PONTIFÍCIA UNIVERSIDADE CATÓLICA
DO RIO DE JANEIRO

Caio de Paiva Garzeri

FX Interventions in Brazil: revisiting impacts with a twofold approach

Dissertação de Mestrado

Masters dissertation presented to the Programa de Pós–graduação em Economia, do Departamento de Economia da PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Economia.

Advisor: Márcio Gomes Pinto Garcia

Rio de Janeiro
April 2024

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A meus pais, Nelson e Mércia

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Abstract

de Paiva Garzeri,Caio; Gomes Pinto Garcia, Márcio (Advisor). **FX Interventions in Brazil: revisiting impacts with a twofold approach**. Rio de Janeiro, 2024. 52p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Benefiting from a novel dataset published by the Central Bank of Brazil (BCB) we estimate the effects of FX Interventions from 1999 to 2023. We first employ a structural VAR with daily frequency identified with an instrument based on the timing of BCB announcements. Interventions are found to be effective in changing the USDBRL level over a period of 20 working days by 0.24 p.p. for each 1USD billion employed. We then implement an Artificial Counterfactual (ArCo) approach to each intervention episode separating them by side and instrument. Compared to SVAR interventions are found to be more effective although with smaller statistical significance. Spot Interventions are more effective than Swaps. We find no effects of interventions over the short-term volatility of the USDBRL.

Keywords

FX Interventions; Structural VAR; Artificial Counterfactual.

Resumo

de Paiva Garzeri,Caio; Gomes Pinto Garcia, Márcio. **Intervenções Cambiais no Brasil: revisitando impactos com uma abordagem dupla**. Rio de Janeiro, 2024. 52p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Usando uma recém publicada base de dados pelo Banco Central do Brazil (BCB), estimamos os efeitos de intervenções cambiais realizadas entre 1999 e 2023. Em primeiro lugar, utilizamos um VAR estrutural em frequência diárias, identificado por meio de um instrumento baseado nos horários de anúncio das interveções. Estima-se que as intervenções são capazes de afetar o nível do Real por um período de 20 dias úteis, em 0.24 p.p. a cada bilhão de dólares empregados.

Palavras-chave

Intervenções Cambiais; VAR Estrutural; Contrafactual Artifical.

Table of contents

1 Introduction **12**

2 Literature **16**

3 Data **18**

4 Intervention Instruments and Episodes **20**

5 SVAR **24**
5.1 Method 24
5.2 Results 27

6 ArCo **29**
6.1 Method 29
6.2 Results 31

7 Discussion **37**

8 Conclusion **40**

9 Bibliography **41**

A Appendix **44**
A.1 Summary of Literature Review 44
A.2 Data 45
A.3 SVAR and Episodes with 10-day gaps 46
A.4 ArCo - Episodes after 2016 47
A.5 FXI using Adler et al. (2021) 48
A.6 Intervention Episodes 49

List of figures

Figure 1.1 FX Intervention and the USDBRL exchange rate - 1999 to 2023 14
Figure 1.2 FX Intervention as share of Brazilian dollar market 15

Figure 4.1 Spot Interventions and the BRLUSD 21
Figure 4.2 Swap Interventions and the BRLUSD 22
Figure 4.3 Repo Interventions and the BRLUSD 22
Figure 4.4 Probabilities of Intervention 23

Figure 5.1 Timing of Announcements 26
Figure 5.2 IRFs - Sale of 1USD billion 27
Figure 5.3 IRFs - Purchase of 1USD billion 28
Figure 5.4 Observed USDBRL and USDBRL with no interventions 28

Figure 6.1 Effects of Intervention - Selected Episodes 32
Figure 6.2 Ilustration - Placebos for selected episodes 33
Figure 6.3 ArCo Counterfactual USDBRL and the Dollar Index 34
Figure 6.4 Average Treatment Effect - USDBRL Level 35
Figure 6.5 Average Treatment Effect - USDBRL Volatility 35

Figure 7.1 Effects of 1USD billion intervention - Selected literature and this work 38

Figure A.1 Average Treatment Effect - Selling and Purchasing Episodes 46
Figure A.2 Average Treatment Effect - Selling and Purchasing Episodes 47
Figure A.3 Average Treatment Effect - Selling and Purchasing Episodes - Adler Database 48

List of Algorithms

Também eu saio à revelia
e procuro uma síntese nas demoras

Ana Cristina Cesar

1
Introduction

Foreign Exchange Interventions (FXI) in Brazil happen very frequently and are quite sizable. From January 1999 to May 2023 the Central Bank of Brazil (BCB) intervened on 40.6% of market days (Figure 1.1) and interventions accounted on average for 2.5% of the total volume of the dollar market in Brazil. In periods of higher volatility that figure rose to up to 15% (Figure 1.2). With these interventions the BCB has primarily intended to provide liquidity to the dollar market preventing excessive volatility of the exchange rate without pursuing a specific level to the exchange rate.[1]

From a theoretical perspective a set of papers has recently shown that in the presence of imperfect financial markets or frictions in capital mobility FXI can indeed be the optimal policy for output stabilization and risk sharing among investors (Gabaix e Maggiori (2015) and Fanelli e Straub (2021)). Empirical papers on the other hand have often struggled to find strong effects for FXI. A quite large empirical literature has focused on the effects of FXI in Brazil but results have been notoriously mixed. Depending on the period and method used by authors, interventions were found to be plainly ineffective (Meurer, Teixeira e Tomazzia (2020)), little effective (Kohlscheen e Andrade (2014)) or quite effective (Chamon, Garcia e Souza (2017)) in changing the level of the USDBRL rate. With regards to the volatility of the USDBRL results have also been varied.

In this paper we benefit from a recently published database by the BCB covering all interventions it conducted since 1999 in order to revisit the question of how interventions affect the level and the volatility of the USDBRL. Apart from the extensive time span it covers, the database also contains information that had not been compiled before such as the timing of announcements by the BCB, which will be instrumental in our empirical strategy.

With respect to method the hardest challenge in this literature is endogeneity. Interventions by the BCB are obviously not random but respond to movements in the USDBRL instead. Additionally the BCB usually acts against the wind which means it will purchase (sell) dollars in periods when the BRL is appreciating (depreciating).

[1]The BCB has defined the goal of FXI in different terms such as: *"assuring the well functioning of the foreign exchange market"* (BCB "Política Cambial" 2023); *"smoothing movements in the foreign exchange market"* (BCB Nota No. 16515); *"providing liquidity to the market"* (BCB Nota No. 16151).

In order to overcome these difficulties our approach is twofold. We first employ a structural VAR in order to study dynamic effects of the intervention over the exchange rate and other macroeconomics variables. The use of VARs for this purpose is common in the literature because it enables us to account for the endogeneity between intervention volumes and the USDBRL.

Identification of intervention shocks relies on an instrumental variable which we build using the timing of announcements by the BCB. These announcements have been used before by Santos (2021) and Mello (2022). In estimating shocks with this instrument our method makes fairly nonrestrictive assumptions about causality and does not rely lagged endogenous variables as instruments, which have been pervasive in the literature.

Our VAR results indicate that interventions do affect the level of the USDBRL: an intervention shock of 1 USD billion in sales by the BCB causes the BRL to appreciate in 0.24 p.p. over a period of close to 20 working days. Interventions do not affect other macroeconomic variables in our model such as interest rate differentials and asset prices at least in the short term.

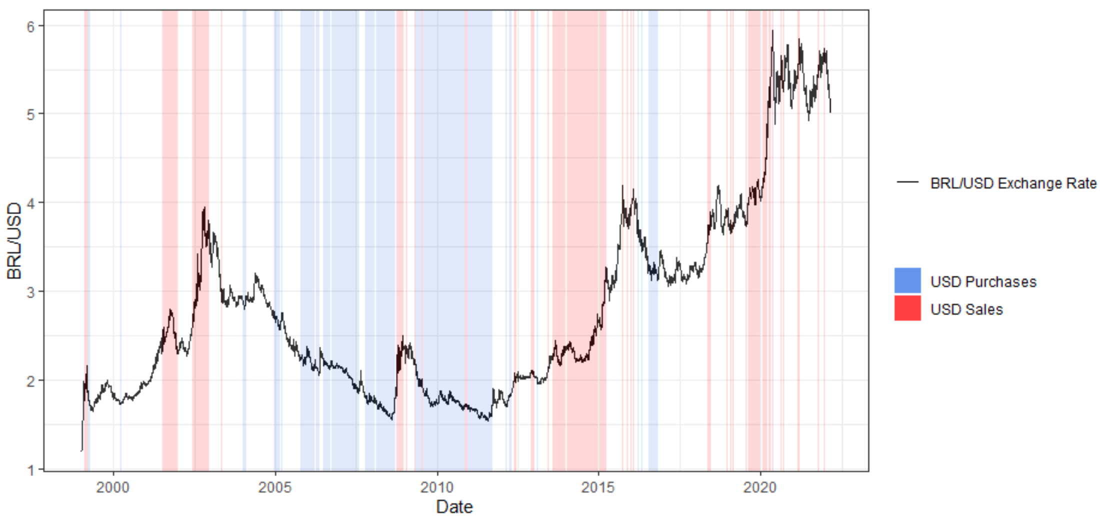
Complementary to this first approach we then estimate the effect of interventions using the Artificial Counterfactual (ArCo) method, proposed by Carvalho, Masini e Medeiros (2018) and first employed in the FXI literature by Chamon, Garcia e Souza (2017). ArCo is one of many existing methods of estimating causal effects of interventions over a treated unit with no existing control group. For each intervention episode in Brazil, we compare the movement of the USDBRL to that of other currencies which suffered no equivalent interventions. Compared to other synthetic control approaches ArCo makes generally less restrictive assumptions over coefficients and treatment characteristics which we discuss in Chapter 6. We draw potential placebo countries from a recently published database constructed by Fratzscher et al. (2022) which covers FXI in 48 countries and reports FXI on a monthly basis.

In this exercise purchasing intervention episodes are found to cause an average daily change in the USDBRL of 0.12%. Computed over the median duration of a purchase episode and its 5 following working days that results in a total excessive devaluation of the BRL of 1.33 p.p. per episode with a mean purchase of USD 2.49 billion, i.e., 0.53 p.p. per 1USD billion. Selling interventions present greater heterogeneity and an average daily effect over the USDBRL of -0.084% per day. Computed over the mean duration of a selling episode that results in a -0.59 p.p. change in the USDBRL rate per episode with USD 2.0 billion or -0.29 p.p. per billion. Average effectiveness per dollar employed by the BCB is estimated to be greater for spot interventions than swap interventions.

We see these two approaches as complementary. Our VAR estimation results in a single vector of coefficients indicating the effect over the USDBRL and other macroeconomic variables for each dollar used in an intervention; however this estimation makes no distinction between side (sale or purchase of dollars) or instrument (swap or spot). We can read the VAR result as the most general one. With the ArCo estimations on the other hand we are able to look into purchase/sale and spot/swap episodes separately.

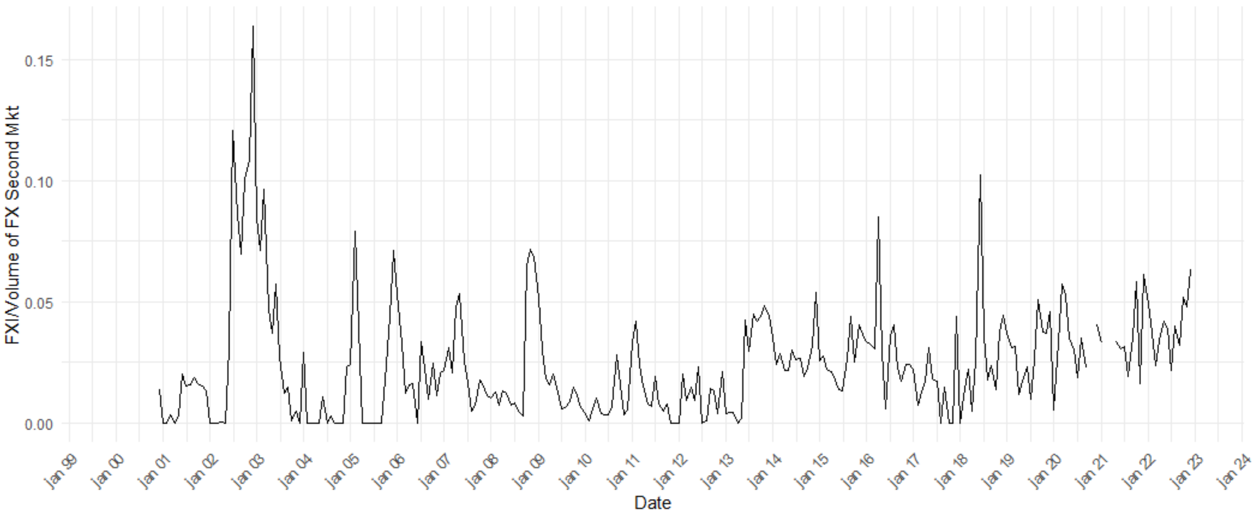
The remainder of the paper is organized as follows. Section 2 presents a review of the empirical literature of FXI in Brazil. Section 3 describes the data and Section 4 describes the intervention instruments and episodes conducted by the BCB since 1999. Section 5 lays out the Structural VAR model and the results of our estimations. Section 6 is then dedicated to the ArCo exercise, presenting both the method and results. In Section 7 we conclude.

Figure 1.1: FX Intervention and the USDBRL exchange rate - 1999 to 2023



The black line is the USDBRL exchange rate (left axis). Shaded areas correspond to periods with FXI by the BCB. In red USD sales and in blue USD purchases.

Figure 1.2: FX Intervention as share of Brazilian dollar market



The graph shows the volume of USD traded by the BCB during interventions as a share of the dollar market in Brazil measured by contracts executed in B3. Data have been grouped to monthly basis. Market volume does not include Over the Counter deals.

2
Literature

Our paper contributes to the empirical literature of FXI in Brazil. In terms of coverage this is to our knowledge the first work to use all intervention episodes conducted by the BCB since 1999 making use of the novel database published in January 2023. From a methodological point of view, VARs have been used before though identification of shocks has been primarily done with arguably less robust strategies. Our approach is based on Fratzscher et al. (2022) and uses recently available data on intervention announcements to estimate policy shocks. Synthetic control approaches have also been used before but they focused on specific periods, e.g. interventions during the Taper Tantrum (Chamon, Garcia e Souza (2017); Doine (2020)). By using the database constructed by Fratzscher et al. (2022) we are able to considerably expand the candidates for placebos for each intervention in Brazil while making sure they in effect were not subject to similar interventions.

Table A.1 in the Appendix summarizes main findings of the literature for FXI in Brazil. Overall most empirical works have found interventions to be somewhat effective in changing the level of the dollar (Chamon, Garcia e Souza (2017), Kohlscheen e Andrade (2014),Nedeljkovic e Saborowski (2019)) but with considerable variance in estimates for the impact. Following an intervention of USD 1.0 billion by the BCB, estimates for the change in the dollar rate were found to vary between 0.3 p.p. (Walker, Yasui e Stone (2009)) and 1.5 p.p. (Nedeljkovic e Saborowski (2019)) for example. Still papers relying on different empirical strategies which have found no significant effect whatsoever of interventions, among which Meurer, Teixeira e Tomazzia (2020)[1]

With respect to effects on the volatility of the exchange rate results are less indicative of a significant effect. Oliveira e Plaga (2011) and Nogueira (2014) find FXI may decrease volatility whereas Chamon, Garcia e Souza (2017) is inconclusive about this issue. Moura, Pereira e Attuy (2012) have concluded instead that interventions actually increase volatility of the exchange rate.

A few works have also tried to measure the impact of FXI over other variables such as the CIP deviation (Doine (2020)) and over the financial and

[1]There is no a priori reason to expect that effects of interventions should be constant over time. Reconciling different effects found in the literature over the years could be possible by employing a structural model in which the impact of interventions interacts with other variables. This is not our objective in this work.

commercial flow of dollars (Roure, Furnagiev e Reitz (2015)). In both cases interventions are found to affect these variables.

Different results in the literature are driven mostly by two factors. First, works have concentrated their analysis on different periods and/or instruments used in intervention. Secondly different methods may result in significant differences in results. The most common approach has been the use of auto-regressive models - i.e. VAR, GARCH, EGARCH - in which interventions and the exchange rate are allowed to influence one another (Kohlscheen e Andrade (2014), Roure, Furnagiev e Reitz (2015)). The fundamental methodological issue then becomes the identification of the model, which usually imposes some hypothesis over the ordering of the variables. Other approaches taken by the literature include the use of synthetic control as in Chamon, Garcia e Souza (2017) or the use of instrumental variables as in Nedeljkovic e Saborowski (2019) or Barroso (2018).

3
Data

FXI in Brazil Data from FXI by the BCB are extracted from the novel database by the BCB, which covers all interventions conducted from January 1999 to May 2023.[1].

Data are organized in the level of the intervention event, i.e., an auction announced by the BCB with a specific amount and instrument. If on a given day the BCB offered USD 1 billion in swaps with 3-month tenor and USD 1 billion in swaps with 6-month tenor these are separate events in the database. We aggregate data to daily level. More detail on FXI data in Brazil is provided in the next section.

FXI in other countries Information on FXI for 48 other countries[2] comes from Fratzscher et al. (2022). In this paper authors construct a database on FXI based on a text classification approach which extracts information about intervention from news articles. The algorithm is calibrated with officially reported data on interventions.Even though authors provide intervention volumes on a monthly basis, our purpose when using these data is to select potential placebos for our synthetic control, i.e., countries that did not intervene on a given period. We therefore ignore intervention volumes. Additionally, time coverage for this database is different, ranging from 1995 to 2016 or shorter periods depending on the country.

An alternative database for FXI in the world is Adler et al. (2021). Even though this database has even greater coverage of countries and periods than Fratzscher et al. (2022) FXI are mainly computed based on the variation of international reserves which is arguably a less reliable predictor for interventions. We nevertheless apply our ArCo estimates using this database as well. Results are shown in Appendix and do not change in any significant way.

Macrovariables Daily data on the exchange rate, interest rates and equity indexes for all countries were extracted from Reuters Refinitiv tool or from central banks, depending on availability. For interest rates, we used overnight interbank rates when available and greater maturities when not. A

[1]The database is updated on monthly basis. May 2023 is the latest month currently available

[2]Argentina, Australia, Bulgaria, Canada, Chile, China, Colombia, Croatia, Czech Republic, Denmark, European Monetary Union, Hong Kong, Hungary, Iceland, India, Indonesia, Israel, Japan, Kenya, Latvia, Lebanon, Malaysia, Malta, Mexico, New Zealand, Nigeria, Norway, Peru, Philippines, Poland, Romania, Russia, Saudi Arabia, Singapore, Slovak Republic, Slovenia, South Africa, South Korea, Sweden, Switzerland, Thailand, Turkey, Ukraine, United Kingdom, United States, Uruguay, Venezuela and Vietnam.

complete description of the data with tickers is presented in the Appendix.

4
Intervention Instruments and Episodes

The BCB has employed mainly three different instruments while conducting FXI since 1999: spot operations; swap agreements and repurchase agreements (repos). Together they accounted for more than 97% of the volume of interventions (Table 4.1). Other instruments (*Compromissadas* and *Empréstimos*) were employed by the BCB on a much smaller basis.

Spot operations and repo agreements involve the actual exchange of USD for BRL between the BCB and the market. In the case of spot operations this exchange is done once while in repos the BCB agrees to repurchase (resell) on a future date dollars that it sold (purchased) before.

Swap agreements executed by the BCB are similar to non-deliverable futures (NDF) in that they do not involve an exchange of the notional principal. Different to traditional NDFs however they are settled solely in BRL. At the agreed maturity one party pays its counterpart the BRL variation against the dollar plus the ex ante Cupom Cambial and receives the ex post Selic. In traditional Swaps the BCB takes the short dollar position which means the swap will serve as a hedge for the market. The existing swap agreements have different maturities and sum up to a stock[1] which will vary as existing agreements expire and new ones are executed. The BCB often executes new agreements simply to roll over swaps which are about to expire. Importantly throughout this paper we only consider new swap agreements, i.e., we do not take into account operations in which the BCB simply rolled over swaps which were about to expire. This is done so that all operations which we take into account represent liquid demand or supply of dollars to the market. [2]

Considering the whole period, swaps have been the preferred instrument for interventions (40.7%) followed by spot (35.0%) and repos (21.7%). In terms of the side of the intervention, USD Sales were more common and represented 58.4% of the total volume (4.1).

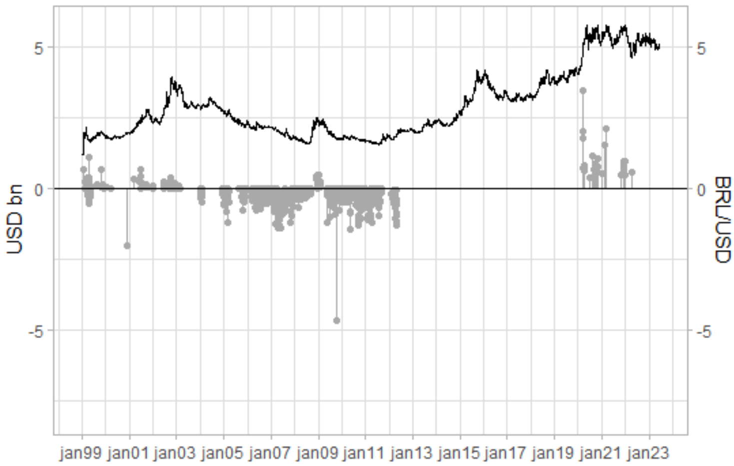
When analyzing these interventions along the years (Figures 4.1, 4.2 and 4.3), one can see how spot interventions concentrate on the years between 2006 and 2012 mainly on the purchasing side. During this period the main objective behind these interventions was arguably accumulating reserves. [3] Swaps and

[1]As of May 2023 this stock was at BRL 503.7 billion.

[2]Although the BCB database does not explicitly categorize swap operations over the new/rolled over basis we have constructed these measure ourselves

[3]According to Palocci (2007) *some people [within the Ministry of Finance] were in favor of accumulating reserves thinking that would influence the exchange rate; others thought it would have absolutely no effect over the exchange rate but it would dampen the impacts of*

Figure 4.1: Spot Interventions and the BRLUSD



The black line corresponds to USDBRL. Bars with dotted ends represent the volume of interventions on monthly basis. Positive values represent USD sales and negative values represent USD purchases.

Table 4.1: Total Interventions (USD Billion) - January 1999 to May 2023

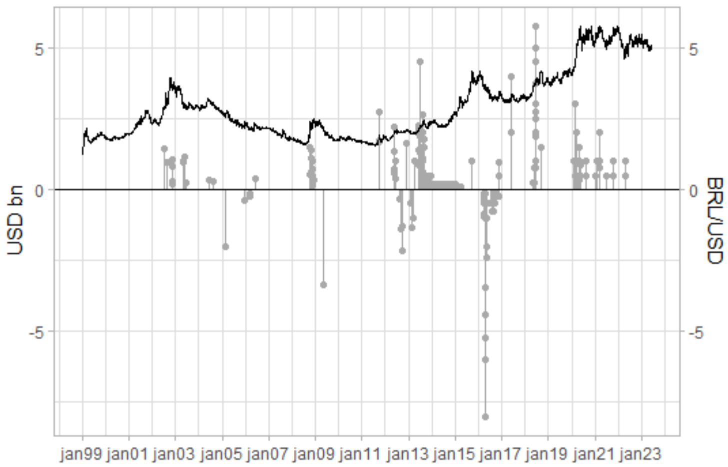
	USD Purchases	**USD Sales**	**Total**
Swap	180.0 (15.6%)	290.6 (25.1%)	470.6 (40.7%)
Spot	291.6 (25.2%)	112.8 (9.8%)	404.4 (35.0%)
Repo	0	251.0 (21.7%)	251.0 (21.7%)
Others*	9.2 (0.8%)	20.2 (1.8%)	29.5 (2.5%)
Total	480.9 (41.6%)	674.6 (58.4%)	1155.4 (100%)

repos were used for the whole period and especially so after 2012. Typically they concentrate on the selling side, i.e., provision of dollars to the market.

An important feature of FXI in Brazil is that they do not happen on isolated days. Once the BCB has decided to intervene it is very likely that it will do so for a sequence of days. This is reflected on the difference between the unconditional probability of an intervention (40.6%) and the conditional probabilities of intervention: if one observes an intervention today the probability that there will be another one tomorrow rises to 87.2% (Figure 4.4). This pattern of intervention has lead part of the literature such as Sarno e Taylor (2001) and Fratzscher et al. (2019) to argue for the grouping of intervention days around intervention episodes.

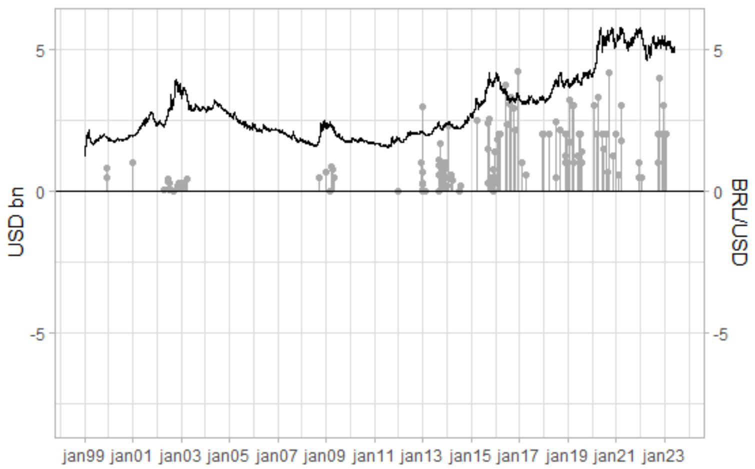
external shocks. For one reason or another all were in favor of the policy.

Figure 4.2: Swap Interventions and the BRLUSD



The black line corresponds to USDBRL. Bars with dotted ends represent the volume of interventions on monthly basis. Positive values represent USD sales and negative values represent USD purchases.

Figure 4.3: Repo Interventions and the BRLUSD



The black line corresponds to USDBRL. Bars with dotted ends represent the volume of interventions on monthly basis. Positive values represent USD sales and negative values represent USD purchases.

Figure 4.4: Probabilities of Intervention

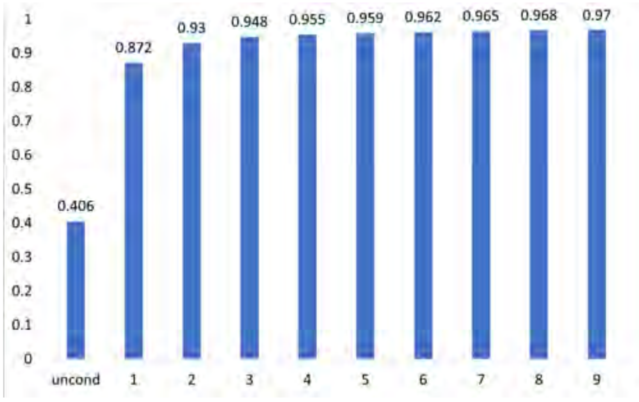


Figure shows the ex-post probabilities of intervention on a given day over the whole sample. Unconditional probability of intervention is 0.406. Probability of intervention given that there was an intervention 1 day before is 0.872; given that there were interventions on the 2 preceding days is 0.930 and so on.

In order to group intervention days into intervention episodes we will follow the method proposed by Fratzscher et al. (2019): interventions in the same direction (i.e., sale or purchase) will be grouped together as long as they are not more than 5 working days apart.

Grouping intervention days into episodes results in 145 interventions episodes (Table 4.2), of which 110 involved the sale of USD by the BCB. On average an episode lasted for 27.9 days and had 7.5 USD billion in volume. The complete list of episodes is provided in the Appendix.

Table 4.2: Intervention Episodes

	Total	**USD Sales**	**USD Purchases**
Number of episodes	145	110	35
Average length (days)	27.9	16.7	63.1
Median length (days)	2	2	6
Average no. of interventions (days)	16.9	9.4	40.8
Median no. of interventions (days)	2	2	3
Average amount (USD million)	7488.7	5816.1	12745.7
Median amount (USD million)	2060.0	2030.0	2490.0
Average daily amount (USD million)	441.6	621.7	312.0
Median daily amount (USD million)	1030.0	1015.0	830.0

5
SVAR

A VAR is the correct method for our purposes because it accounts for the fact that interventions and the exchange rate endogenously influence each other. It will also provide us with dynamic responses of the exchange rate over the days following an intervention shock. Additionally by adding other macroeconomic variables to our system we will be able to estimate the impact of interventions over them as well.

Our model follows closely the one in Menkhoff, Rieth e Stöhr (2021). As it will become clear, paramount to the identification strategy is the hypothesis that the decision by the central bank to start an intervention sequence on a given day is not reacting to shocks that hit on that same day. In Menkhoff, Rieth e Stöhr (2021) a specific institutional arrangement between the Bank of Japan and the Ministry of Finance of that country ensures that this hypothesis holds. We in turn use data on the timing of announcements by the BCB in order to select interventions episodes in which this hypothesis is indeed valid.

5.1
Method

In reduced form, the VAR can be postulated as follows:

$$\begin{aligned} y_t &= c_t + \Pi(L)y_{t-1} + \Gamma x_t + u_t \\ V(u_t) &= \Sigma \qquad u_t \sim N(0, \Sigma) \end{aligned} \tag{5-1}$$

and variables are at daily frequency with y_t representing a vector of endogenous variables; c_t a vector of constants; $\Pi_t(L)$ a lag operator and x_t a vector of exogenous variables. We further assume that the VAR innovations u_t are normally distributed with variance Σ and mean zero.

Endogenous Variables Our endogenous variables always include interventions (INT_t) and the exchange rate (E_t). In the benchmark specification we also add the Brazilian interest rate differential (i_t) and the Bovespa Index ($ibov_t$) as endogenous variables.

$$y_t = [INT_t \quad E_t \quad i_t \quad ibov_t]' \tag{5-2}$$

In our variable specification we follow Fratzscher et al. (2019). Interest rate differential is measured as the difference between Fed Funds effective rate and the Brazilian effective Selic. The series is used in first differences. E_t corresponds to the USDBRL measured by the BCB PTAX in level. Therefore increases in this rate represent a depreciation of the BRL. The variable $ibov_t$ is used in differences. Importantly INT_t is a measure of cumulative interventions over time, i.e., a stock variable. Simply for presentation purposes we arbitrarily constructed it so that it grows with selling interventions and declines with purchasing interventions.

The inclusion of the other variables other than the interventions and the exchange rate themselves is useful in measuring potential unintended effects of interventions. To the extent that interventions are sterilized by the BCB one should not expect effects over real variables or prices other than the exchange rate itself, which is an assumption that can be tested.

Exogenous Variables Our vector x_T of exogenous variables is composed of dummies for day of the week and month. This is to deal with potential time patterns in interventions and demand for dollars in the Brazilian market. Literature has for instance documented increased demand for dollars by market operatives in December Garcia e Urban (2005).

Identification and Instrument We assume that the VAR innovations u_t are linearly driven by a FXI policy shock (ϵ_t^p) and other structural shocks (ϵ_t^*). We want to identify the former while recognizing that our system of endogenous variables may be subject to other sorts of shocks. The vector of parameters b^p represent the response of the VAR innovation to an intervention policy shock.

$$u_t = b^p \epsilon_t^p + B^* \epsilon_t^* \tag{5-3}$$

The main challenge in solving for b^p is obviously the endogeneity in Equation (1). Following on Menkhoff, Rieth e Stöhr (2021) we will use an external instrument (z_t) in order to identify the shocks. Conditions for the validity of the instrument are well known:

$$E(z_t \epsilon_t^p) \neq 0 \qquad E(z_t \epsilon_t^*) = 0 \tag{5-4}$$

Our instrument will be a discrete variable assuming values {1, -1, 0}: 1 for days with interventions that initiate a selling episode; -1 for days with interventions that initiate a purchasing episode and 0 for the other interventions days and for days with no intervention.

The idea behind z_t is that the decision by the BCB to begin an intervention episode on a given day is taken in advance and does not respond to shocks (ϵ_t^*) that hit on that same day, i.e.:

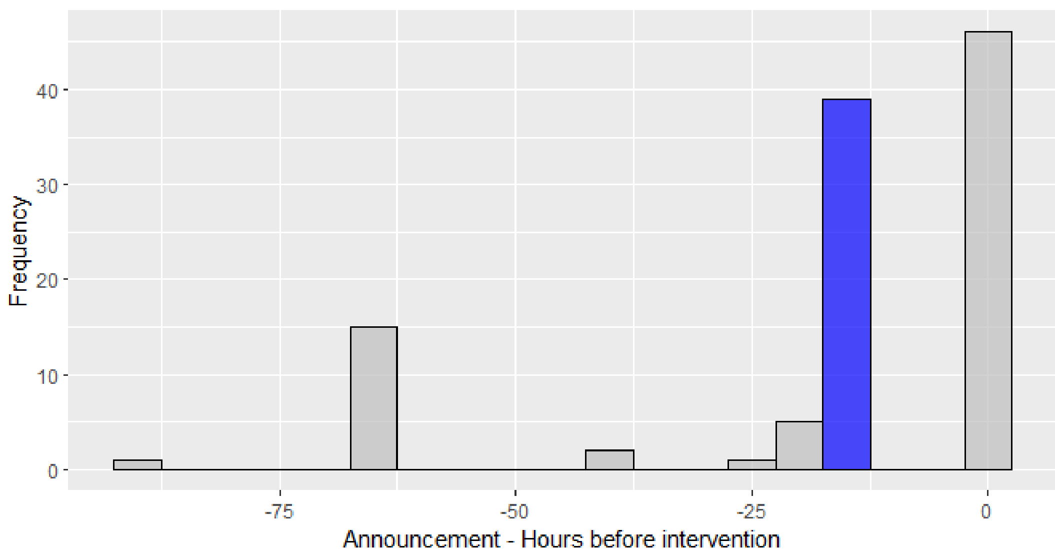
$$E_t(z_{t+1} \epsilon_{t+1}^*) = 0 \tag{5-5}$$

Episode N.131, for example, began on 18 December 2020 ('18DEC2020') and lasted for 15 working days (Table A.3 in Appendix). The decision to intervene on that day was announced by the BCB on 17DEC2020 at 6:30pm. Note that because of the way we group interventions into episodes we are sure that no selling intervention had taken place for at least 5 days before 18DEC2020. Moreover because of the pattern of interventions we described before market should expect that following on from the intervention on 18DEC2020 the BCB should keep offering swaps for a couple of days. In the way we construct z_t we will say there is a shock on 18DEC2020 only. The fact that z_t may be correlated to the history of (ϵ_t^*) will not cause bias of any sort and may only turn it into a weak instrument. In the example we are providing this means that the decision to intervene on 18DEC2020 may be correlated to shocks that hit on the days leading to 18DEC2020 but not on that day itself.

Even though our instrumental variable z_t only uses days which initiate interventions announced on the previous day, all interventions are accounted for in our variable INT_t. It is just the intervention shocks which we estimate with z_t.

Thanks to information on the timing of announcements of the interventions we can select only the episodes with this feature. Figure 5.1 depicts the timing of announcements for all 145 episodes. In blue we highlight the episodes for which interventions were announced on the day before after market hours. Those are the ones we use to build the instrument z_t.

Figure 5.1: Timing of Announcements



For each beginning of episode the figure displays its time of announcement. Announcements concentrate on three intervals: the day of intervention; the day before intervention after market hours (in blue) and 3 days before.

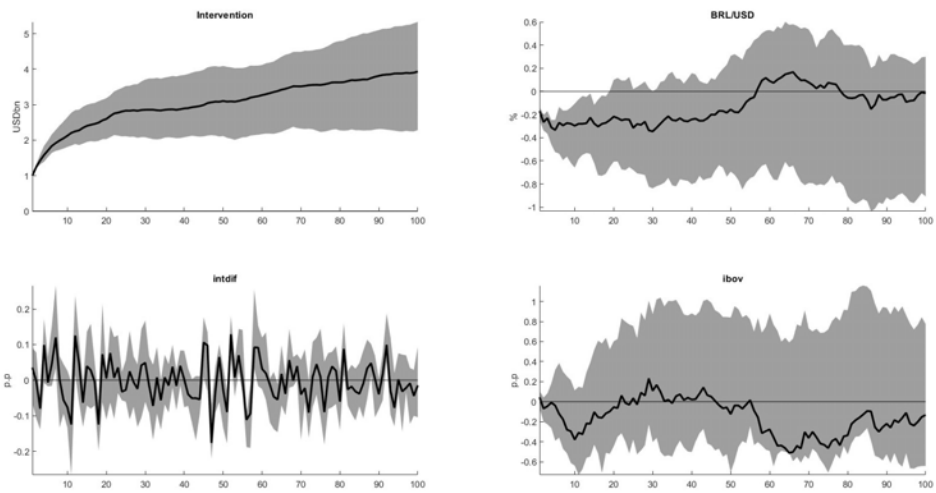
5.2 Results

Results indicate the BCB can indeed affect the level of the USDBRL exchange rate. Considering the full sample, we find that an intervention shock of 1 USD billion affects the BRLUSD level in about 0.24 p.p. over a period of 20 working days.

Figure 5.2 depicts the IRFs of our VAR variables after an intervention shock in which the BCB sells 1USD billion. Figure 5.3 displays a shock of the same size but in which the BCB purchases dollars. Confidence intervals for the IRFs are used a bootstrap technique using pseudo data.

Other than the USDBRL itself we find small and not significant changes in the other two variables of our system. In sterilized interventions there should be indeed no effect over other asset prices as a direct effect of the intervention. However interventions could have spillovers if they change market expectations about inflation or future monetary policy, for example. Menkhoff, Rieth e Stöhr (2021) finds significant effects for interest rates in Japan and Mello (2022) for stock prices in Brazil albeit in very short time windows. We cannot observe such effects in our exercise.

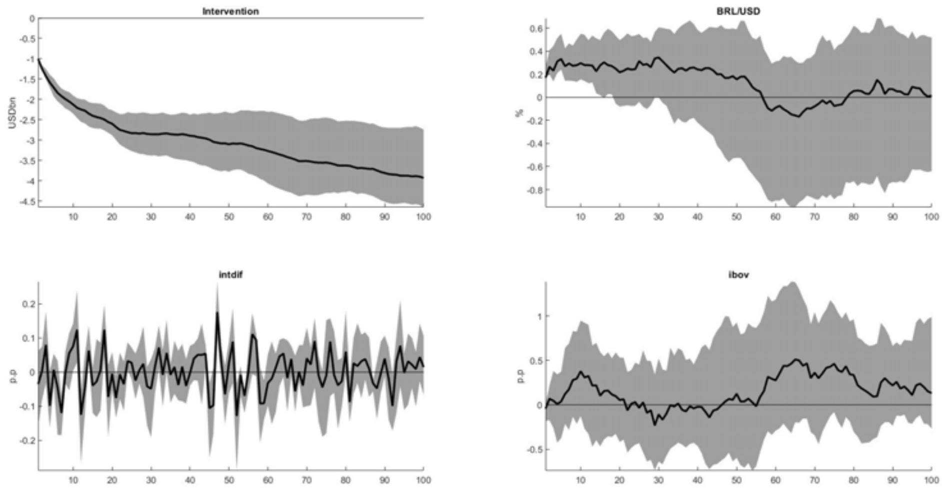
Figure 5.2: IRFs - Sale of 1USD billion



Picture depicts IRFs after a sale shock of USD 1 billion. The BRL appreciates in close to 0.2 p.p. (top right). The interest rate differential in differences (bottom left) is never statistically different from zero. Ibovespa index (bottom right) us similarly not affected.

By rewriting Equation (1) in a moving average form and shutting down interventions we can estimate a counterfactual USDBRL rate with no

Figure 5.3: IRFs - Purchase of 1USD billion



As in Figure 6 this depicts the IRFs for an intervention shock. In this case of USD 1 billion in purchases. The BRL depreciates in close to 0.2 p.p.

interventions over the years. This counterfactual estimate is depicted in Figure 5.4.

Figure 5.4: Observed USDBRL and USDBRL with no interventions

The black line represents USDBRL as observed in data. The red dotted line is the estimated counterfactual for the rate with no interventions

6
ArCo

Complementary to our first exercise we now implement a synthetic control estimation, using the ArCo estimator Carvalho, Masini e Medeiros (2018). As in all synthetic control methods, the idea is to compare a unit which underwent some sort of intervention to a synthetic counterfactual which represents the outcome that would have been observed if that unit had not been treated. The synthetic counterfactual is built with data coming from untreated units.

In our case the treated unit will always be Brazil during an episode of FXI by the BCB. Our pool of untreated units, i.e., placebos come from the database in Fratzscher et al. (2022). For each intervention episode in Brazil, we select countries which did not conduct FXI for the whole period of the episode, the preceding estimation window and the post treatment projection window as detailed below. We will be interested in the effect of intervention over the USDBRL level and volatility.

Compared to the canonical synthetic control method proposed by Abadie, Diamond e Hainmueller (2010) we chose ArCo because it was shown to be more adequate to deal with time series data where issues of non stationarity may arise Masini e Medeiros (2022). Most importantly although the ArCo approach needs the treatment (an intervention in Brazil) to be orthogonal to untreated units variables (exchange rates, interest rates and equity indexes in other countries) it allows for it to be correlated with the treated unit variables. This is very much the case of this paper because as we argued before interventions are driven by movements of the USDBRL. Additionally, the ArCo estimator does not impose a convex hull for the combination of untreated units, i.e., weights do not need to be in the $[0, 1]$ interval.

6.1
Method

In this section we briefly summarize the method by Carvalho, Masini e Medeiros (2018). As in others methods of synthetic control, this approach relies on the following setting: (i) units indexed by $i = 1, 2, ..., n$; (ii) variables z_{it} which are observed for units i and time t; (iii) an intervention that took place at some time and affected only one unit ("treated unit"). In our case, units will be countries. The outcome variable of interest will be the exchange rate; interest rate and equity indexes will also be used for estimation as part of z_t. A complete description of the Data is provided in Appendix.

Assume the treated unit is the first ($i = 1$). Then let $z_{1t}^{(0)}$ and $z_{1t}^{(1)}$ be the outcomes of the treated unit without treatment under treatment and, respectively. We usually do not observe $z_{1t}^{(0)}$. Let D_t be a binary variable flagging periods when the intervention was in place. Then:

$$z_{1t} = D_t z_{1t}^{(1)} + (1 - D_t) z_{1t}^{(0)} \tag{6-1}$$

An intervention can generally be written in the following form:

$$y_{1t} = \begin{cases} y_{1t}^{(0)}, & t = 1, ..., T_0 - 1 \\ y_{1t}^{(0)} + \delta_t, & t = T_0, ..., T \end{cases} \tag{6-2}$$

where $y_t^{(j)} h(z_{1t}^j)$, $h(.)$ is a measurable function of z_{1t} and $\{\delta_t\}_{t=T_0}^T$ is a deterministic sequence. Function $h(.)$ could represent interventions affecting the mean, variance or covariance of variables of interest, for example. The relevant hypothesis is then:

$$\mathcal{H}_0 : \Delta_T = \frac{1}{T - T_0 + 1} \sum_{t=T_0}^{T} \delta_t = 0 \tag{6-3}$$

with Δ_T being the average treatment effect over the treatment period which is very commonly used in the literature.

We do not observe $y_t^{(0)}$ for $t > T_0$. This is precisely a counterfactual, i.e., what would be the values of transformation $h(.)$ over the variable of interest without the intervention for the treated unit. ArCo consists of modeling it in the following way:

$$y_t^{(0)} = \mathcal{M}_t + \nu_t, \tag{6-4}$$

where $\mathbb{E}(\nu_t) = 0$ and $\mathcal{M}_t = \mathcal{M}(Z_{0t})$. Equation (4) should be estimated using the first $T_0 - 1$ observations, periods in which $y_t = y_t^{(0)}$, resulting in $\widehat{\mathcal{M}_{t,T_1}} = \widehat{\mathcal{M}_{T_1}(Z_{0t})}$.

With regards to $\mathcal{M}(.)$ ArCo allows for a very general mapping, ranging from OLS to LASSO or random forest structures. We opted for a Generalized Method of Moments (GMM) method, which we implemented using the ArCo package by Fonseca et al. (2018).

We use daily data. Following the logic in Chamon, Garcia e Souza (2017) for each episode we will consider the first day of the episode as the day of treatment. For an episode with length of T days, we will generally use the same amount of days before the beginning of the episode to estimate the ArCo coefficients. If the episode lasts less than 15 days then our pre-treatment estimation window is set to 15 days. We will estimate the counterfactual USDBRL for the duration of the episode and 5 days after the last intervention.

Placebo candidates are countries which experienced no intervention before, during and after the episode.

Data on FXI in foreign countries ranges from 1996 to 2016 which is shorter than the data we have for Brazil. Therefore from the 145 episodes described in Table 4.2 our ArCo estimates cover only the first 99 episodes, which happen until 2016. In Appendix we overcome this limitation be considering as potential placebos the countries which conducted interventions on less than 10% of the months from 1996 to 2016 and compute effects for all 145 episodes. Results do not change significantly.

6.2 Results

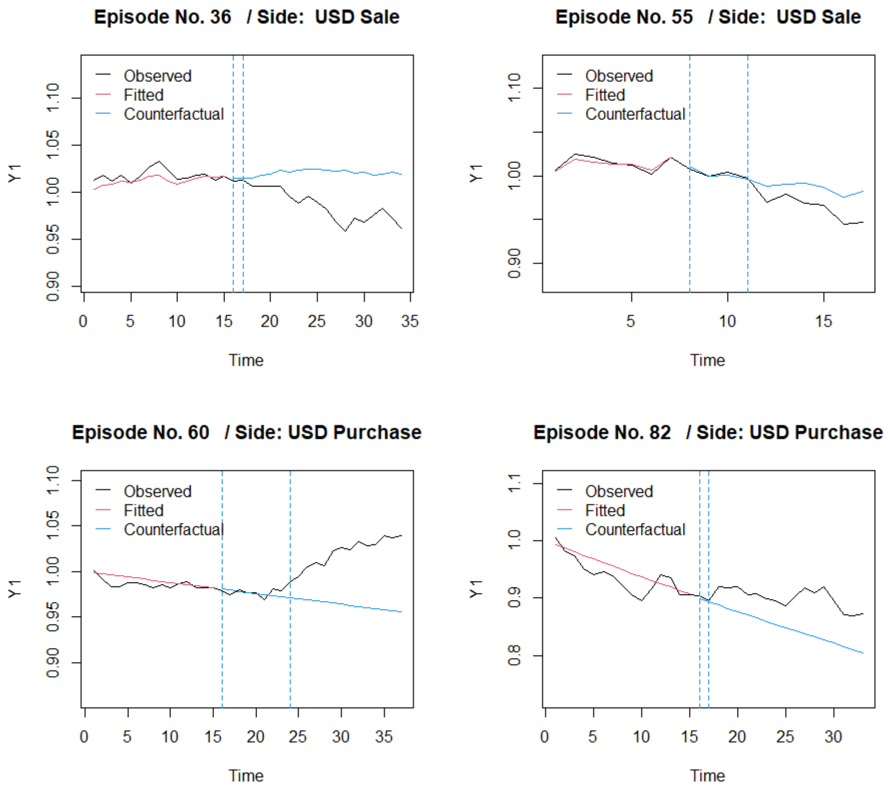
For each intervention episode we are able to compute counterfactual rates to the USDBRL and estimate the impact of the intervention by the BCB. For illustration purposes Figure 6.1 depicts selected sale and purchases episodes. Similar graphs for all episodes can be found in Appendix. For each one of the episodes we select potential placebos from countries that did not conduct interventions at the period (examples are provided in Figure 6.2).

Before going through aggregate results one question to be answered is whether our counterfactual estimates for the USDBRL could be simply exchanged for some other readily available basket of currencies. In Figure 6.3 we compare our counterfactual estimates for the USDBRL to the Dollar Index (DXY). For each day which begins an intervention episode we update the DXY with the estimated variation of the counterfactual USDBRL. Correlation of the series reaches 92.6% for the whole sample (2000-2016). However there are periods (2013 for example) when the series do not comove. For those periods using the DXY would not be a good counterfactual to the USDBRL under no intervention.

Effects over the USDBRL level Figure 6.4 depicts the point estimates for the daily average treatment effect over the BRLUSD for all episodes along with their 95% confidence intervals. Sale episodes in red are expected to present a negative delta as they decrease the exchange rate and purchase episodes in blue are expected to have a positive delta.

First thing to note is that even though point estimates generally fall into the expected region, for this measure of effectiveness the majority of intervention episodes do not have a statistically significant effect. In fact from the 99 episodes 16 have a statistically significant delta. One should note however that average daily effect is a rigorous measure for the effect of an intervention episode since it is computed over the duration of the episode (21

Figure 6.1: Effects of Intervention - Selected Episodes



Graphs depict cumulative change in USDBRL. Vertical blue lines represent beginning and end of intervention episodes.Time is measured in days.

days on average) and the following 5 working days.

Overall effects for dollar purchases are in line with the expected. Except for eight episodes mostly concentrated in 1999, average daily effect is positive, meaning the interventions cause the BRL to depreciate. Average daily effect is of 0.12% over the BRL level compared to the counterfactual. Computed over the median duration of a purchase episode and its 5 following working days (11 days - Table 4.2) that results in a total excessive devaluation of the BRL of 1.33 p.p. per episode with a median purchase of USD 2.49 billion or 0.53 p.p. per 1USD billion.

Sale interventions on the other hand present considerable heterogeneity in results, especially in episodes between 1999 and 2005. Average daily effect is estimated at -0.084% per day. Computed over the median duration of a selling episode and its 5 following days (7 days) that would result in a -0.59 p.p. change in the USDBRL rate per episode of USD 2.0 billion or -0.29 p.p. per 1USD billion. Average daily effect does not vary considerably through time.

Using the average daily treated effect in absolute value we regress them against a group of intervention episodes characteristics. We use as baseline a

Figure 6.2: Ilustration - Placebos for selected episodes

Ep. ID	Side	First Day	Last Day	Selected Placebos
36	Sale	26/02/2003	27/02/2003	AUD,CAD,CNY,CZK,DKK,HKD,HUF,INR,ILS,KES,MYR,MXN,NZD,NOK,PEN,PLN,RUB,SAR,SOK,SEK,TWD,THB,TRY,VND
55	Sale	29/04/2009	04/05/2009	AUD,CAD,CLP,CNY,COP,HRK,CZK,DKK,HKD,HUF,INR,ILS,JPY,KES,MYR,MXN,NZD,NOK,PLN,RUB,SAR,SOK,SEK,CHF,TWD,THB,TRY,VND
60	Purchase	22/02/2012	05/03/2012	AUD,CAD,CNY,HRK,CZK,DKK,HKD,HUF,INR,ILS,KES,MYR,NZD,NOK,PLN,RUB,SAR,SOK,SEK,CHF,TWD,THB,TRY,VND
82	Purchase	02/03/2016	23/03/2016	AUD,CAD,CLP,CNY,COP,HRK,CZK,HKD,HUF,IDR,INR,ILS,JPY,KES,MYR,MXN,NZD,NOK,PEN,PHP,PLN,RUB,SAR,SOK,SEK,TWD,THB,TRY,VND

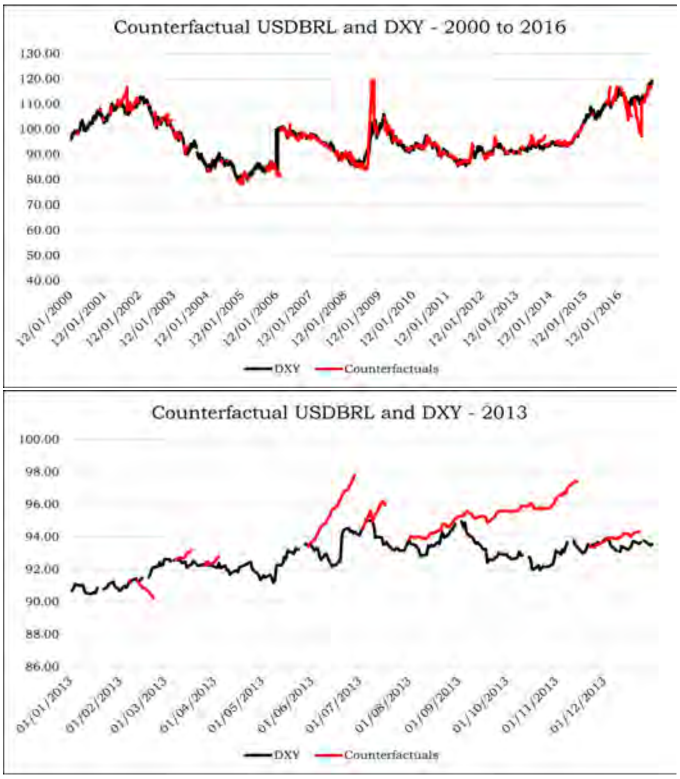
selling and spot intervention. The variables *Swap*, *Repo*, *Purchase* are dummies which are flagged in the corresponding episodes.The variable *Size* represents the amount of dollars per day employed by the BCB measured in million of dollars.

Estimated coefficients are displayed in Table 6.1. With regards to *Swap* its value is positive although not statistically significant. The estimated coefficient means that for each additional million dollar employed by the BCB the average daily effect over the BRLUSD (either positive or negative) increases in 0.003%. The coefficient in *Swap* means interventions which used this instrument were found to be less effective than Spot interventions: 0.38 p.p. against 0.24 p.p. in absolute values for selling interventions. With regards to the direction of the intervention purchases were found to be less effective but not in a statistically significant way.

Effects over the USDBRL volatility In Figure 6.5 point estimates are shown for the daily average treatment effect over the BRLUSD volatility for all episodes along with their 95% confidence intervals. Reducing volatility after an intervention means negative deltas both for purchasing and selling episodes.

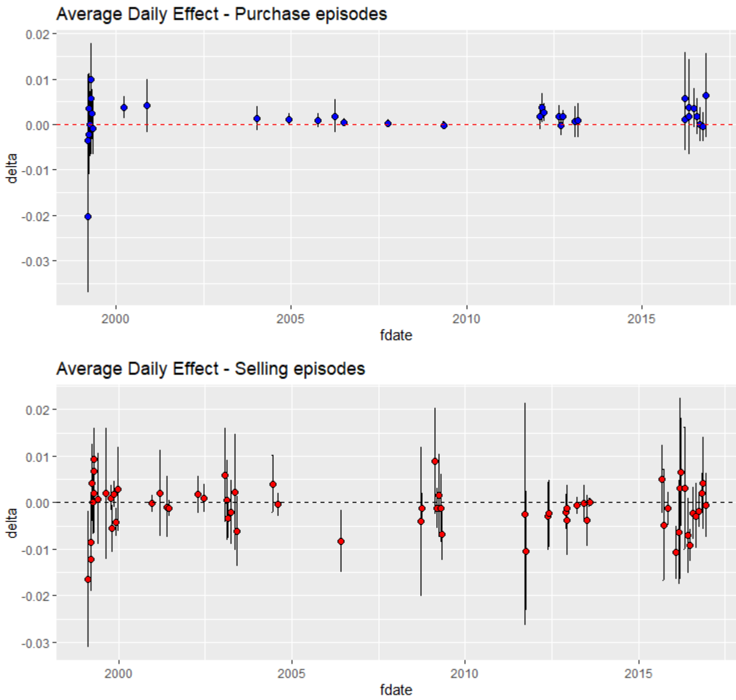
Although one can observe an estimated reduction in volatility for the very first episodes in 1999 overall effect is inconclusive. The mean average treatment effect over all episodes has the expected direction but has very small magnitude: -0.0004% . Moreover three selling episodes stand out as outliers with large and positive effects, i.e., these interventions were estimated to have increased volatility.

Figure 6.3: ArCo Counterfactual USDBRL and the Dollar Index



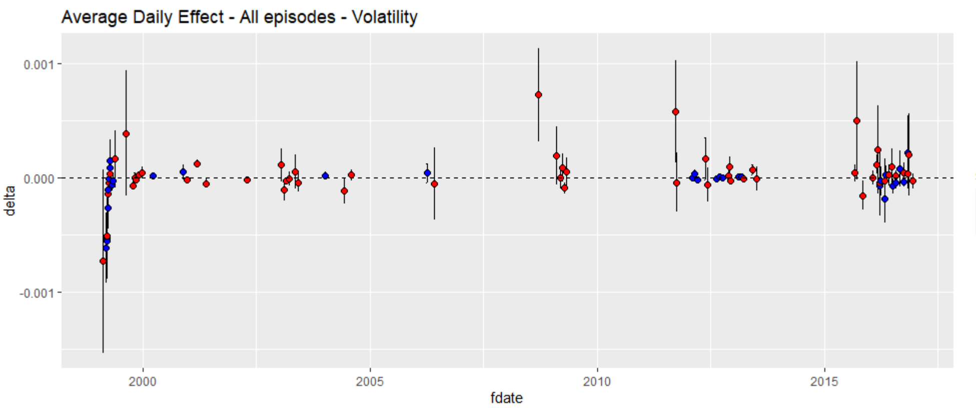
Graphs depict DXY in black along with ArCo Counterfactuals for the USD-BRL in red. For each beginning of episode we apply the variation in ArCo counterfactual to the DXY.

Figure 6.4: Average Treatment Effect - USDBRL Level



Graphs depict the ATE estimates over the USDBRL level using ArCo for the intervention episodes. Dots correspond to point estimates and bars present the 95% confidence interval.

Figure 6.5: Average Treatment Effect - USDBRL Volatility



Graphs depict the ATE over the USDBRL volatility estimates using ArCo for the intervention episodes. Dots correspond to point estimates and bars present the 95% confidence interval.

Table 6.1: Determinants of ATE - Level

	Dependent variable:
	Delta (Absolute)
Size	0.00003
	(0.00004)
Swap	-0.137^{*}
	(0.079)
Repo	-0.071
	(0.102)
Purchase	-0.039
	(0.078)
Constant	0.380^{***}
	(0.063)
Observations	99
R^2	0.039
Adjusted R^2	-0.002
Residual Std. Error	0.337 (df = 94)
F Statistic	0.942 (df = 4; 94)
Note:	*p<0.1; **p<0.05; ***p<0.01

7
Discussion

In this section we compare our results with prior empirical literature of FXI in Brazil. We focus on the impact over the level of the USDBRL since we found no stastically significant impact on its volatility. As we mentioned before from the point of view of methods our work is to our knowledge the first one to combine the grouping of interventions into episodes with the use of an instrument based on timing of announcements. This strategy addresses an important feature of FXI in Brazil, i.e., the fact that interventions usually take place over consecutive and not isolated days. Making use of a novel dataset we were also able to cover all interventions made by the BCB since 1999 while papers in the existing literature focus on specific periods of time.

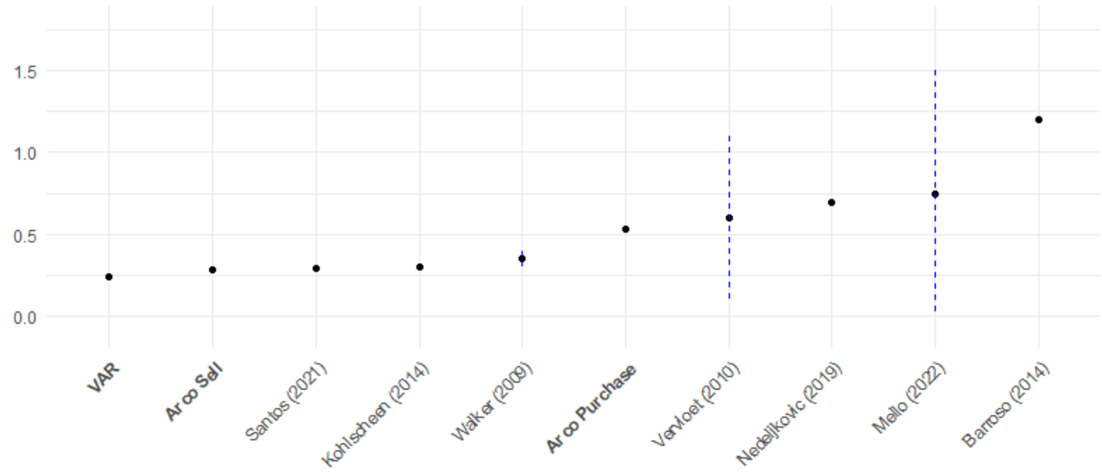
Regarding the point estimates for the impact of interventions over the USDBRL level Figure 7.1 depicts our estimates and some of the findings in the literature for the effect of a 1USD Billion intervention. This is obviously not a measure of effectiveness used in all papers. Chamon, Garcia e Souza (2017) for instance use the deviation of USDBRL from an artificial counterfactual computed over some months as the main indicator of effectiveness.[1] The papers we are plotting also covered different periods. Although our ArCo estimates point to no particular heterogeneity in effects over time, there is no a priori reason to believe interventions should have the same effect in different years or that different types of intervention should provide similar effects per USD billion used.

Our VAR estimate (0.24 p.p./ 1USD billion) is the smallest compared to the literature. Since we compute this coefficient for the whole sample (1999-2023) this could be the result of putting together periods with potentially higher and lower effects. This result could also be related to the fact that interventions shocks in our VAR are exclusively identified with intervention episodes in which the announcements happened on the day before. Mello (2022) for instance finds that interventions are more effective when they take place on the same day as the announcement.

One of the most recent papers we covered in our literature review is Santos (2021). Although his result for the effect of interventions is the closest to ours in size, Santos (2021) estimates a shorter duration for these effects - 5 working days after the intervention. There are however many differences in his

[1]Other papers such as Janot e Macedo (2016) and Nogueira (2014) also find interventions to be effective but regression coefficients cannot be transformed to a p.p. / USD billion impact.

Figure 7.1: Effects of 1USD billion intervention - Selected literature and this work



Graphs depict the estimates for the absolute effect over the USDBRL level after a 1USD Billion intervention. Estimates in this paper are VAR, ArCo Sell and ArCo Purchase.

approach among which: restricting his sample to the 2011-2013 period and to traditional swaps; using USDBRL future prices as instrument for intervention shocks (in the case of discretionary interventions) and using event studies with commonly used controls (equity prices, news shocks and interest rates) for pre-announced[2] interventions; in both cases intradaily data are used. Santos (2021) is ultimately interested in contrasting the effect discretionary and pre-announced interventions. He finds both to be capable of changing the level of the USDBRL but in the case of pre-announced interventions most of the impact effect is concentrated on the announcement itself.

With regard to the difference between the effects of a selling (0.29 p.p. / 1USD billion) and purchasing (0.53 p.p / 1USD billion) intervention that we estimate in our ArCo exercise we have identified no other work in the literature which used the same method to evaluate the effects of selling and purchasing interventions. This is most likely because authors have focused on the most common situation in which the BCB was offering USD trying to offset BRL depreciation. Janot e Macedo (2016) for instance cover a large period of time (2011-2015) in which the BCB intervened in both directions but estimate one coefficient per instrument regardless of the direction of the intervention. Nedeljkovic e Saborowski (2019) also used data both on USD purchases and sales but focus on the difference between spot and swap instruments.

[2]We acknowledge that *pre-announced* is a pleonasm but choose to use it given its widespread adoption in the literature.

Finally - as we mentioned in Section 5 - even though our primary interest lies in the effects of interventions over the USDBRL itself our VAR specification allowed us to test for effects over the Ibovespa index and the spread between the effective Fed Funds Rate and the Selic as well. We could not find any statistically significant effect over these prices. Arguably this result is what the BCB actually desires when conducting sterilized interventions but the literature (Menkhoff, Rieth e Stöhr (2021)) has pointed out to other effects which could affect asset prices such as signaling effects. For instance if markets believe that the BCB is pursuing a certain range for the exchange rate that could have implications over prices of exporting firms.

Using intraday data and a local projection approach Mello (2022) identifies clear effects of FXI by the BCB over the Ibovespa and the prices of different Brazilian bonds. These effects however last a couple of minutes or hours depending on the model specification and asset. By the end of the longest estimation window (9 hours) the only effect which can be distinguished from a statistical zero is indeed the effect over the USDBRL. In this way notwithstanding important methodological differences among our work and Mello (2022) we consider that our results converge. Our choice of a daily VAR has the advantage of identifying effects over the USDBRL which potentially last for days but on the other hand is silent about the impact of interventions over asset prices in the minutes and hours which follow an intervention. Regarding the effects over the USDBRL itself estimations in Mello (2022) present great heterogeneity over intervention type. The impact of a 1USD Billion intervention ranges from 0 to 1.5 p.p. considering the 9-hour window.

8
Conclusion

Foreign exchange interventions are a very common policy tool employed by the BCB. The existing empirical literature has so far found quite different estimates for the effect of those interventions over the USDBRL mainly because papers have focused on different periods, apart from using different methods.

Our paper does not pose new questions but contributes to the literature in at least two ways. First, benefiting from a novel database we were able to cover all interventions by the BCB since 1999. With that we were first able to provide a single and general estimate for their effectiveness. Second from a methodological perspective we combined a Structural VAR with information on the timing of BCB announcements. With that we were able to overcome the inherent endogeneity issue which abounds in the use of VARs in this literature. Data on announcements had been mostly used in event studies which typically measured effects of intervention on very short windows of time.

In terms of results the VAR estimation confirms the effectiveness of interventions in altering the USDBRL level for the whole 1999-2023 sample. A 1USD billion intervention shock induces a 0.24 p.p. change in the USDBRL for approximately 20 working days.We found no effects over equity prices (Ibovespa) or interest rate differential over the same time span.

By using the ArCo methodology we then studied interventions episodes separately. Even though results are weaker in terms of statistical significance interventions are again found to be effective in changing the USDBRL level. For the median intervention episode in which the BCB sells USD (lasting 2.0 days and comprising USD 2.0 billion) we estimate a a decrease in the exchange rate of 0.59 p.p., i.e., 0.29 per 1USD billion. We have identified no evident pattern of change in the efficiency of interventions throughout time but have found Spot interventions to be more effective than swap interventions.Lastly our work falls within the sizable group of papers which could find no significant effects of interventions over the volatility of the USDBRL.

9
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A
Appendix

A.1
Summary of Literature Review

Table A.1: Summary of Empirical Literature

Year	Authors	Methods	Period	Summary of Findings
2009	WALKER; YASUI; STONE	IV with lagged variables as instruments	2007-2009	USD 1B intervention in the spot market leads to change of 0.3/0.4 p.p in level. Announcement of swap line lowers volatility by 6.0/9.0 p.p.
2010	VERVLOET	IV and GARCH	2004-2010	USD 1B cause a change in the level of exchange rate estimated at 0.1 p.p. to 1.1. p.p.
2010	MEURER; TEIXEIRA; TOMAZZIA	EGARCH	1999-2008	No effect over level or volatility.
2011	OLIVEIRA; PLAGA	EGARCH	1999-2006	Interventions are able to affect volatility both in periods of crises and normal times. Depending on the period, volatility actually increases.
2013	MOURA; PEREIRA; ATTUY	Propensity Score Matching	1999-2012	No effect over the level. Interventions increase volatility.
2014	NOGUEIRA	Event Study and OLS	2011-2014	Significant effect over level and volatility when interventions are not pre-announced.
2014	KOHLSCHEEN; ANDRADE	GARCH	2011-2013	Swaps had significant effect over level. Contracts where BCB went short were more effective. USD 1B in the spot market leads to 0.3 p.p movement in level.
2014	BARROSO	Realized Volatility as IV	2007-2011	Effective over the level: USD 1B leads to change of 1.2 p.p.
2015	ROURE; FURNAGIEV; REITZ	SVAR	2009-2012	Interventions affects behavior of financial customers and changes financial order flow. No direct impact over level of the excahnge rate.
2016	JANOT; MACEDO	Event Study and OLS	2011-2015	Impact over level but not over volatility. Size of interventions influences change. Announcements tend to dampen effect of intervention.
2017	CHAMON; GARCIA; SOUZA	Synthetic Control	2013-2015	Effects over the level of the exchange rate. Over the extension of the program appreciation of the BRL in excess of 10%.Inconclusive about effects over volatility.
2019	NEDELJKOVIC; SABOROWSKI	Continuously updated GMM	2008-2013	USD 1B intervention in the spot market leads to change of 0.7 p.p over the level. Futures intervention ineffective.
2020	DOINE	Synthetic Control and Local Projection	2009-2020	Paper studies effects over the CIP not over the FX rate. Spot interventions affect CIP deviation.
2021	SANTOS	Daily SVAR	2011-2013	FX level changes by 29.4 bps in the futures market for each USD 1B of intervention
2023	SANDRI	Test profitability of swaps	2013	Swaps are profitable ex-ante, suggesting that FXI is used to stabilize the exchange rate against temporary excessive fluctuations.

A.2 Data

The table below lists data extracted from Reuters and used in our ArCo estimators. Interest rates are interbank overnight rates when available. Longer tenders were used when overnight rates were not available. Tickers used by Reuters Refinitiv are provided in parenthesis.

Table A.2: Data used in ArCo estimations

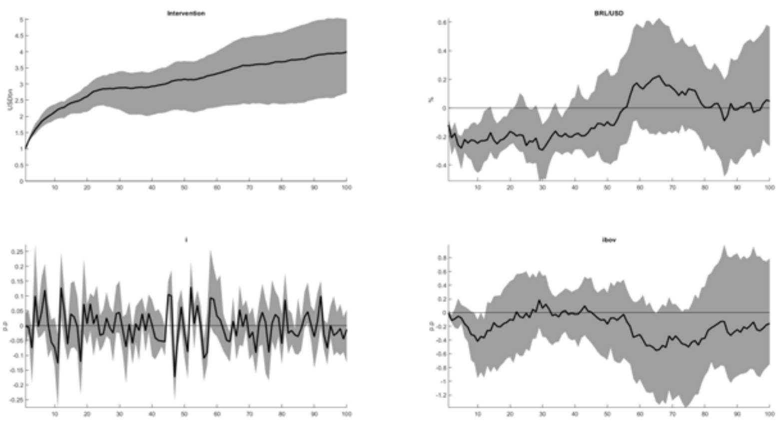
Country	Currency	Equity Index	Interest Rate
Australia	AUD	S&P/ASX 200 (AXJO)	AONIA Interbanrk Cash Rate (AUCASHH)
Brazil	BRL	Ibovespa (BVSP)	CDI (BRCDICETIP)
Switzerland	CHF	Swiss Mkt Index (SSMI)	SARON (SARON)
Canada	CAD	TSX (GSPTSE)	Canadian CORRA Overnight Repo (CORRA)
Chile	CLP	S&P/CLX (SPCLXIGPA)	IBOR 1M CLP Fixing (CLPTAB1M)
China	CNY	Shanghai Shenzhen CSI 300 (CSI300)	ON CNY SHIBOR (SHICNYOND)
Colombia	COP	MSCI COLCAP (COLCAP)	COP IBOR (COIIR)
Czechia	CZK	PX Prague SE (PX)	ON PRIBOR (PRICZKOND)
Denmark	DKK	OMXC 25 CAP (OMXC25CAP)	SW DKK CIBOR(CIDKKSWD)
United Kingdom	GBP	FTSE 100 Index (FTSE)	LIBOR and SONIA O/N (SONIAOSR)
Hong Kong	HKD	Hang Seng Index (HSI)	ON HIBOR (HIHKDOND)
Croatia	HRK	CROBEX Index (CRBEX)	SW EURIBOR (EURIBORSWD)
Hungary	HUF	Budapest SE Index (BUX)	ON BUBOR (BUHUFOND)
Indonesia	IDR	Jakarta SE Composite Index (JKSE)	SW JIBOR (JIIDRSWD)
Israel	ILS	Tel Aviv 35 Index (TA35)	ON TELBOR (TELILSOND)
India	INR	S&P BSE Sensex Index (BSESN)	INR ON Repo (INONRP)
Japan	JPN	Nikkei 225 Index Close (N225E)	ON Risk Free rate (JPONMU)
Kenya	KES	Nairobi Stock Exchange All Share Index (NASI)	ON KEIBR (KEIBR)
Korea	KRW	Korea SE Kospi Index (KS11)	1W KORIBOR (KIKRW1WD)
Mexico	MXN	S&P/Bmv Ipc (MXX)	1MTIIE (MXTIIE1M)
Malaysia	MYR	FTSE Bursa Malaysia KLCI Index (KLSE)	1M KLIBOR(KLIMYR1MD)
Norway	NOK	Oslo Stock Exchange Equity Index (OBX)	SW OIBOR (OINOKSWD)
New Zealand	NZD	S&P/NZX 50 Index (NZ50)	NZD 30D Repo (NZ30DBB)
Peru	PEN	S&P/BVL Peru General Index (SPBLPGPT)	VAC Rate Index (PEVAC)
Philippines	PHP	The Philippine Stock Exchange PSEi (PSI)	PHP ON Repo (PHONRP)
Poland	PLN	Warsaw SE WIG Poland Index (WIG)	ON WIBOR (WIPLNOND)
Russia	RUB	MOEX Russia Index (IMOEX)	ON MOSPRIME(MOSPRIMEOND)
South Africa	SAR	FTSE/JSE SA All Share Index (JALSH)	1M JIBAR (SFX1MYLD)
Sweden	SEK	OMX Stockholm 30 Index (OMXS30)	TN STIBOR(STISEKTNDFI)
Thailand	THB	SET Index (SETI)	ON BKIBOR(BKITHBOND)
Turkey	TRY	BIST 100 Index (XU100)	ON Reference Rate Index (TLREF)
Taiwan	TWD	Taiwan SE Weighted Index (TWII)	1W TAIBOR (TATWD1WD)
Vientam	VND	Vietnam Index (VNI)	ON VNIBOR(VNIVNDOND)

A.3
SVAR and Episodes with 10-day gaps

In this Appendix we show how our SVAR results are robust for a different criterion for defining episodes. Instead of using a 5-day gap between intervention days in order to define the beginning of a new episode we use a 10-day gap. This changes the total number of episodes from 145 to 115.

Our results do not change in any significant way. Figure A.1 depicts the same IRFs we show in Section 5 but now intervention shocks come from episodes which were defined in the way we mentioned above. The effect over the USDBRL is actually slightly stronger than in the benchmark estimate with a decrease that reaches -0.28 p.p. after 5 working days. Effects are estimated to last roughly for the same 20 working days. Similarly no statistically sifnigicant effect can be observed for the other two variables - Ibovespa Index and interest rate differential.

Figure A.1: Average Treatment Effect - Selling and Purchasing Episodes



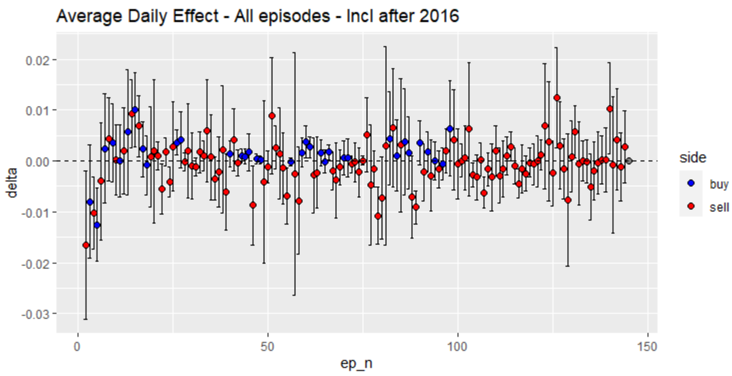
Graphs depict the IRFs from the USDBRL exchange rate (top-right); interest rate differential change (bottom-left) and Ibovespa index (bottom-right) after an intervention shock in which the BCB sells USD 1billion.

A.4
ArCo - Episodes after 2016

ArCo estimates in Section 5 do not cover the 2017-2023 period because we have no date on FXI in other countries for those years. In this Appendix we consider as potential placebos for the period the countries which conducted interventions on less than 10% of the months from 1996 to 2016: Australia, Canada, Denmark, Great Britain, Hong Kong, Hungary, Israel, Kenya, Malaysia, Mexico, New Zealand, Norway, Poland, South Africa, Sweden, Switzerland, Thailand, Vietnam.

Compared to the main estimation the addition of episodes after 2016 do not change results in any significant way. The daily average effect for purchasing episodes changes from 0.12% to 0.14%. Purchasing episodes on their turn are estimated to have an average daily impact over the USDBRL of -0.055% compared to the previously estimated -0.084%. For the whole period 22 out of 145 episodes have statistically significant average daily effects.

Figure A.2: Average Treatment Effect - Selling and Purchasing Episodes



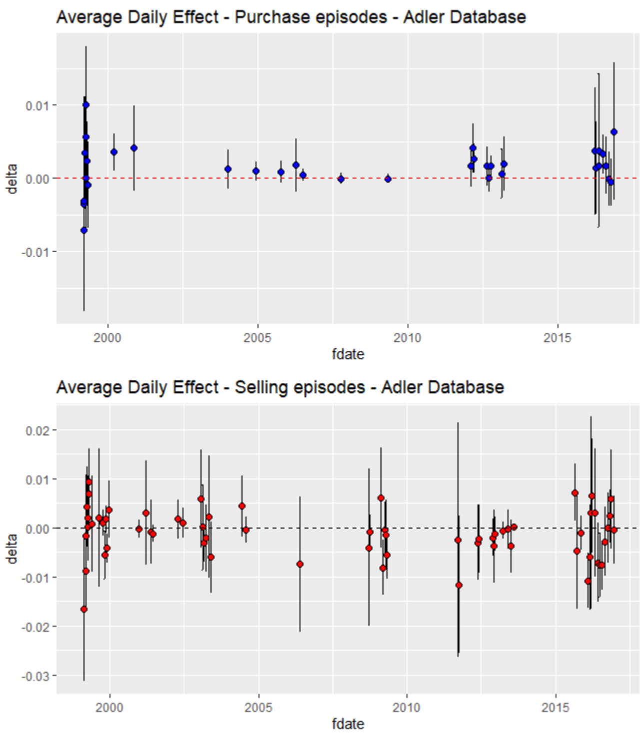
Graphs depict the ATE estimates using ArCo for the intervention episodes. Dots correspond to point estimates and bars present the 95% confidence interval.

A.5
FXI using Adler et al. (2021)

In this appendix we use the database created by Adler et al. (2021) for FXI in the world. Interventions in this database are defined mainly by using the variation in international reserves. We proceed in the same way as in Section 5. Countries which did not conduct any intervention are used as potential placebos in ArCo estimations.

Figure A.3 depicts the average treatment effect for purchase and selling episodes. Results do not change in any significant way. Average treatment effect for selling interventions is estimated at -0.115 % per day - against -0.084 % in our main estimates. For purchasing episodes the average treatment is estimated at 0.160 % - against 0.12 % in our main estimates.

Figure A.3: Average Treatment Effect - Selling and Purchasing Episodes - Adler Database



Graphs depict the ATE estimates using ArCo for the intervention episodes. Dots correspond to point estimates and bars present the 95% confidence interval.

A.6
Intervention Episodes

Table A.3: Interventions Episodes - 5 day gap

Ep	First Day	Last Day	Side	Instrument	Duration	USD	Interventions
1	22/01/1999	01/02/1999	Sale	Spot	11	905.8	2
2	12/02/1999	12/03/1999	Sale	Spot	29	1870.4	15
3	15/03/1999	16/03/1999	Purchase	Spot	2	22.0	2
4	17/03/1999	17/03/1999	Sale	Spot	1	95.0	1
5	18/03/1999	18/03/1999	Purchase	Spot	1	76.0	1
6	19/03/1999	22/03/1999	Sale	Spot	4	196.0	2
7	24/03/1999	26/03/1999	Purchase	Spot	3	552.9	3
8	29/03/1999	29/03/1999	Sale	Spot	1	373.0	1
9	30/03/1999	31/03/1999	Purchase	Spot	2	316.0	2
10	05/04/1999	06/04/1999	Sale	Spot	2	375.0	2
11	08/04/1999	09/04/1999	Purchase	Spot	2	315.0	2
12	12/04/1999	12/04/1999	Sale	Spot	1	1099.9	1
13	13/04/1999	13/04/1999	Purchase	Spot	1	420.0	1
14	14/04/1999	14/04/1999	Sale	Spot	1	302.5	1
15	15/04/1999	15/04/1999	Purchase	Spot	1	541.4	1
16	16/04/1999	27/04/1999	Sale	Spot	12	1081.0	5
17	30/04/1999	30/04/1999	Purchase	Spot	1	10.0	1
18	10/05/1999	11/05/1999	Purchase	Spot	2	435.0	2
19	25/05/1999	25/05/1999	Sale	Spot	1	60.0	1
20	18/08/1999	18/08/1999	Sale	Spot	1	150.0	1
21	13/10/1999	13/10/1999	Sale	Spot	1	664.6	1
22	27/10/1999	27/10/1999	Sale	Spot	1	50.0	1
23	10/11/1999	23/11/1999	Sale	Spot	14	425.0	4
24	01/12/1999	10/12/1999	Sale	Spot	10	1390.0	4
25	23/12/1999	04/01/2000	Sale	Spot	13	110.0	3
26	24/03/2000	24/03/2000	Purchase	Spot	1	20.0	1
27	21/11/2000	21/11/2000	Purchase	Spot	1	2003.0	1
28	21/12/2000	21/12/2000	Sale	Repo	1	1000.0	1
29	15/03/2001	15/03/2001	Sale	Spot	1	310.0	1
30	25/05/2001	25/05/2001	Sale	Spot	1	250.0	1
31	18/06/2001	26/12/2001	Sale	Spot	192	7665.0	125
32	19/04/2002	19/04/2002	Sale	Repo	1	30.0	1
33	14/06/2002	30/12/2002	Sale	Spot	200	25811.4	109
34	21/01/2003	29/01/2003	Sale	Spot	9	735.0	4
35	13/02/2003	13/02/2003	Sale	Spot	1	10.0	1
36	26/02/2003	27/02/2003	Sale	Repo	2	328.0	2
37	26/03/2003	26/03/2003	Sale	Repo	1	429.0	1
38	07/05/2003	09/05/2003	Sale	Swap	3	1920.4	2
39	02/06/2003	04/06/2003	Sale	Swap	3	1409.8	2

Ep	First Day	Last Day	Side	Instrument	Duration	USD	Interventions
40	08/01/2004	04/02/2004	Purchase	Spot	28	2627.0	17
41	09/06/2004	09/06/2004	Sale	Swap	1	340.0	1
42	04/08/2004	04/08/2004	Sale	Swap	1	290.0	1
43	06/12/2004	16/03/2005	Purchase	Spot	101	21786.6	52
44	03/10/2005	24/03/2006	Purchase	Spot	173	43260.7	116
45	03/04/2006	16/05/2006	Purchase	Spot	44	6558.4	28
46	31/05/2006	31/05/2006	Sale	Swap	1	400.0	1
47	03/07/2006	13/08/2007	Purchase	Spot	407	96408.9	272
48	08/10/2007	10/09/2008	Purchase	Spot	339	30291.2	224
49	19/09/2008	26/09/2008	Sale	Repo	8	1000.0	2
50	06/10/2008	03/02/2009	Sale	Swap	121	70178.4	71
51	11/02/2009	11/02/2009	Sale	both	1	1913.4	1
52	12/03/2009	12/03/2009	Sale	both	1	1701.2	1
53	30/03/2009	03/04/2009	Sale	Repo	5	3061.6	3
54	16/04/2009	16/04/2009	Sale	Repo	1	750.0	1
55	29/04/2009	04/05/2009	Sale	Repo	6	2082.0	2
56	05/05/2009	13/09/2011	Purchase	Swap	862	134642.7	561
57	22/09/2011	22/09/2011	Sale	Swap	1	2753.8	1
58	03/10/2011	04/10/2011	Sale	Swap	2	3365.0	2
59	03/02/2012	08/02/2012	Purchase	Termo	6	7190.0	3
60	22/02/2012	05/03/2012	Purchase	Spot	13	3571.0	9
61	15/03/2012	27/04/2012	Purchase	Spot	44	9096.0	17
62	18/05/2012	25/05/2012	Sale	Swap	8	5430.0	5
63	05/06/2012	11/06/2012	Sale	Swap	7	2435.0	3
64	21/08/2012	21/08/2012	Purchase	Swap	1	350.0	1
65	12/09/2012	17/09/2012	Purchase	Swap	6	5705.0	3
66	05/10/2012	05/10/2012	Purchase	Swap	1	1290.0	1
67	23/11/2012	23/11/2012	Sale	Swap	1	1625.0	1
68	03/12/2012	03/12/2012	Sale	both	1	2151.0	1
69	12/12/2012	28/12/2012	Sale	Repo	17	7265.0	9
70	08/02/2013	15/02/2013	Purchase	Swap	8	1850.0	2
71	11/03/2013	11/03/2013	Purchase	Swap	1	1000.0	1
72	27/03/2013	27/03/2013	Sale	Swap	1	1000.0	1
73	31/05/2013	21/06/2013	Sale	Swap	22	19667.0	8
74	04/07/2013	10/07/2013	Sale	Swap	7	4700.0	3
75	02/08/2013	31/03/2015	Sale	Swap	607	134297.0	390
76	31/08/2015	10/09/2015	Sale	Repo	11	4200.0	3
77	21/09/2015	29/09/2015	Sale	Repo	9	9750.0	5
78	03/11/2015	30/12/2015	Sale	Repo	58	6745.0	14

Ep	First Day	Last Day	Side	Instrument	Duration	USD	Interventions
79	29/01/2016	29/01/2016	Sale	Repo	1	1800.0	1
80	29/02/2016	29/02/2016	Sale	Repo	1	2000.0	1
81	09/03/2016	09/03/2016	Sale	Repo	1	2000.0	1
82	22/03/2016	23/03/2016	Purchase	Swap	2	1350.0	2
83	24/03/2016	24/03/2016	Sale	both	1	3000.0	1
84	29/03/2016	22/04/2016	Purchase	Swap	25	32523.0	14
85	29/04/2016	29/04/2016	Sale	both	1	80.0	1
86	02/05/2016	03/05/2016	Purchase	Swap	2	2490.0	2
87	11/05/2016	18/05/2016	Purchase	Swap	8	4398.5	3
88	31/05/2016	31/05/2016	Sale	Repo	1	3760.0	1
89	23/06/2016	23/06/2016	Sale	Repo	1	2350.0	1
90	01/07/2016	28/07/2016	Purchase	Swap	28	9500.0	19
91	29/07/2016	29/07/2016	Sale	Repo	1	3080.0	1
92	01/08/2016	30/08/2016	Purchase	Swap	30	12500.0	22
93	31/08/2016	31/08/2016	Sale	Repo	1	3300.0	1
94	01/09/2016	29/09/2016	Purchase	Swap	29	7000.0	20
95	30/09/2016	30/09/2016	Sale	Repo	1	2905.0	1
96	03/10/2016	28/10/2016	Purchase	Swap	26	4750.0	19
97	31/10/2016	31/10/2016	Sale	Repo	1	2150.0	1
98	01/11/2016	08/11/2016	Purchase	Swap	8	1250.0	5
99	11/11/2016	18/11/2016	Sale	Swap	8	2452.5	4
100	13/12/2016	13/12/2016	Sale	Repo	1	4200.0	1
101	31/01/2017	31/01/2017	Sale	Repo	1	1000.0	1
102	31/03/2017	31/03/2017	Sale	Repo	1	550.0	1
103	18/05/2017	23/05/2017	Sale	Swap	6	10000.0	4
104	05/12/2017	26/12/2017	Sale	Repo	22	8000.0	4
105	29/03/2018	29/03/2018	Sale	Repo	1	2000.0	1
106	14/05/2018	27/06/2018	Sale	Swap	45	45791.0	29
107	30/08/2018	31/08/2018	Sale	Swap	2	3650.0	2
108	27/11/2018	27/12/2018	Sale	Repo	31	12250.0	10
109	30/01/2019	31/01/2019	Sale	Repo	2	4925.0	2
110	27/02/2019	27/02/2019	Sale	Repo	1	3000.0	1
111	28/03/2019	29/03/2019	Sale	Repo	2	4000.0	2
112	20/05/2019	22/05/2019	Sale	Repo	3	3750.0	3
113	18/06/2019	26/06/2019	Sale	Repo	9	6000.0	4
114	19/07/2019	26/07/2019	Sale	Repo	8	4400.0	3
115	27/08/2019	28/08/2019	Sale	both	2	2060.0	2
116	23/09/2019	24/09/2019	Sale	both	2	3600.0	2
117	28/10/2019	28/10/2019	Sale	both	1	1500.0	1
118	25/11/2019	28/11/2019	Sale	both	4	4421.0	4
119	13/12/2019	18/12/2019	Sale	both	6	5800.0	4

Ep	First Day	Last Day	Side	Instrument	Duration	USD	Interventions
120	31/01/2020	31/01/2020	Sale	Repo	1	3000.0	1
121	13/02/2020	14/02/2020	Sale	Swap	2	2000.0	2
122	26/02/2020	08/06/2020	Sale	Swap	104	64129.0	46
123	25/06/2020	30/06/2020	Sale	Repo	6	3867.5	3
124	28/07/2020	28/07/2020	Sale	Repo	1	2000.0	1
125	12/08/2020	26/08/2020	Sale	Swap	15	3940.0	5
126	18/09/2020	18/09/2020	Sale	Repo	1	4150.0	1
127	28/09/2020	28/09/2020	Sale	Spot	1	877.0	1
128	13/10/2020	13/10/2020	Sale	Spot	1	560.0	1
129	28/10/2020	30/10/2020	Sale	Spot	3	1829.0	2
130	24/11/2020	24/11/2020	Sale	Repo	1	1260.0	1
131	18/12/2020	11/01/2021	Sale	Repo	25	3530.0	4
132	29/01/2021	29/01/2021	Sale	Repo	1	550.0	1
133	09/02/2021	09/02/2021	Sale	Swap	1	1000.0	1
134	22/02/2021	25/03/2021	Sale	both	32	19245.0	11
135	08/07/2021	08/07/2021	Sale	Swap	1	500.0	1
136	13/10/2021	20/10/2021	Sale	Swap	8	4500.0	6
137	01/12/2021	01/12/2021	Sale	Repo	1	1000.0	1
138	10/12/2021	23/12/2021	Sale	Spot	14	5337.0	7
139	24/01/2022	24/01/2022	Sale	Repo	1	500.0	1
140	22/04/2022	03/05/2022	Sale	Spot	12	2071.0	3
141	23/09/2022	27/09/2022	Sale	Repo	5	3000.0	2
142	19/10/2022	19/10/2022	Sale	Repo	1	4000.0	1
143	01/12/2022	08/12/2022	Sale	Repo	8	5000.0	2
144	22/12/2022	27/12/2022	Sale	Repo	6	4000.0	2
145	20/01/2023	20/01/2023	Sale	Repo	1	2000.0	1