With control variables, we are able to explain about 40% of the variation. As a reference point, the related study of Iwatsubo and Marsh (2011) is able to explain only 5% of the variation of the USD/EUR exchange rate variation between 2001 and 2004.

4 The Effects of Intervention

4.1 Estimation

To assess whether exchange rate interventions in the spot market have an effect on the link between private sector order flows and the exchange rate we reestimated the regressions in Table 2 for a subsample that contains only days in which the BCB did not intervene in the spot USD market and for a subsample of intervention days. The results are reported in Tables 3 and 4. By and large, the qualitative pattern of results does not change relative to the previous sub-section: order flows (in particular those that originate in the trade sector) are tightly linked to exchange rate variations. However,

[15] The coefficient of the accumulated non-financial order flow in the cointegration equation is 0.004216 (t-stat=7.49). This implies that a permanent 1% depreciation takes $ 2.37 bn away from the net (accumulated) non-financial flow.

the quantities change considerably. More specifically, the response of the exchange rate to order flows is much stronger on days when the Central Bank refrained from intervening. [16] A $ 1 bn USD sale by an end-user is associated with a 0.50% appreciation of the Real when the Central Bank is not present in the spot market. On days in which the Central Bank is in the market, the appreciation is limited to 0.18%. Again, the effect is stronger if the sale is performed by an exporter, rather than a financial institution. To put it differently, on average, a 1% appreciation of the Real would have required the sale of 2.0 bn USD by final customers on days in which the Central Bank refrained from intervening. This compares to required sales of 5.5 bn USD on days in which the Central Bank was present in the market. This difference is considerable if one takes into account that the average daily intervention amount in the spot market during the period, in absolute terms, was only of 119 mn USD (standard deviation of 224 mn). [17]

4.2 Effects by Size of Intervention

In order to scrutinize the effects of intervention further, we subdivided the 1,345 days of the intervention sample into three groups, according to whether the magnitude of the intervention was small, medium or large in

[16] This is valid in all specifications, with the exception of IV, where β was not found to be significant.

[17] Note that, in principle, endogeneity should work against finding such effect as in general a monetary authority that worries about excessive short-term volatility is probably more likely to intervene on days in which the exchange rate is more sensitive to order flows.

relative terms. The terciles of the intervention sample were at 72 mn USD and at 216 mn USD. In other words, we classified daily interventions whose amount was up to 72 mn USD in absolute terms as being small, those whose volume was between 72 mn and 216 mn USD as being medium size and those above 216 mn USD as being large. We then reestimated regression III for each of the three groups. Figure 2 shows the β estimates for each of the subsamples. The coefficient falls as the intervention amount increases. [18] Put differently, a stronger presence of the Central Bank in the market appears to weaken the link between private net order flows and the exchange rate further. This provides additional evidence to the notion that intervention de-links private order flows from exchange rate variations. It should be noted, however, that the gradient between the intervention subsamples is not very large. Indeed, going from no intervention to small intervention reduces the correlation by more than switching from the small intervention to the large intervention sample.

4.3 Propensity Scores

In order to check for the robustness of the finding that intervention operations by the Central Bank weaken the link between private order flows and exchange rate variations (and large ones, in particular) we performed

[18] To be precise, β falls from 0.000502 (t-stat=6.02) for the no intervention sample, to 0.000230 (t-stat=3.64) in the small intervention sample, to 0.000211 (t-stat=3.18) in the medium intervention sample and to 0.000126 (t-stat=2.96) in the large intervention sample.

an additional robustness check. More specifically, we run a first stage logit regression in which we estimate the probability of exchange rate intervention on a given day and then compare the estimated βs, as we did in the previous subsections, for the low and the high propensity score samples separately. The propensity score estimation was performed using a parsimonious specification that included a variable that indicated whether there had been an intervention on the previous day, the (log) difference between the exchange rate on the previous day and a 250 day moving average and the VIX, as an indicator for global market volatility. The evolution of the intervention propensity score over time is shown in Figure 3, while β estimates are reported in Table 5. Note that, since the logit specification predicts intervention activity quite well, [19] the estimates in the second and the third column of the Table are based on much smaller sample sizes - meaning much greater uncertainty for the estimates in these cases.

As before, the sensitivity of the exchange rate to order flows is larger for the no intervention sample in both, the low and the high propensity score samples. The conjecture that it is not intervention that drives β down, but some third variable, that is highly correlated with intervention seems unwarranted. If this where indeed the case, one should see lower point estimates for β in the high propensity score sample. In the case where the difference in the point estimates is substantial, however (i.e., the sample without in-

[19] The model predicts 91.1% of the outcomes correctly when the 0.50 cutoff probability is used.

tervention), β increases with the propensity score - which goes against the above conjecture. [20] All in all, the results provide further indication that intervention does induce changes in private pricing.

5 Concluding Remarks

This study used a uniquely comprehensive dataset of foreign exchange operations to investigate the link between end user order flows and the value of the Brazilian Real. The results we present suggest that interventions in the foreign exchange market are effective in the sense that relatively small intervention amounts do induce considerable changes in private pricing behavior. We interpret this evidence of an indirect *damping channel* (as in Girardin and Lyons (2008)) as an indication that the monetary authority could have a coordinating role to play in price setting. Furthermore, we find stronger effects of intervention than those reported in studies of advanced economies.

Our results seem to suggest that some studies may have failed to find significant effects of BCB interventions due to a problem of reverse causality, as in a regime of discretionary interventions the decision to intervene is often taken during trading hours. Moreover, we find that order flows coming from outside of the financial sector clearly have a greater impact on the BRL/USD exchange rate than those coming from financial customers.

[20] Note that, as a result of the smaller sample size, the link between order flows and exchange rate variations loses statistical significance when the Central Bank is in the market in the low propensity score subsample.

The findings of this paper seem to corroborate the notion that the Central Bank has two effective instruments at its disposal (see Ostry *et. al.* (2012)). Future research efforts could focus on longer run effects of exchange rate interventions and on the determinants of order flows.

References

[1] Bjonnes, G.H., D. Rime and H.O Solheim (2005) Liquidity provision in the overnight foreign exchange market. *Journal of International Money and Finance* 24, 175-196.

[2] Dominguez, K. (2003) The market microstructure of central bank intervention. *Journal of International Economics* 59, 25-45.

[3] D'Souza, C. (2001) A market microstructure analysis of FX intervention in Canada. Bank of Canada.

[4] Evans, M.D.D. and R.K. Lyons (2002) Order flow and exchange rate dynamics. *Journal of Political Economy* 110, 170-180.

[5] Evans, M.D.D. and R.K. Lyons (2005) Understanding order flow. NBER Working Paper no. 11748.

[6] Evans, M.D.D. (2010) Order flows and the exchange rate disconnect puzzle. *Journal of International Economics* 80, 58-71.

[7] Girardin, E. and R.K. Lyons (2008) Does intervention alter private behaviour? Mimeo. UC Berkeley - Haas School of Business.

[8] Iwatsubo, K. and I.W. Marsh (2011) Order flows, fundamentals and exchange rates. Kobe University. Discussion Paper 1120.

[9] Killeen, W.P., R.K. Lyons and M.J.Moore (2006) Fixed versus flexible: lessons from EMS order flow. *Journal of International Money and Finance* 25, 551-579.

[10] Kohlscheen, E. (2010) Emerging floaters: pass-throughs and (some) new commodity currencies. *Journal of International Money and Finance* 29, 1580-1595.

[11] Kohlscheen, E. (2011) The impact of monetary policy on the exchange rate: a higher frequency exchange rate puzzle in emerging economies? Banco Central do Brasil. Working Paper 259.

[12] Lyons, R.K. (2001) *The microstructure approach to exchange rates.* MIT Press, Cambridge - MA.

[13] Marsh, I.W. (2011) Order flow and central bank intervention: an empirical analysis of recent Bank of Japan actions in the foreign exchange market. *Journal of International Money and Finance* 30, 377-392.

[14] Menkhoff, L. (2008) High-frequency analysis of foreign exchange interventions: what do we learn? CESIfo Working Paper 2473.

[15] Neely C.J. (2005) An analysis of recent studies of the effect of foreign exchange intervention. Federal Reserve Bank of St. Louis Working Paper 2005-030B.

[16] Ostry, J., A.R. Ghosh and M. Chamon (2012) Two targets, two instruments: monetary and exchange rate policies in emerging market economies. IMF Staff Discussion Note.

[17] Reitz, S., M.A. Schmidt and M.P. Taylor (2011) End-user order flow and exchange rate dynamics. *European Journal of Finance* 17, 153 -168.

[18] Sager, M. and M.P. Taylor (2006) Under the microscope: the structure of the foreign exchange market. *International Journal of Finance & Economics* 11, 81-95.

[19] Sarno, L. and M.P. Taylor (2001) Official intervention in the foreign exchange market: is it effective, and if so, how does it work? *Journal of Economic Literature* 39, 839-868.

[20] Vitale, P. (1999) Sterilized central bank intervention. *Journal of International Economics* 49, 245-267.

[21] Wu, T. (2010) Order flow in the south: anatomy of the Brazilian FX market. Mimeo. UC Santa Cruz.

Figure 1
BCB's Spot USD Purchases

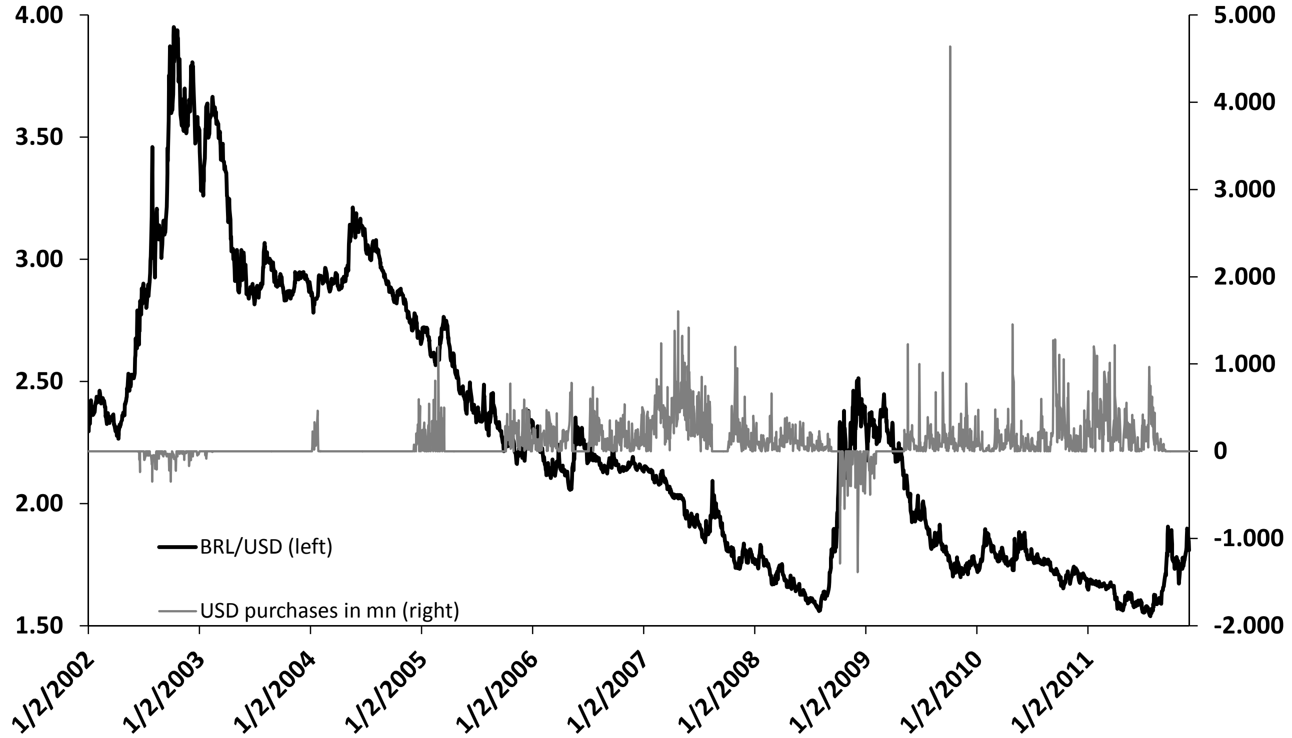

Table 1

Table of Correlations

	Δ(BRL/USD)	aggregate flow	financial flow	non-financial flow	Δ(SELIC - Fed F)	Δ EMBI	Δ VIX	Δ CRB
Δ(BRL/USD)	1							
aggregate flow	0.211	1						
financial flow	0.038	0.824	1					
non-financial flow	0.302	0.379	-0.213	1				
Δ(SELIC - Fed F)	-0.056	-0.023	0.008	-0.053	1			
Δ EMBI	0.494	0.079	0.008	0.123	-0.019	1		
Δ VIX	0.428	0.176	0.050	0.221	-0.036	0.224	1	
Δ CRB	-0.213	-0.093	-0.018	-0.131	0.003	-0.084	-0.170	1

The sample covers daily data from 01/02/2002 to 11/30/2011.

Table 2

End-user order flow and the Real

change in the BRL/USD rate

	I	II	III	IV	V	VI
aggregate order flow	0.000446**		0.000245**			
t-statistic	8.04		5.30			
financial customer order flow		0.000237**		0.000039		0.000134*
t-statistic		4.00		1.04		2.85
non-financial customer order flow		0.001172**			0.000638**	0.000690**
t-statistic		7.26			4.88	5.91
d (SELIC - Fed Funds)			-0.245740	-0.260233	-0.204053	-0.203840
t-statistic			1.32	1.37	1.11	1.11
d (EMBI)			1.954465**	1.975973**	1.914981**	1.91156**
t-statistic			10.19	10.31	10.01	9.98
d (VIX)			0.182750**	0.193366**	0.173661**	0.170146**
t-statistic			8.49	9.03	7.97	7.81
d (CRB)			-0.273625**	-0.290163**	-0.252787**	-0.248361**
t-statistic			4.51	4.79	4.29	4.21
no. of observations	2399	2399	2242	2242	2242	2242
R2	0.0441	0.1010	0.3792	0.3667	0.3949	0.3983
Adjusted R2	0.0438	0.1002	0.3779	0.3653	0.3935	0.3967
Log-likelihood	-3722.8	-3649.3	-3015.7	-3038.2	-2987.0	-2980.7
F / chi2	110.74	134.59	273.21	258.91	291.89	246.60
Durbin-Watson	2.054	2.059	2.166	2.171	2.154	2.151

Note: t-statistic based on Newey-West standard errors. †, * and ** denote statistical significance at the 10%, 5% and 1% confidence levels, respectively.
The sample covers data from 01/02/2002 to 11/30/2011.

Table 3

End-user order flow and the Real - days without intervention

change in the BRL/USD rate

	I	II	III	IV	V	VI
aggregate order flow	0.000980**		0.000502**			
t-statistic	9.93		6.02			
financial customer order flow		0.000656**		0.000031		0.000134**
t-statistic		6.51		0.40		4.17
non-financial customer order flow		0.001913**			0.000823**	0.000690**
t-statistic		13.98			7.50	8.62
d (SELIC - Fed Funds)			-0.160819	-0.146620	-0.085814	-0.203840
t-statistic			1.17	1.05	0.63	0.79
d (EMBI)			1.965433**	2.051464**	1.913973**	1.91156**
t-statistic			14.18	14.61	13.81	13.69
d (VIX)			0.209695**	0.228150**	0.206335**	0.170146**
t-statistic			11.45	12.40	11.39	10.85
d (CRB)			-0.392843**	-0.419636**	-0.377004**	-0.248361**
t-statistic			6.15	6.47	5.95	5.80
no. of observations	1054	1054	991	991	991	991
R2	0.0857	0.1573	0.4107	0.3892	0.4220	0.4321
Adjusted R2	0.0848	0.1557	0.4078	0.3861	0.4191	0.4286
Log-likelihood	-1672.8	-1629.8	-1354.3	-1372.1	-1344.7	-1336.0
F / chi2	98.56	98.10	137.32	125.52	143.86	124.78
Durbin-Watson	1.951	1.864	2.086	2.066	2.002	2.025

Note: †, * and ** denote statistical significance at the 10%, 5% and 1% confidence levels, respectively.

The sample covers data from 01/02/2002 to 11/30/2011.

Table 4
End-user order flow and the Real - days with BCB intervention in the spot market

change in the BRL/USD rate

	I	II	III	IV	V	VI
aggregate order flow	0.000310**		0.000182**			
t-statistic	6.76		4.60			
financial customer order flow		0.000146**		0.000035		0.000085*
t-statistic		2.98		0.81		2.03
non-financial customer order flow		0.000894**			0.000546**	0.000570**
t-statistic		10.70			7.37	7.61
d (SELIC - Fed Funds)			-0.418761†	-0.484185*	-0.417045†	-0.390613†
t-statistic			1.78	2.04	1.80	1.68
d (EMBI)			1.905864**	1.909108**	1.879140**	1.881504**
t-statistic			18.96	18.83	18.92	18.97
d (VIX)			0.161656**	0.170470**	0.152212**	0.149922**
t-statistic			12.16	12.86	11.52	11.32
d (CRB)			-0.180452**	-0.195918**	-0.161178**	-0.157537**
t-statistic			3.65	3.94	3.29	3.22
no. of observations	1345	1345	1251	1251	1251	1251
R2	0.0329	0.0799	0.3665	0.3560	0.3827	0.3847
Adjusted R2	0.0321	0.0785	0.3639	0.3535	0.3802	0.3817
Log-likelihood	-2026.3	-1992.8	-1642.3	-1652.5	-1626.1	-1624.1
F / chi2	45.63	58.27	144.05	137.67	154.34	129.62
Durbin-Watson	2.035	2.044	2.084	2.094	2.090	2.084

Note: †, * and ** denote statistical significance at the 10%, 5% and 1% confidence levels, respectively.
The sample covers data from 01/02/2002 to 11/30/2011.

Figure 2
β vs. magnitude of intervention

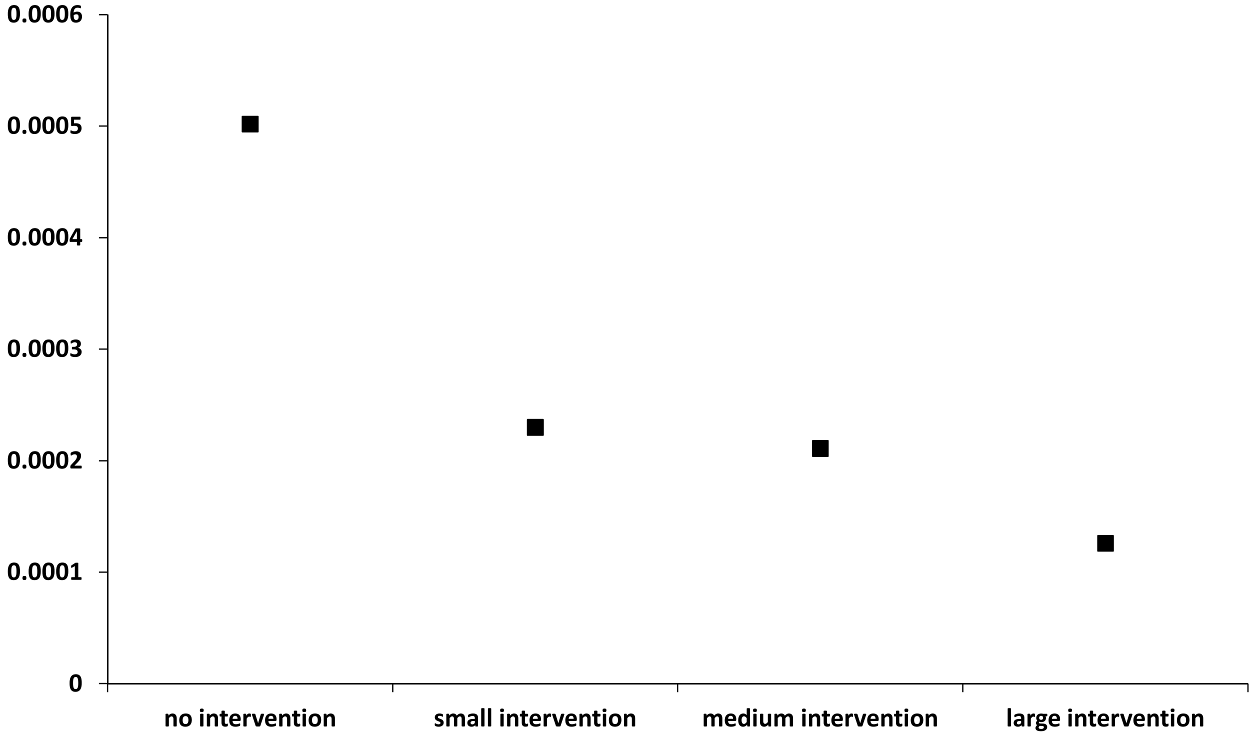

Figure 3
Intervention propensity scores

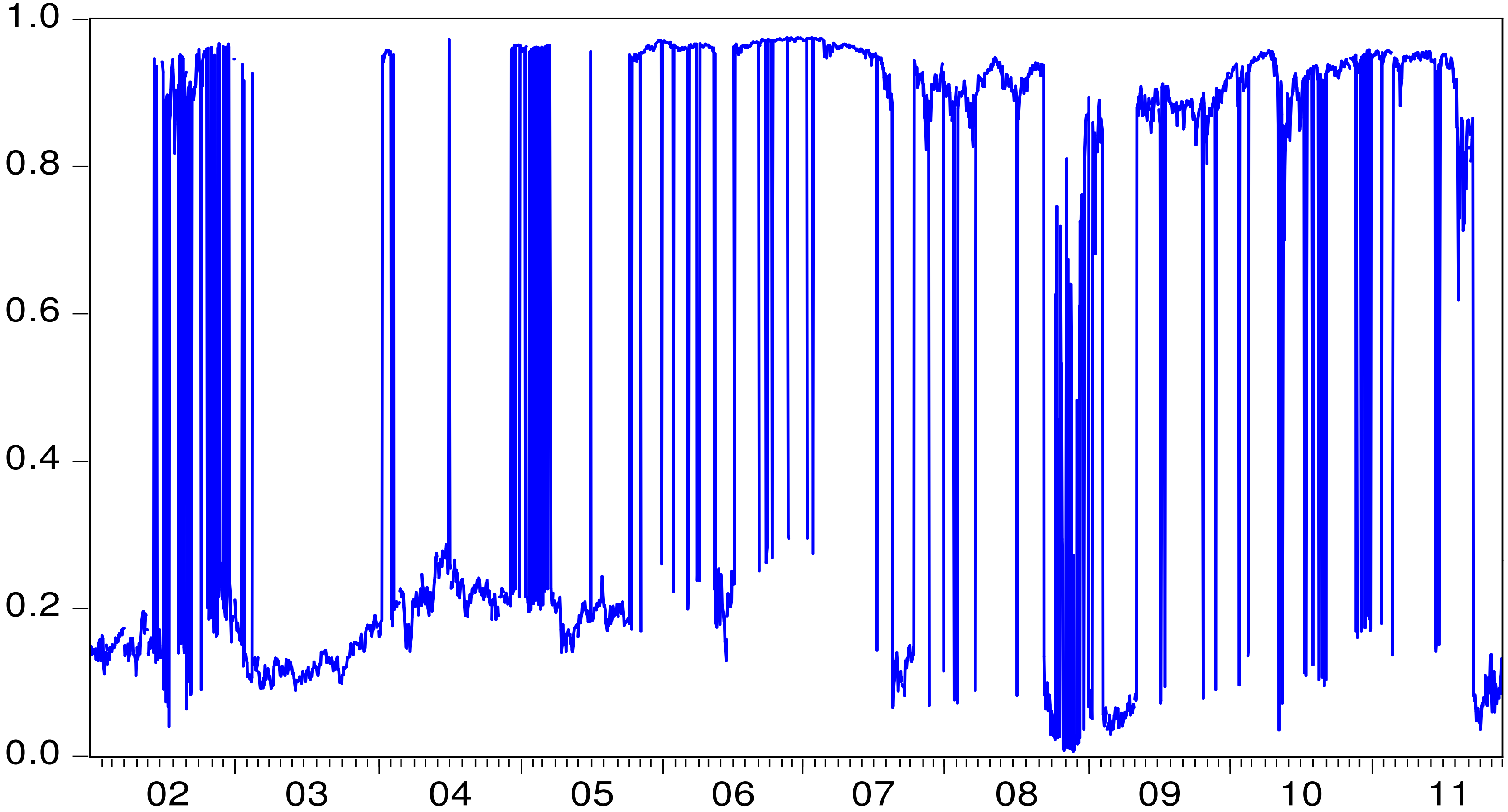

Table 5
End-user order flow and the Real - by propensity score

change in the BRL/USD rate

	p-score ≤ 0.50		p-score > 0.50	
	no interv	interv	no interv	interv
aggregate order flow	0.000439**	0.000290	0.000931**	0.000185**
t-statistic	5.03	1.07	3.32	4.74
d (SELIC - Fed Funds)	-0.158915	-0.812735	-0.002150	-0.382107
t-statistic	1.15	0.73	0.00	1.61
d (EMBI)	2.300060**	1.431931**	1.144967**	1.972191**
t-statistic	14.13	3.72	3.49	18.97
d (VIX)	0.195489**	0.190553**	0.205395**	0.153246**
t-statistic	9.75	5.01	3.99	10.33
d (CRB)	-0.373591**	-0.173732	-0.390010†	-0.186156*
t-statistic	5.57	0.91	1.85	3.62
no. of observations	896	104	95	1147
R2	0.4098	0.3967	0.4900	0.3589
Adjusted R2	0.4065	0.3659	0.4613	0.3561
Log-likelihood	-1206.2	-171.7	-138.1	-144.9

Note: †, * and ** denote statistical significance at the 10%, 5% and 1% confidence levels, respectively.
The sample covers data from 01/02/2002 to 11/30/2011.