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Is Foreign Exchange Intervention through derivative instruments effective?
An analysis of the Peruvian case

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Abstract

This paper presents an empirical analysis of the effectiveness of foreign exchange (FX) intervention in Peru, with emphasis on the intervention carried out through derivative instruments. I use two different but related approaches to estimate the impact of these kind of interventions between 2014 and 2023. First, I estimate a proxy SVAR with daily data which uses an instrument constructed with intraday data. Results show that FX interventions have an impact on the level of the exchange rate in the expected direction: an FX sale intervention of between USD 60 and USD 120 million generates an appreciation of between 0.02 and 0.04 percent of the currency in the same day. On the other hand, spot intervention is found to be slightly more effective. The estimations, however, do not provide sufficient evidence to conclude on the impact on the exchange rate volatility in the short run. Second, I estimate event study regressions with intraday data, which allowed to confirm that these interventions have the expected effect after around 10 minutes. However, no evidence of the existence of an information channel is found since the announcement of these interventions does not significantly impact the exchange rate.

Keywords: foreign exchange intervention, currency, derivatives, derivate instruments, Peru, exchange rate.

JEL: F31, G11, G14, G15.

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1 Introduction

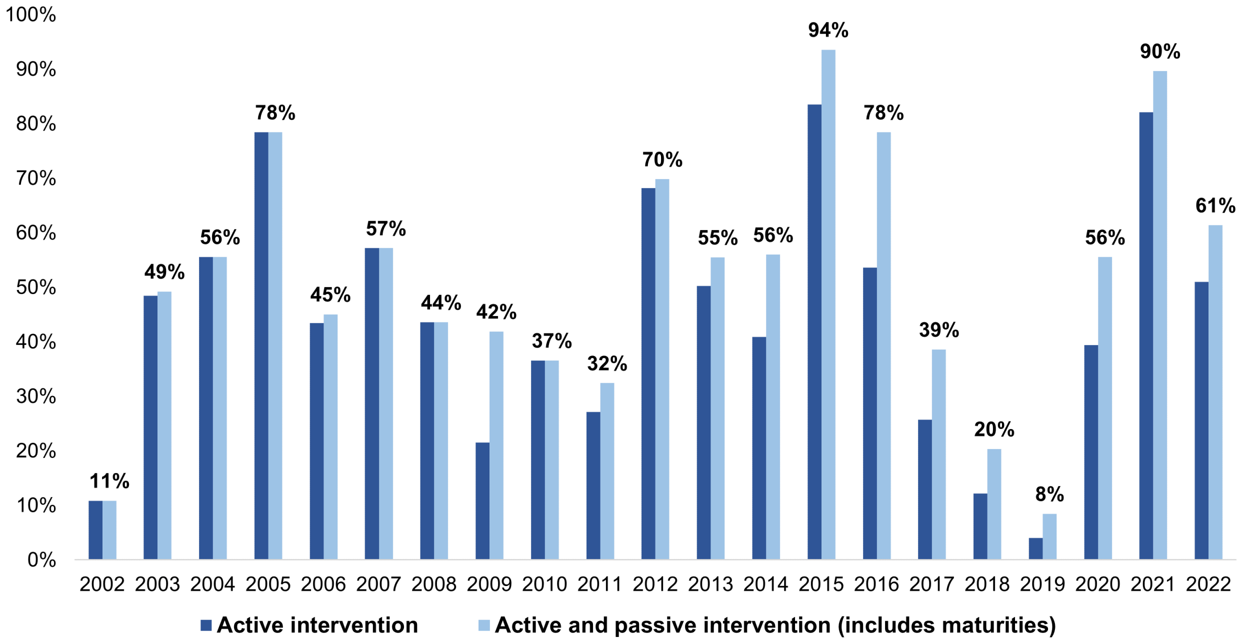
In the last couple of decades, despite abandoning their fixed exchange rate systems, many emerging market economies have continued to use policy tools like foreign exchange (FX) intervention to face capital flow shocks that can increase macroeconomic volatility and have important effects in the real economy through the financial channel (Adrian et al., 2021). During the Global Financial Crisis, for example, FX intervention was highly used both among emerging and advanced economies (Adler et al., 2021; Basu et al., 2022). For this reason, the question of whether these interventions are actually effective to attain the goals monetary authorities attempt to reach with them (usually, either affect the level of the exchange rate or reduce its volatility) is specially relevant. This research intends to contribute to the existing literature by analyzing the impact of exchange rate intervention in the specific case of the Peruvian economy.

The Central Bank of Peru (BCRP) has been a very active institution in the foreign exchange market. Figure 1 shows the percentage of trading days in which this institution has intervened in the foreign exchange market since 2002. In 11 of the last 21 years, the BCRP has intervened in more than 50% of the days. The frequency of these interventions in the Foreign Exchange (FX) market is justified by the existence of a financial channel that makes the Peruvian economy more vulnerable to suffering negative real effects due to excessive exchange rate volatility. This financial channel is strong mainly because the high degree of financial dollarization of bank deposits (Armas and Vega, 2019).

The literature, specially the one related to Peru, has mostly focused either on operations carried out in the spot market or has studied both spot and derivatives operations combined. Less attention has been given to the intervention in the derivatives market and to contrast its effectiveness with that of the intervention in the spot market. This is probably because spot interventions are the most common kind of FX intervention around the world. However, countries like Brazil, Mexico and Colombia have implemented it as a complement to their usual spot operations, due to the advantages that intervention in the derivatives market provide. Besides the fact that it does not require the central bank to use reserves to execute it, derivatives intervention does not affect liquidity in national currency, since it is carried out through instruments, which makes it easier to implement without interfering with monetary policy. Also, as will be explained in this paper, theoretical channels involved in the impact of FX intervention may work differently when it is done with derivative instruments than when it is done through spot operations, which could turn out to be an advantage under certain circumstances. Central banks who intervene in the derivatives market usually do it when exchange rate pressures come from that market instead of originating from pressures in the demand for liquidity in foreign currency (spot market). However, in the Peruvian case, derivatives intervention has recently been used as a first resource, since banks are usually willing to hedge their change in FX position with derivatives even if it was generated by spot operations. Spot intervention, on the other hand, is employed when FX pressures are too large and the central bank wants to send a stronger signal to the market. Still, derivative intervention is normally executed in scenarios of higher uncertainty or risk aversion, under which private agents want to hedge against a potential depreciation of the domestic currency.

In the Peruvian case, intervention through derivative instruments has grown in relevance in the last few years, especially since 2014, as shown in figure 2. Since that year, there has been a clear increase in the total amount of derivatives intervention and, with the exception of 2017, it has been higher than

FIGURE 1: Percentage of trading days in which the Central Bank of Peru intervened.

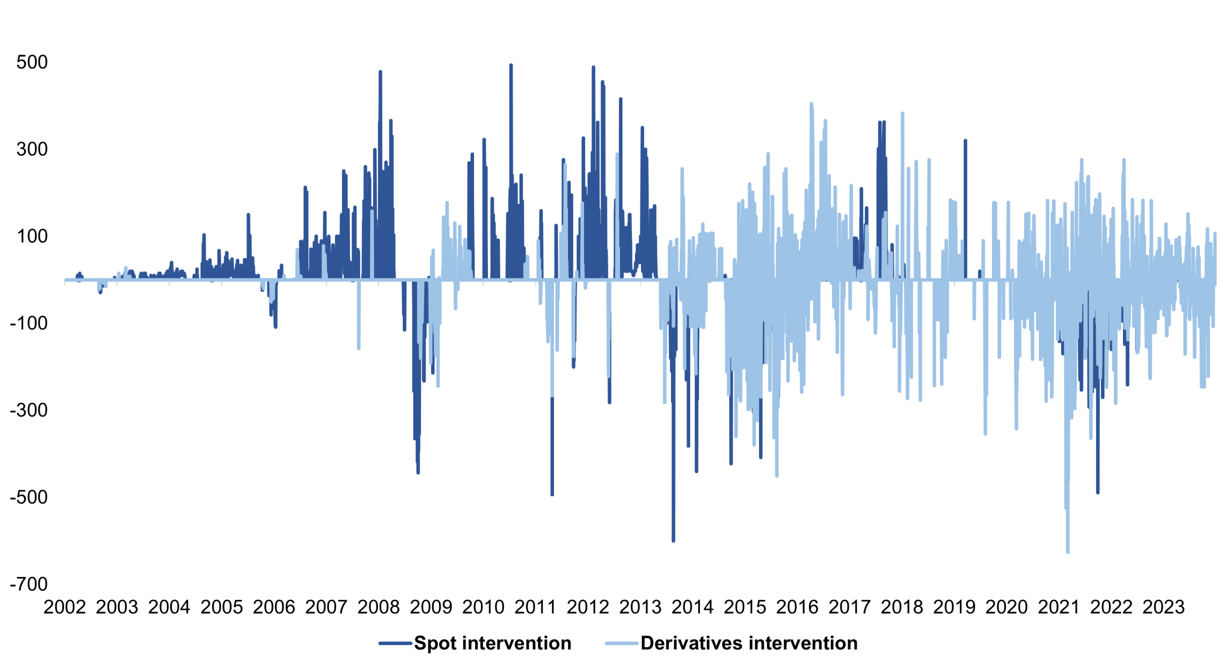


Note: Active intervention refers to issued instruments and passive intervention refers to maturing instruments.

the amount of spot intervention. The increasing participation of FX intervention through derivative instruments in the total intervention makes it relevant to discuss whether it is as effective as the spot intervention has been found to be. Hence, the main research question of this project is: Is Foreign Exchange Intervention from the Central Bank of Peru in the derivatives market effective to dampen exchange rate depreciative or appreciative pressures and to reduce its volatility? Therefore, the purpose of this study is to properly estimate the impact of the intervention in the FX derivatives market on the exchange rate level or its volatility, which will allow to argue if the growing use of this sort of intervention is justified. Also, a precise quantification of the effect of these interventions sets the path ready for future research on their impact on other relevant variables like the output growth or the inflation level. Additionally, this paper intends to investigate on the channels through which the intervention with derivative instruments is effective, which will provide a better understanding of the way these type of interventions work, and even allow to make suggestions about how their implementation could be improved.

To deal with the endogeneity problem present when trying to estimate the effect of FX intervention in the exchange rate, this study takes advantage of the particular way in which the BCRP intervenes in the FX market. First of all, the Central Bank of Peru is characterized by its high degree of transparency in the operations it carries out, which makes of it an interesting case study, since data about its intervention is precise and of easy access, specially at the daily level. On the other hand, interventions can take place at two different moments of the day, either in the early morning or in the afternoon, after a committee has more thoroughly discussed what to do based on the recent market developments. Thanks to this feature, combined with the fact that intervention in Peru is done systematically and on a daily basis, high frequency data can be exploited to identify FX intervention shocks. In this paper, I follow two alternative but related approaches. First, I propose a daily-frequency Structural VAR approach,

FIGURE 2: **Total amount of active spot and derivatives intervention (USD million).**



in which the FX intervention shock is identified by using an exogenous instrument constructed taking into account the features of the market previously described. As an alternative approach, I propose an event study regression framework using intraday data, exploiting the fact, at that frequency, intervention will inevitably happen with a lag, hence breaking the contemporaneous two-way causality between FX intervention and the exchange rate.

2 Theoretical mechanisms behind FX intervention effectiveness

The theoretical literature proposes three potential mechanisms through which FX intervention can be effective (see Sarno and Taylor (2001), for a detailed review of the existing literature about these mechanisms).

The first and most important one is the portfolio balance channel. This channel is based on a portfolio balance model, which is an exchange rate determination model in which agents are risk-averse, and domestic and foreign assets are imperfect substitutes (Dooley and Isard, 1983). In this model, the wealth allocation between domestic and foreign currency depends on interest rates and the expected rate of appreciation of the exchange rate. In this framework, exchange rate movements depend on the interest rate differential and an exchange rate risk premium. Hence, the Uncovered Interest Rate Parity (UIP) does not hold, since a premium is required for agents to be indifferent between uncovered holdings of domestic and foreign currency (if agents were risk neutral, this premium would be zero).

The most recent version of a model that captures the portfolio balance channel is the one developed by Gabaix and Maggiori (2015). In their model, exchange rates are mainly determined by financial forces. An important one is the willingness of financial intermediaries (a market concentrated by a few large institutions) to absorb the imbalances in the demand and supply of assets in different currencies generated by international flows. This willingness depends on a financial constraint that is determined by their risk-bearing capacities and balance sheet risks. Since these intermediaries absorb a portion of the currency risk, changes in the composition of their balance sheet induces changes in their pricing of currency risk, which affects both the level and volatility of the exchange rate. Therefore, for example, an increase in the demand for a given currency requires this intermediaries to be long in that currency. This, at the same time, requires an increase in the expected return of this currency, in order to provide incentives to the intermediaries to absorb this imbalance using their limited risk-bearing capacity. In this case, the currency has to depreciate today in order to generate an expected appreciation in the future. In this model, the UIP condition is not fulfilled because of the risk premium demanded by the financial intermediaries.

This model is founded on the existence of financial frictions faced by the financial intermediaries, which limit their capacity to absorb any demand flow without demanding a change in the price of the exchange rate. Such frictions can be clearly found in the Peruvian financial system, which is characterized by an important level of credit dollarization, and a high level of concentration in the banking system, which is dominated by four big players. As explained by Gabaix and Maggiori (2015), under this kind of frictions, FX intervention by the central bank is effective because it represents a capital flow that affects the balance sheet of intermediaries. Hence, it can counter the effect of other demand flows, relieving financial intermediaries from having to totally absorb FX imbalances. In that way, the effect on the exchange rate is limited.

In the light of this model, FX operations carried out by a central bank generate changes in the asset composition between foreign and domestic currency of financial intermediaries. Given the frictions mentioned before, their risk aversion and the imperfect substitutability of assets in different currency, FX interventions represent demand flows that induce a change in the exchange rate. For example, when facing an excessive demand of foreign currency, financiers would like to keep their FX position (balance sheet's currency composition) unchanged. In order to be willing to absorb this demand flow and function as intermediaries, they will demand a higher compensation on the currency in which they are taking a long position (foreign currency). A sale of foreign currency by the central bank will help them at least partially restore their initial asset composition. Since the change in the FX position of intermediaries has been limited by this operation, its effect on the exchange rate will also be dampened.

It is to expect this channel to be more relevant in countries where foreign exchange markets are underdeveloped, not only because they are more prone to face the frictions that enhance this channel, but also because the central bank's reserves and the size of their interventions are larger relative to the size of the market (Galati and Melick, 2002). Blanchard, Adler, and de Carvalho Filho (2015) also developed a simple theoretical framework to understand the way this channel operates and how FX intervention can mitigate the effect of financial shocks through its effect on capital flows.

On the other hand, the asset composition (balance sheet) of financial intermediaries depends not only on their currency holdings but also on other assets that affect their degree of exposure to the exchange rate, like the derivative instruments they hold. Therefore, this channel, which operates through changes in the asset composition of agents, is present both in spot interventions and interventions made through derivative instruments.

The second channel is the signaling channel, which operates through the information that exchange rate intervention provides about future changes in monetary policy, which is a determinant of the exchange rate. Finally, the coordination channel, also an information channel as the latter, refers to the way intervention helps anchor exchange rate expectations by providing information about its fundamental value (or its long run nominal value), especially when the central bank intends to keep the exchange rate close to that level and limit excessive fluctuations. In this case, intervention provides a signal that induces the market to move in the same direction of the central bank.

When intervention is not sterilized, FX operations carried out by the central bank can additionally influence the exchange rate by affecting the interest rate differential. However, since most of the spot intervention in Peru is sterilized (in the sense that it is executed making sure monetary policy is not altered), this monetary channel is not relevant for this study.

3 FX intervention in the derivatives market by the BCRP

The peruvian exchange rate market is open for four and a half hours every day from Monday through Friday, between 9:00 am and 1:30 pm. It is within this interval that the BCRP conducts its FX operations. The participants in this market are the commercial banks, and the market is dominated by a few big players. Every business day, at around 12:15 pm, a committee meets for around one hour to determine both the monetary and FX operations that will be carried out. However, the BCRP also conducts monetary and FX operations early in the morning if the market circumstances require it. When it comes to spot FX interventions, the BCRP usually carries them out only in the afternoon, after the daily committee has begun. Derivatives interventions, on the other hand, take place prior to the committee almost as frequently as after the committee.

The BCRP carries out derivative intervention mainly through the issuance of what they call FX Swaps, especially the FX Swap Sell. The FX Swap Sell is a derivative instrument in which the commercial bank agrees to pay a fixed or floating interest rate in soles (domestic currency) to the central bank in exchange for the payment of a fixed interest rate in US dollars (foreign currency) plus a payment equal to the variation of the exchange rate (during the contract period) times the nominal value of the instrument. This means that, setting the interest payments aside, a bank holding an FX Swap Sell will benefit from a depreciation of the domestic currency (which represents a positive variation of the exchange rate). Therefore, an issuance of this instrument is equivalent to a sale of US dollars in the spot market, in the sense that it provides a hedge against currency depreciation to commercial banks with a short position in foreign currency. Under common terminology, an FX Swap is actually a different kind of instrument than the one issued by the BCRP. The latter actually resembles more an “FX Cross Currency Swap”, with a few differences. First, all payments are made in domestic currency (peruvian soles) using the average exchange rate of the payment day. Second, there are no exchanges of nominal values at the beginning and the end of the contract. Third, there are no interest payments during the contract and there is a single net payment at the end of the contract. Despite this differences, for simplicity, I will stick to the name used by the local institution (FX Swap). For further details on the operational aspects of the FX Swap, consult Morán (2017)

A much less frequently used instrument, but which has also been issued during some specific periods, is the FX Linked Certificate of Deposit (CDR BCRP). A Certificate of Deposit (CD BCRP) is a sterilization instrument which works as a term deposit for commercial banks. A CDR BCRP is a variation of this monetary instrument in which the central bank agrees to repay, at the maturity, the nominal value adjusted by the variation of the exchange rate. If the currency depreciates, the payment received by the asset holder is higher than the nominal value. Hence, the issuance of this instrument also works as a sale of US dollars to commercial banks.

An increase (decrease) in the commercial bank's holdings of either of these two instruments generates an increase (decrease) in their foreign exchange position and therefore decreases (increases) their degree of exposure to a depreciation of the domestic currency. It is for this reason that issuing these instruments is similar, for FX intervention purposes, to a sale of US dollars carried out by the central bank. Based on the portfolio balance channel explained in section 2, this sort of FX intervention will be effective to counter exchange rate changes generated by excessive demand flows. Since these instruments provide a hedge against currency depreciation, the amount of risk banks bear will not increase when absorbing these demand flows (assuming a full hedge). Therefore, banks do no longer need to demand a higher compensation on foreign currency to be willing to absorb these currency imbalances.

Besides this theoretical mechanism, it is convenient to explain under what circumstances supplying these derivative instruments actually affect the spot exchange rate. In the context of an emerging market like Peru, in which the FX market is not highly developed, especially the forward FX market, the access to hedging instruments by the private sector is limited. Due to the small size of this market and its high level of concentration, there can be episodes in which most or all of the market participants are demanding a long position in the foreign currency, but there are not enough participants willing to be the counterpart of a forward contract. To fulfill their role of market makers, in these scenarios, banks will simultaneously tend to shorten their foreign exchange position, which will lead them to demand instruments that can offset these operations. Otherwise, they will demand an increase in the compensation obtained for holding domestic currency (which requires an exchange rate depreciation).

This can happen, for example, if there are high demand flows of US dollars coming from non-resident agents, in an scenario of high levels of uncertainty or risk aversion. If this demand flows are taking place in the derivative market (private agents are demanding forward contracts to get a longer position in the foreign currency), commercial banks, as market makers, will have to play the counterpart, thus shortening their US dollar position. According to the portfolio balance channel, banks will want to offset this change in their asset composition by demanding a higher expected return on their holdings of domestic currency (soles), which will make them adjust the price of the sol down, leading to a depreciation of the currency. To avoid or dampen this pressure in the exchange rate, the central bank can act as a supplier of the hedge instruments that the banks require to obtain their desired position. By issuing FX Swaps Sell, commercial banks acquire a long position in US dollars, offsetting the short position they initially assumed due to the demand flows of private agents.

Considering that not only the issuance but also the maturity of any of these instruments generates a variation in the FX position of banks and their asset composition (though in the opposite direction), both should be considered as FX intervention. This is often controversial, as it could be argued that only active intervention (issuance of instruments) should be considered as FX intervention. However, the theory described before supports that maturities of instruments should also be taken into account as a sort of passive intervention. For this reason, the measure of FX intervention chosen for the baseline estimations is the net supply (or net issuance) of derivative instruments, which is equal to the total amount of instruments issued minus the total amount of instruments maturing in a day. This is also equivalent to the change in the net stock of instruments issued.

The FX intervention in Peru can be described as systematic, because it is executed on a regular basis, almost at the daily frequency, either with the active issuance of instruments or by letting previously issued instruments mature. Moreover, it follows a pattern in the sense that interventions are executed in two moments of the day, in the morning (before the committee) and in the afternoon (after the committee). Also, despite being systematic, when mapped in a continuous timeline (like at the intraday frequency), interventions take place with a natural lag, because the BCRP has to evaluate the market circumstances before deciding to intervene. In this last case, there is no longer a contemporaneous correlation between the exchange rate market conditions and the FX intervention. This last two features are seized in this paper to deal with endogeneity issues present when trying to identify FX intervention shocks.

4 Literature review

This project is related to the vast literature that empirically studies the effect that central bank's intervention in the foreign exchange market has on the exchange rate dynamics. Among that literature, for instance, Fratzscher et al. (2019) analyzed foreign exchange intervention in a panel of 33 countries with daily data and verified its effectiveness using different criteria (directional change of the exchange rate, reduction of its volatility or smoothing of its path, and stabilizing it within a narrow band). Fuentes et al. (2014) use intraday data to quantify the effectiveness of foreign exchange market operations in Chile, Colombia, Mexico, and Peru.

The literature dedicated to this topic in the case of Peru is also abundant. Flores (2003) found that FX intervention between 1999 and 2001 was effective in 64% of the cases and that it reduced the intraday volatility of the exchange rate. Shiva (2003) estimated an ARCH model and reported that, from 1997 to 2004, purchase operations were not effective to dampen appreciative pressures, but did reduce the exchange rate volatility. Humala and Rodríguez (2010) use a Markov Switching VAR model and find a negative correlation between net foreign exchange purchases and the exchange rate between 1994 and 2007, which becomes stronger in periods with higher volatility until 2003. These articles, however, do not fully address the endogeneity issues present in the relationship between FX intervention and exchange rate.

In order to assess this problem, the literature has proposed a wide array of strategies. Some articles have taken advantage of high frequency data, since it allows to evaluate the impact of an intervention over a very short period of time, which makes the evolution of the exchange rate less likely to be affected by other factors correlated with the intervention itself. This allows for the application of methodologies like event study regressions to unbiasedly estimate the impact of the intervention, as proposed by Lahura and Vega (2013) or Fuentes et al. (2014). In fact, if the frequency is sufficiently high, it is even reasonable to assume that the exchange rate does not contemporarily determine the intervention operations, in such a way that a Cholesky decomposition may be valid to identify an exchange rate intervention shock in a SVAR approach, as suggested by Kohlscheen and Andrade (2014). Lahura and Vega (2013) also estimate these effects using an SVAR with intraday data, but assuming that FX intervention has no effect on the exchange rate in the long run.

Fratzscher et al. (2019) address the endogeneity problem using a matching approach to create a treatment and control group by linking episodes that occur in similar circumstances. Another very common strategy that articles have followed to identify the desired effect is the use of instrumental variables. Kearns and Rigobon (2005) take advantage of an exogenous change in the way the central banks of Australia and Japan intervene (they stopped intervening through small operations to concentrate on larger ones). Adler and Tovar (2014) follow an IV-panel data approach with weekly data, using as instrument the predicted values from a censored reaction function estimated through a Tobit model. For the case of Peru, Tashu (2014) applies a similar strategy, in which they use a Probit model to predict the probability of FX interventions based on deviations from a target level of the variation and volatility of exchange rate between 9:00 am and 11:30 am. Brandao-Marques et al. (2020) also construct an FX intervention shock using quarterly data by estimating a linear rule of intervention per country, but using the residuals obtained from the regression, instead of the fitted values. Filardo, Gelos, and McGregor (2022) follow a similar strategy in a panel framework, but their intervention rule depends on the volatility of the real exchange rate.

5 Empirical estimation

5.1 Data

Daily and intraday data are obtained mainly from Bloomberg and complemented with some other sources, as detailed in Table 1. The measure of foreign exchange intervention selected for the baseline estimation is the net supply of derivative instruments issued by the BCRP. Therefore, both the active issuance and the passive maturing of instruments are considered as intervention operations. The reason behind this selection is that, as explained previously, both the issuance and the maturing of instruments have an impact (though in the opposite direction) on the hedged foreign exchange position of banks, which triggers the portfolio balance channel and can potentially generate pressures in the exchange rate market.

5.2 VAR analysis at daily frequency

5.2.1 Methodology

The estimation of the effect of foreign exchange intervention on the evolution of the exchange rate or its volatility requires addressing some endogeneity issues. Since central banks tend to carry out foreign exchange operations intending to lean against the wind, i.e., they tend to sell (buy) foreign exchange when the currency is depreciating (appreciating), their intervention is usually correlated with the evolution of the exchange rate. In other words, monetary authorities take into account the contemporary and recent dynamic of the exchange rate when deciding to intervene, bringing about a simultaneity bias issue when estimating the effect of these interventions.

In order to address this problem, this study proposes a proxy SVAR model using daily data, which relies on a constructed instrument to obtain consistent estimations of the effect of FX intervention. This represents a combination of two frequently used methodologies in this literature (but up to date never combined in the branch of the literature related to FX intervention): a VAR model and identification through an instrumental variable. The instrument proposed is constructed in such a way that represents an "intervention surprise". For that purpose, a reaction function for the intervention is estimated con-

TABLE 1: Source, frequency and sample frame of used variables

Variable	Source	Frequency	Sample
Exchange rate PENUSD	Bloomberg	Daily/intraday	Jan 2014 - Dec 2023
Forward Exchange rate PENUSD	Bloomberg	Daily	Jan 2014 - Dec 2023
FX intervention	BCRP databases	Daily/intraday	Jan 2014 - Dec 2023
Time of intervention	BCRP website	Intraday	Jan 2014 - Dec 2023
VIX	Bloomberg	Daily/intraday	Jan 2014 - Dec 2023
DXY	Bloomberg	Daily	Jan 2014 - Dec 2023
Copper price	Bloomberg	Daily	Jan 2014 - Dec 2023
Interbank interest rate of Peru	BCRP databases	Daily	Jan 2014 - Dec 2023
Fed Funds Rate	FRED Database	Daily	Jan 2014 - Dec 2023
Exchange rate of other currencies in the region	Bloomberg	Daily	Jan 2014 - Dec 2023
Demand flows in the peruvian foreign exchange market	BCRP databases	Daily	Jan 2014 - Dec 2023
Hedged FX position of commercial banks	BCRP databases	Daily	Jan 2014 - Dec 2023

sidering the market circumstances in the early morning (between 9:00 am and 11:00 am). Contrary to what other studies follow, I do not use the estimated values from this reaction function to construct the instrument, but rather the residuals from the regression, which can be interpreted as a deviation from what the central bank would normally do under the circumstances described by the regressors. In fact, these residuals should represent the fraction of the intervention that is not related to the first developments of the day in the foreign exchange market, and therefore should be exogenous. This instrument may have a contemporary correlation with the exchange rate, but only through the effect that the FX intervention has on this market, and not due to the prior developments that led to the central bank's intervention. In the construction of this instrument, I also control for the late exchange rate developments in the previous day and the exchange rate variation between the close price of the previous day and the open price of the current day. This is because these developments may also influence the early operations carried out by the BCRP, which would lead to some remaining endogeneity. The application of this method is convenient because it only requires using one valid instrument to identify the specific shock of interest, the foreign exchange intervention, and no additional assumptions are needed to identify all structural shocks. The model estimated is as follows:

$$Y_t = B_0 + \sum_{i=0}^{p} B_i Y_{t-i} + \sum_{i=0}^{p} A_i X_{t-i} + \mu_t \tag{1}$$

$$Y_t = \begin{bmatrix} DERIV - FXI_t \\ exc_t \\ SPOT - FXI_t \\ FWD_t \\ HEDGE_t \end{bmatrix} X_t = \begin{bmatrix} VIX_t \\ DXY_t \\ COPP_t \\ MATUR_t \\ RES_t \\ NR - FLOWS_t \end{bmatrix} \tag{2}$$

Where Y_t is the vector of endogenous variables and X_t is the vector of exogenous variables. $DERIV - FXI_t$ is the measure of foreign exchange intervention in the derivatives market (in this case, net supply of derivative instruments), exc_t is the change in the log of the exchange rate, $SPOT - FXI_t$ is the level of FX intervention in the spot market, FWD_t is the 1-month forward exchange rate (a measure of exchange rate expectations), and $HEDGE_t$ is the hedged FX position of the commercial banks (which captures the porfolio balance channel). When analizing the impact of FXI on exchange rate volatility, the standard deviation of the exchange rate in the last five days is included in the set of endogenous variables. VIX_t is the change in the log of the VIX index (which should capture external uncertainty and capital flows), DXY_t is the change in the log of the dollar index, $COPP_t$ is the change in the log of the copper spot price, $MATUR_t$ is the total amount of maturing instruments of the day, RES_t is the level of the central bank's reserves, and $NR - FLOWS_t$ is the amount of FX flows coming from non-resident agents (which should reflect local uncertainty or risk). Additionally, weekday fixed effects are included to control for potential seasonality in the foreign exchange market.

Let e_t be the structural shocks of the VAR. Then the reduced-form shocks u_t can be mapped by matrix S as a function of e_t:

$$u_t = Se_t \tag{3}$$

Following the steps proposed in Känzig (2021), the structural parameters can be recovered from the reduced-form estimates by imputing values on the matrix S. This methodology does not require all shocks to be identified, since each column in matrix S is related to a specific shock. Since we are interested in identifying an exogenous FXI shock (the first variable), it is sufficient to impose values in the first column of this matrix. Normalizing the FXI shock to 1 (the first element of the first column of S, $s_{1,1} = 1$), the remaining values of the column $s_{i,1}$ are filled with the coefficient estimated in a regression of the corresponding reduced-form shock $u_{i,t}$ on $u_{1,t}$ using a common instrument z_t, for i = 2 to n.

The instrument proposed is the residuals ε_t obtained from estimating the following reaction function for FXI:

$$DERIV - FXI_t = \beta_0 + \beta_1 exc_{early} + \beta_2 exc_{open-close} + \beta_3 exc_{late-yesterday} + \gamma X_t + \varepsilon_t \tag{4}$$

Where exc_{early} is the exchange rate log-return between 9:00 am and 11:00 am, $exc_{open-close}$ is the exchange rate log-return between the open price of the day and the close price of the previous day, $exc_{late-yesterday}$ is the exchange rate log-return between 1:00 pm and the close price of the previous day, and X_t is a vector of additional control variables, which include the exchange rate variation of other currencies in the region and the total amount of maturing instruments of the day as it conditions how much is issued in the day.

The advantage of considering the early variations of the exchange rate in the reaction function is that they only have imperfect influence over the close price of the exchange rate, since there are around two and a half hours left before the market's closure after 11:00 am. Hence, when controlling for those early market conditions, we are isolating the exogenous part of the intervention, while leaving room for that intervention to have an impact in the next few hours.

Within this framework, impulse response functions (IRF) can be computed to analyze the dynamic impact of a foreign exchange intervention on the exchange rate. In this paper, I analyze the period between January 2014 and December 2023, but I also work with two additional sub-samples: a pre-pandemic sample (between January 2014 and December 2019) and a post-pandemic sample (between January 2020 and December 2023).

5.2.2 Results

Reaction function

The results of estimating equation (4) for both sub-samples and the full sample are presented in Appendix A. The estimated coefficients have the expected positive sign (since any increase of the exchange rate, which is a depreciation, should lead to a higher intervention, which is a sale of US dollars). The only exception is the coefficient of the exchange rate change between the open price of today and the close price of yesterday. However, this coefficient is not significant in any of the samples. Also the sign of the coefficient of the amount of maturing instruments of the day is positive and highly significant, which confirms the idea that day-to-day intervention is highly influenced by the instruments maturing each day. Each of the regressions have an R-squared higher than 20%, which means that the reaction function does explain an important fraction of total intervention. Therefore, the residuals will be highly but not perfectly correlated with FX intervention.

Graphs of the residuals and fitted values are also presented for each regression in Appendix A. In every sample, it is clear that the predicted values of the reaction function are less noisy than the actual values, which supports the idea that their difference (the residuals), which are used as the instrument, reflect intervention surprises that are likely to be exogenous.

Effect on the exchange rate's level

Figures 4 to 6 show the IRF obtained after estimating the proxy SVAR proposed in section 4. Due to the strong regime switch and volatility increase that took place during the Covid-19 pandemic, estimation was done for two different periods: 2014 to 2019 (period of high level of FX derivatives intervention, as shown in Figure 2) and 2020 to 2023. As can be seen in Figure 9, for the prepandemic period, the effect of a positive FXI shock, which represents a sale of FX, generates an appreciation (reduction) of the exchange rate the same day of the intervention, but it reverses in the following days. After about a week (6 days), the shock no longer has an effect on the exchange rate, which means that the FX intervention of the BCRP only had a short-term impact. The forward price follows a very similar dynamic to that of the spot exchange rate. The hedged FX position of banks shows, as expected, a permanent increase due to FX intervention, since the duration of the instruments issued is usually of 3 months or higher.

In Figure 10, results for the pandemic period are shown. Similar responses are found for each variable, both in their dynamic and magnitude. The main difference is that the attenuation of the effect on the exchange rate takes a few more days. Figure 11 displays the IRF obtained by using the entire sample (2014-2023), and the results are very similar to the previous two estimations, as well.

Quantitatively, results allow to conclude that an FX sale derivatives intervention between USD 60 and USD 120 million (range in which the size of a single intervention is usually located) leads to a currency appreciation between 0.02% and 0.04% the first day, and this effect quickly dissipates in the next days. An intervention operation (instrument issued) of the average size during the sample period (USD 75 million) generates an appreciation of around 0.025%. Similarly, a total active intervention (intervention without considering maturing instruments) of USD 134 million during a day (the average in the sample) leads to an appreciation of around 0.044%. I also find that the effect is slightly stronger during the pandemic.

FIGURE 3: Impulse Response Functions to an FX derivatives intervention shock (USD millions) (2014-2019) - Level.

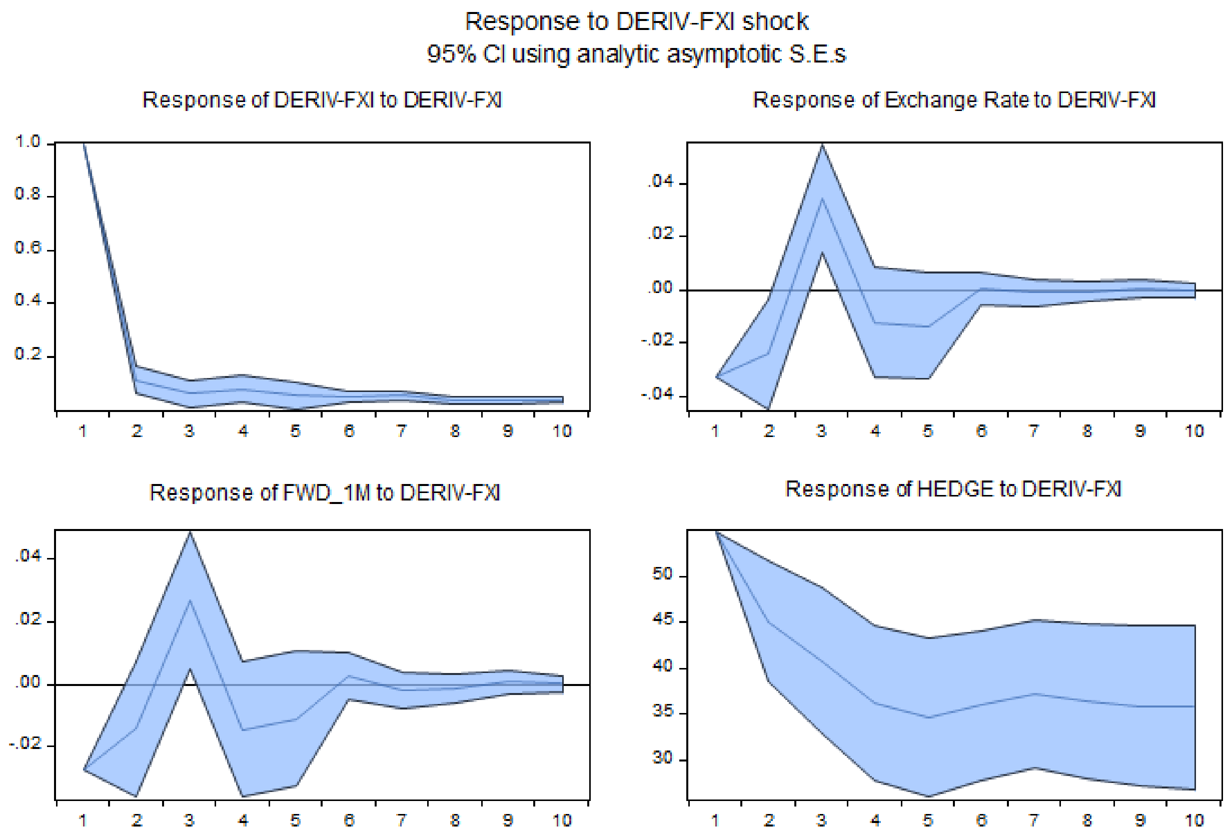


FIGURE 4: Impulse Response Functions to an FX derivatives intervention shock (USD millions) (2020-2023) - Level.

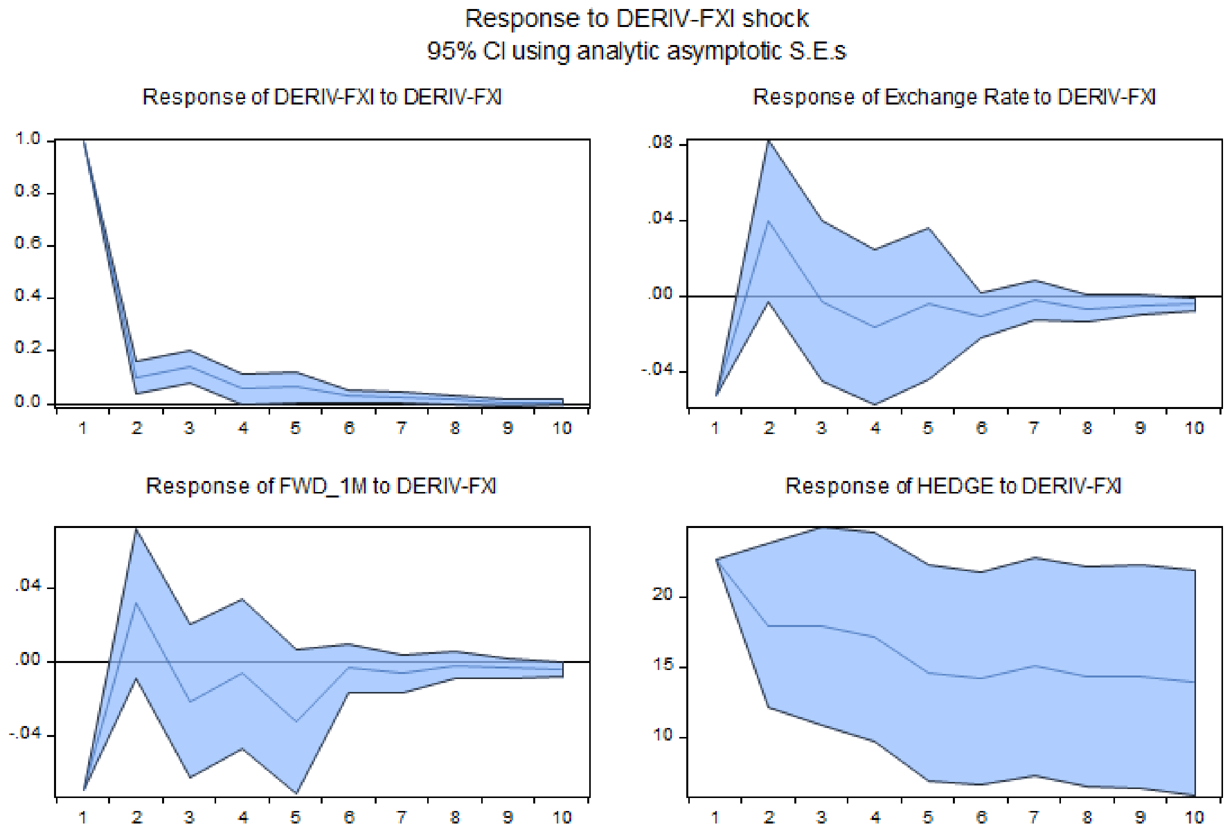
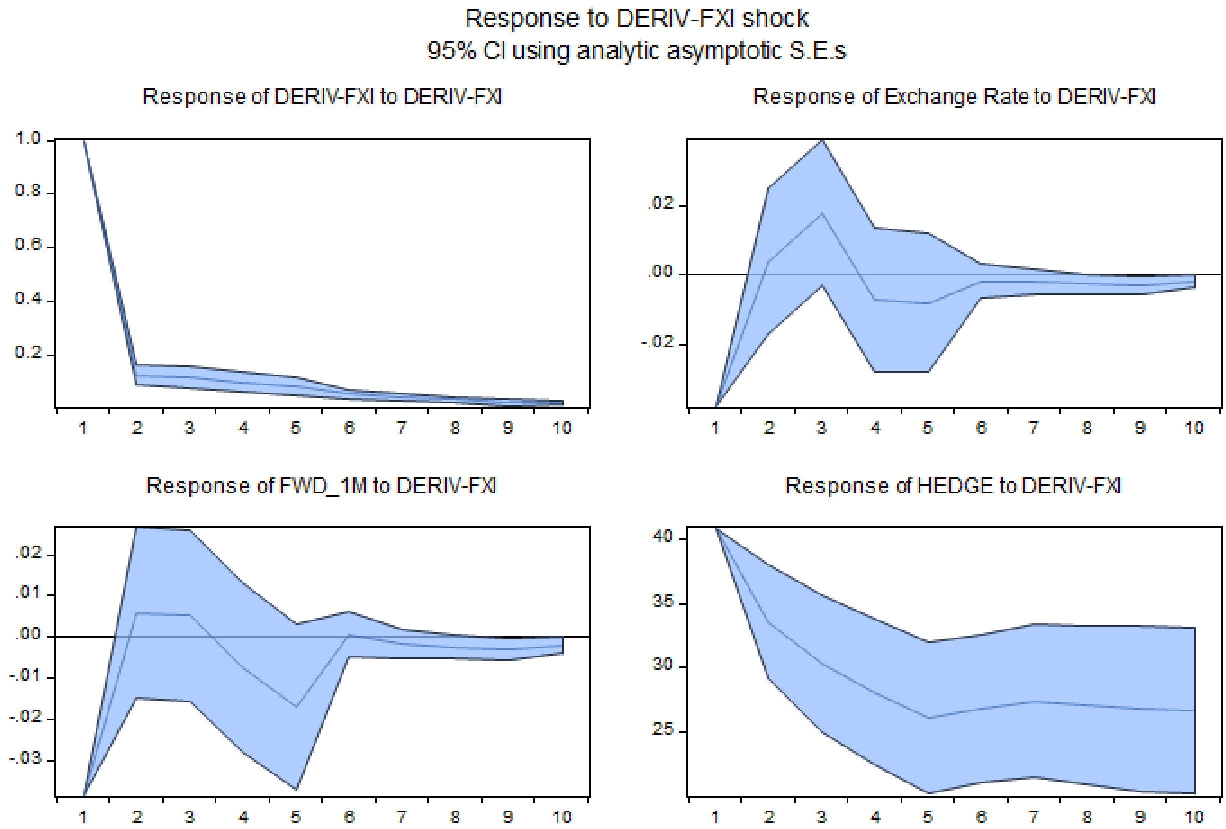


FIGURE 5: Impulse Response Functions to an FX derivatives intervention shock (USD millions) (2014-2023) - Level.



Effect on the exchange rate's volatility

In order to analyze the impact of an FX derivatives intervention on the exchange rate's volatility, the standard deviation of the exchange rate is included as an additional endogenous variable in the same VAR specification. A window of five days is used to calculate the standard deviation, as it provides narrower confidence intervals. The response using larger windows is similar but less precisely estimated. Results are presented in Figures 7 to 9, for the same samples displayed before. In all of the three estimations, the responses of the variables are very similar to those obtained without including the volatility variable. Regarding the impact on volatility, during the prepandemic period (Figure 12), an FX intervention in the derivatives market induces a decrease in the volatility of the exchange rate. This reduction starts the day after the intervention, and reaches its peak 2 days after. This reduction exhibits high persistence over the next weeks, but not at a statistically signficant level. However, during the pandemic (Figure 13), results show that BCRP interventions did not reduce the market's volatility, despite being able to affect the exchange rate level in the desired direction. This feature of the pandemic takes precedence in the estimation using the entire sample (Figure 14), though in this case it seems that a reduction in the exchange rate's volatility is achieved after some weeks.

Since these results could be influenced by the volatility measure used, I estimate the IRF using an alternative one: the volatility estimated from an stochastic volatility (SV) univariate model of the exchange rate, like the one proposed in Kim, Shephard, and Chib (1999). Appendix B shows the results of this approach. IRF using the accumulated intervention in the last 30 days instead of the intervention of the day are also shown. In both cases, the effect on volatility is estimated more precisely than when using the standard deviation as volatility measure, and it is very close to zero and not significant. Only full sample results are reported, but during the pandemic a significant negative effect on volatility is found when using the accumulated intervention, but the effect on the level has the wrong sign. This could be explained by the fact the identification strategy works for the intervention of a single day and not for an accumulated intervention.

These results can be surprising, since one of the main reasons why the BCRP intervenes is to reduce the volatility of the exchange rate, so that temporary (non-fundamental) fluctuations in its level do not generate real economic effects. However, the reason behind these results might be related to the fact that the shock being identified is an FX intervention surprise, and not FX intervention in its entirety. In other words, the effect found on the exchange rate is the impact of the most volatile component of FX intervention, the unexpected one. As a matter of fact, FX interventions are carried out through open-market operations, which should increase FX volatility in the short run. Therefore, FX intervention is not actually supposed to reduce volatility in the next days after being executed, but it should decrease, in average, the market's volatility in the long run, thanks to the effects it has on market's expectations. For example, market participants are less likely to overreact to news if they know the central bank is an active institution in the FX market, as in the case of Peru, which should reduce long-term market volatility. In order to assess how effective FX intervention in reducing volatility, one would need to compare the volatility in an scenario with FX intervention with the volatility in an scenario without it, throughout a large period of time. Doing this would require a counterfactual policy scenario and it is not possible to do in the model I propose.

FIGURE 6: Impulse Response Functions to an FX derivatives intervention shock (USD hundred millions) (2014-2019) - Level and Volatility.

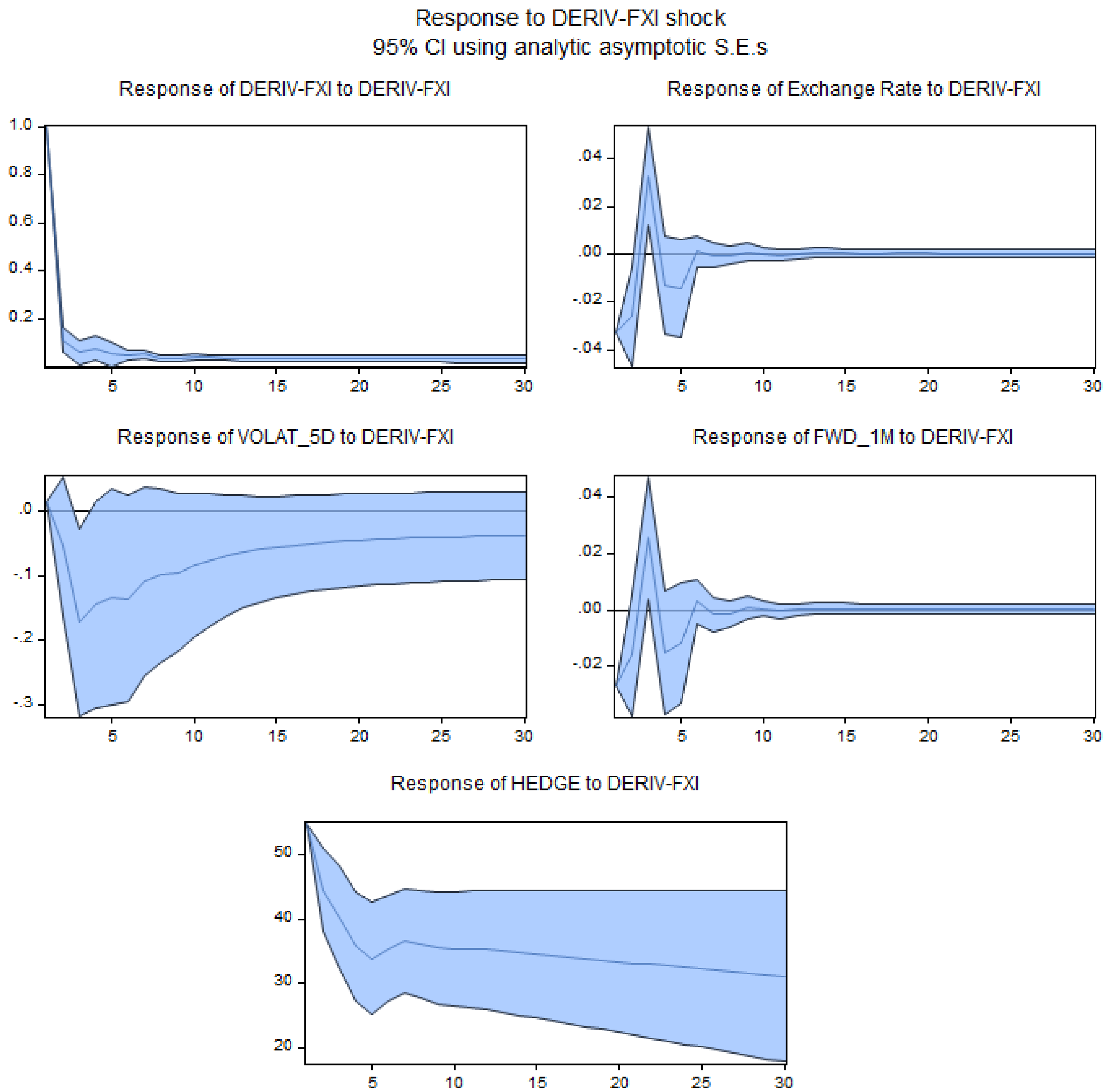


FIGURE 7: Impulse Response Functions to an FX derivatives intervention shock (USD hundred millions) (2020-2023) - Level and Volatility.

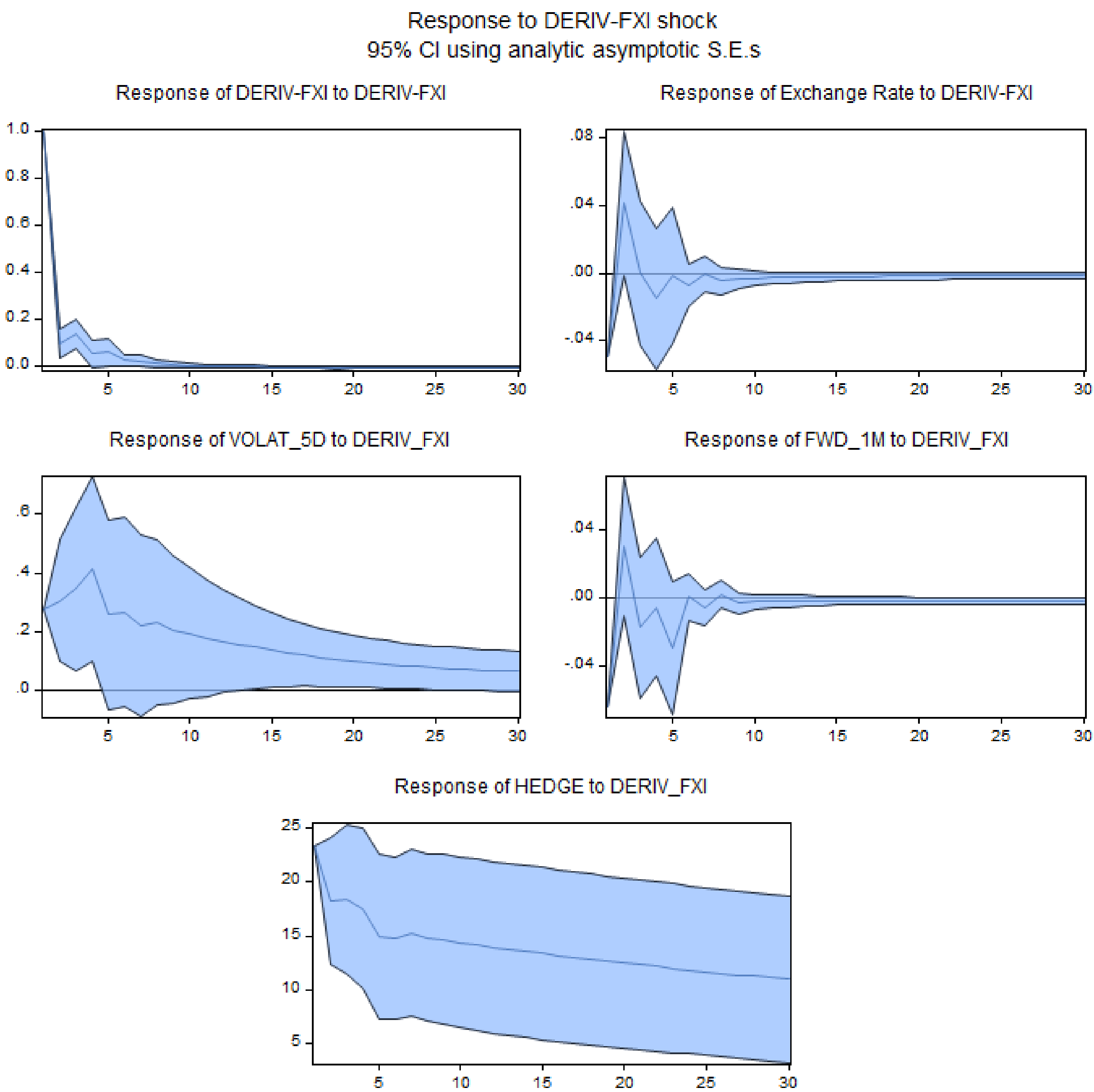
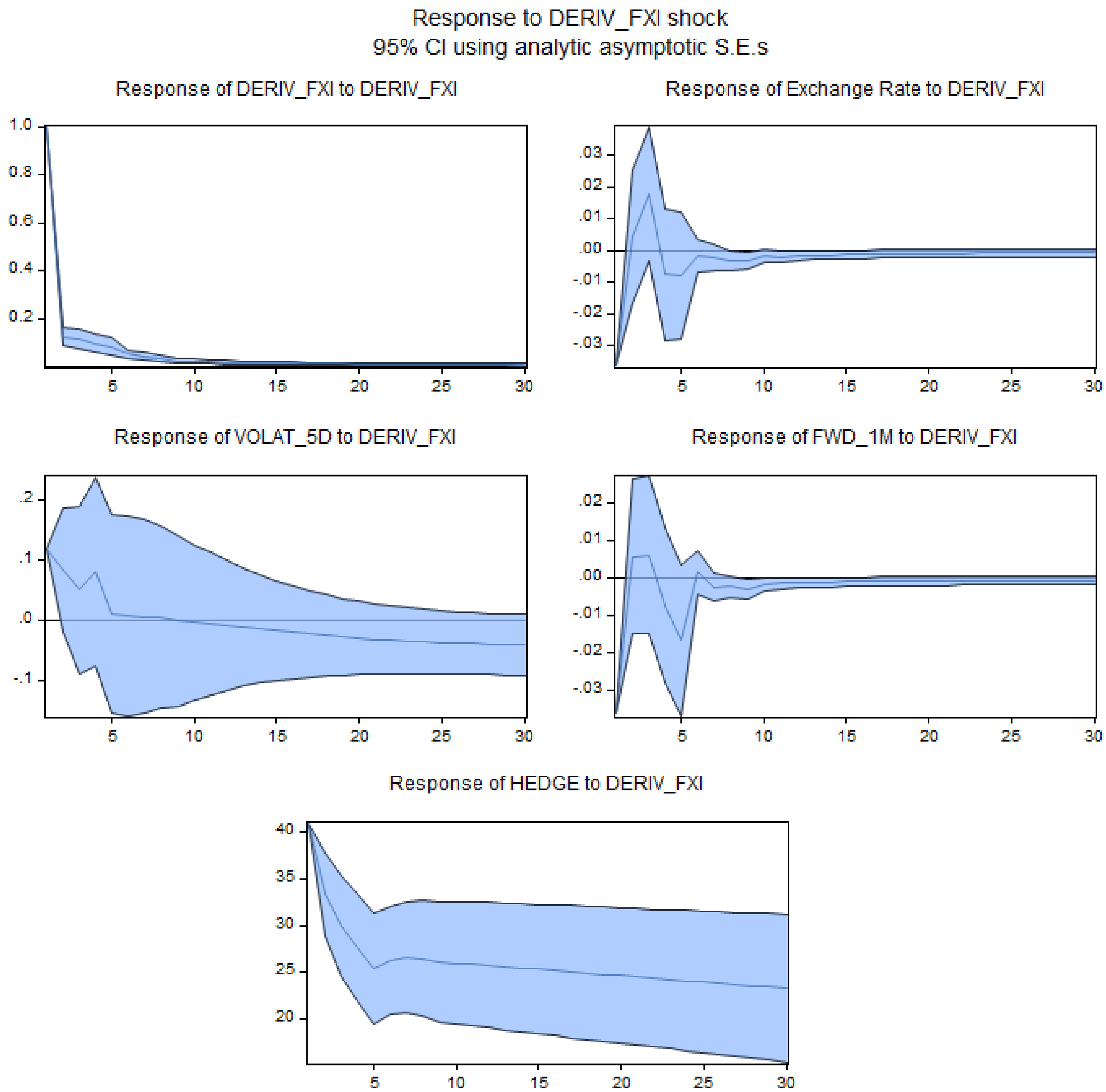


FIGURE 8: Impulse Response Functions to an FX derivatives intervention shock (USD hundred millions) (2014-2023) - Level and Volatility.



Effect of spot intervention

In order to compare the effectiveness of derivatives intervention with that of spot intervention, the same Proxy SVAR framework is used, but the instrument is constructed replacing the endogenous variable $DERIV - FXI_t$ for $SPOT - FXI_t$ in equation (4). Then, $SPOT - FXI_t$ is placed as the first variable of the endogenous variables of the VAR, since it is the shock that will be identified. Figures 9 to 11 show the impulse response functions obtained after estimating this VAR for each sub-sample. Dynamics are similar to the ones found in the case of FX derivatives intervention for each variable along the different sub-samples. The main difference is that spot intervention seems to have the strongest effect a day after the intervention and not the same day, as in the case of derivatives intervention. Quantitatively, an spot sale of USD 100 million leads to a currency appreciation of around 0.06% the second day, and this effect quickly dissipates in the next days. During the pandemic sample, the effect in the second day is even stronger (around 0.1%), but the opposite effect is found during the first day. This counter-intuitive result could be explained by the lower frequency of spot interventions after the pandemic. Regarding the effect on exchange rate's volatility, there is no significant impact found during the pre-pandemic period, and there is an slightly significant positive effect in the post-pandemic sample and the full sample.

FIGURE 9: Impulse Response Functions to an FX spot intervention shock (USD hundred millions) (2014-2019) - Level.

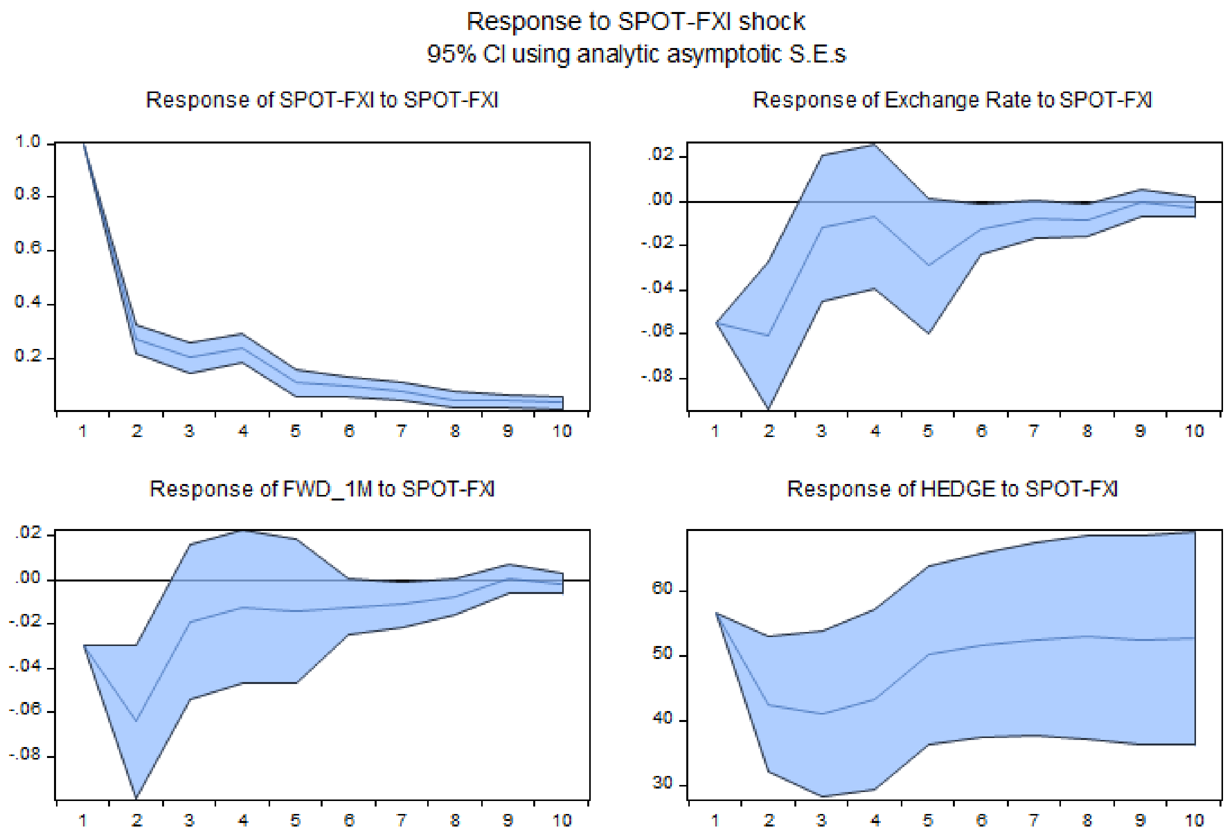


FIGURE 10: Impulse Response Functions to an FX spot intervention shock (USD hundred millions) (2020-2023) - Level.

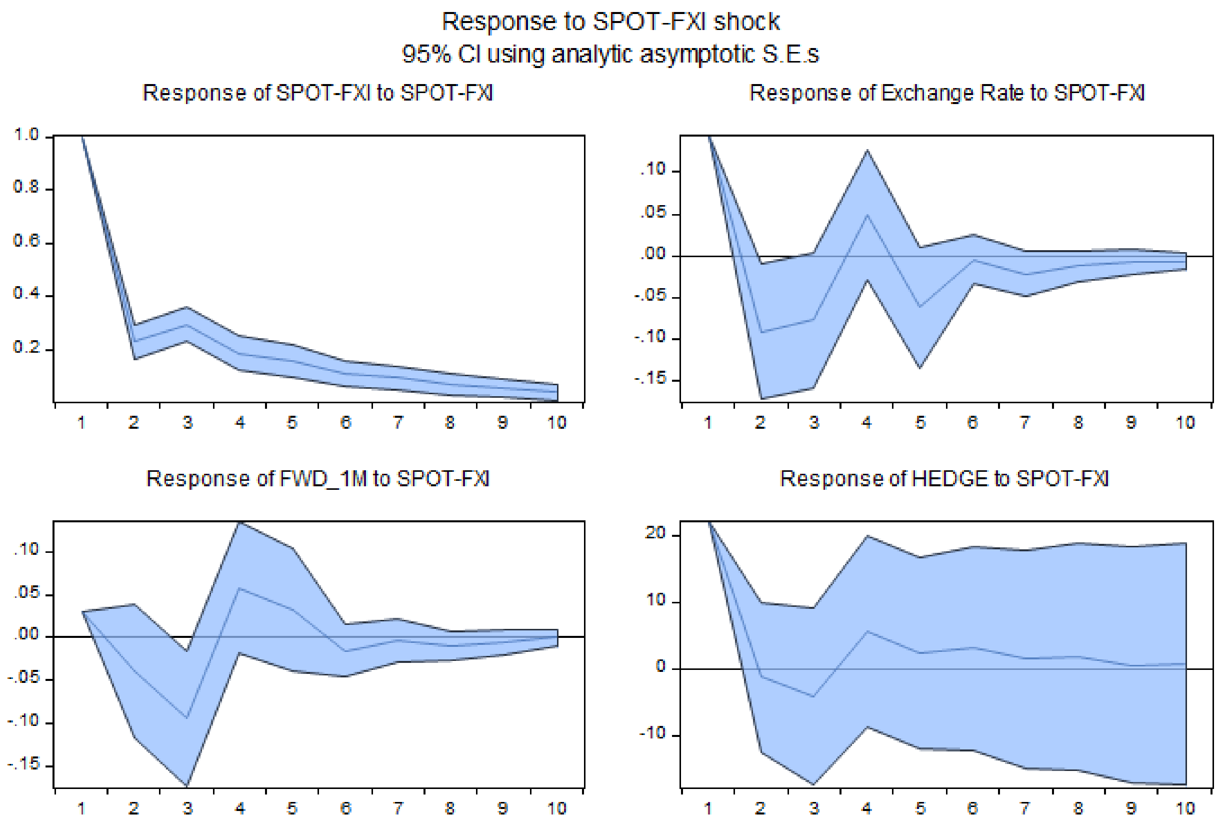


FIGURE 11: Impulse Response Functions to an FX spot intervention shock (USD hundred millions) (2014-2023) - Level.

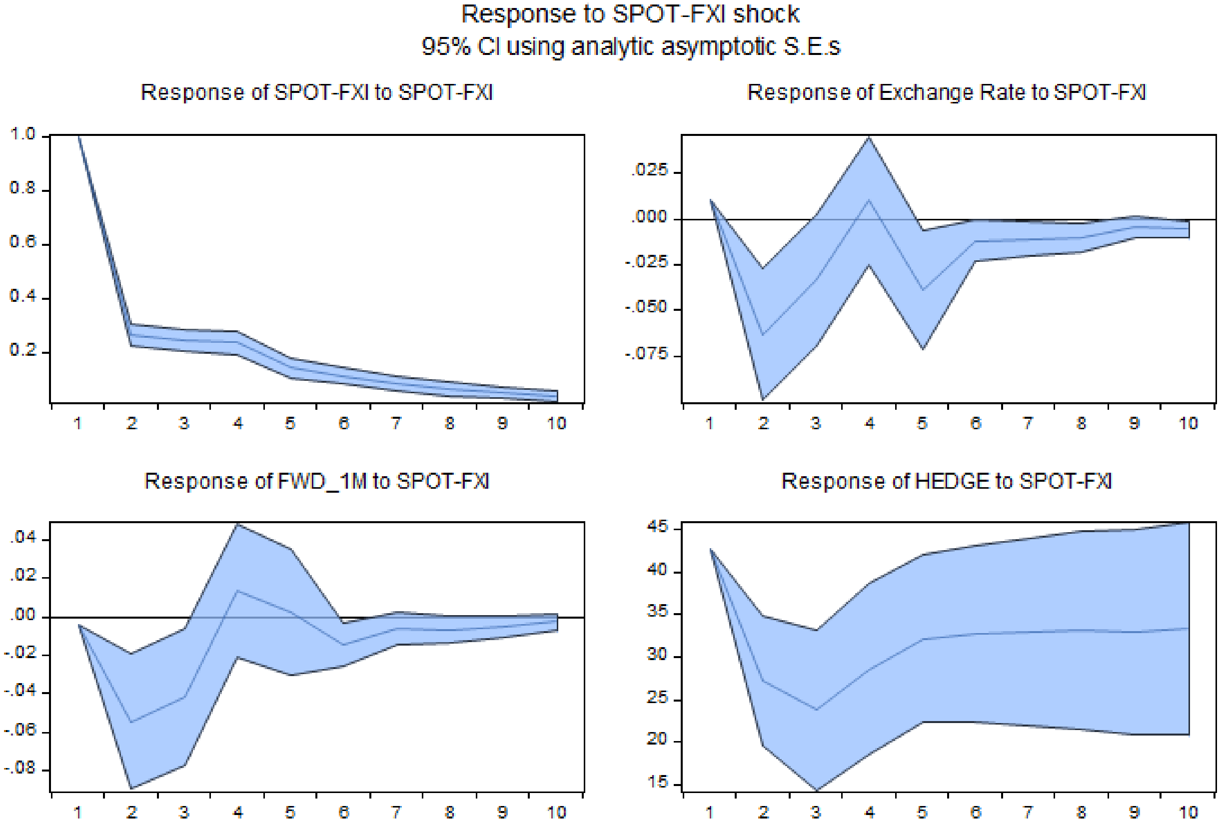


FIGURE 12: **Impulse Response Functions to an FX spot intervention shock (USD hundred millions) (2014-2019) - Level and Volatility.**

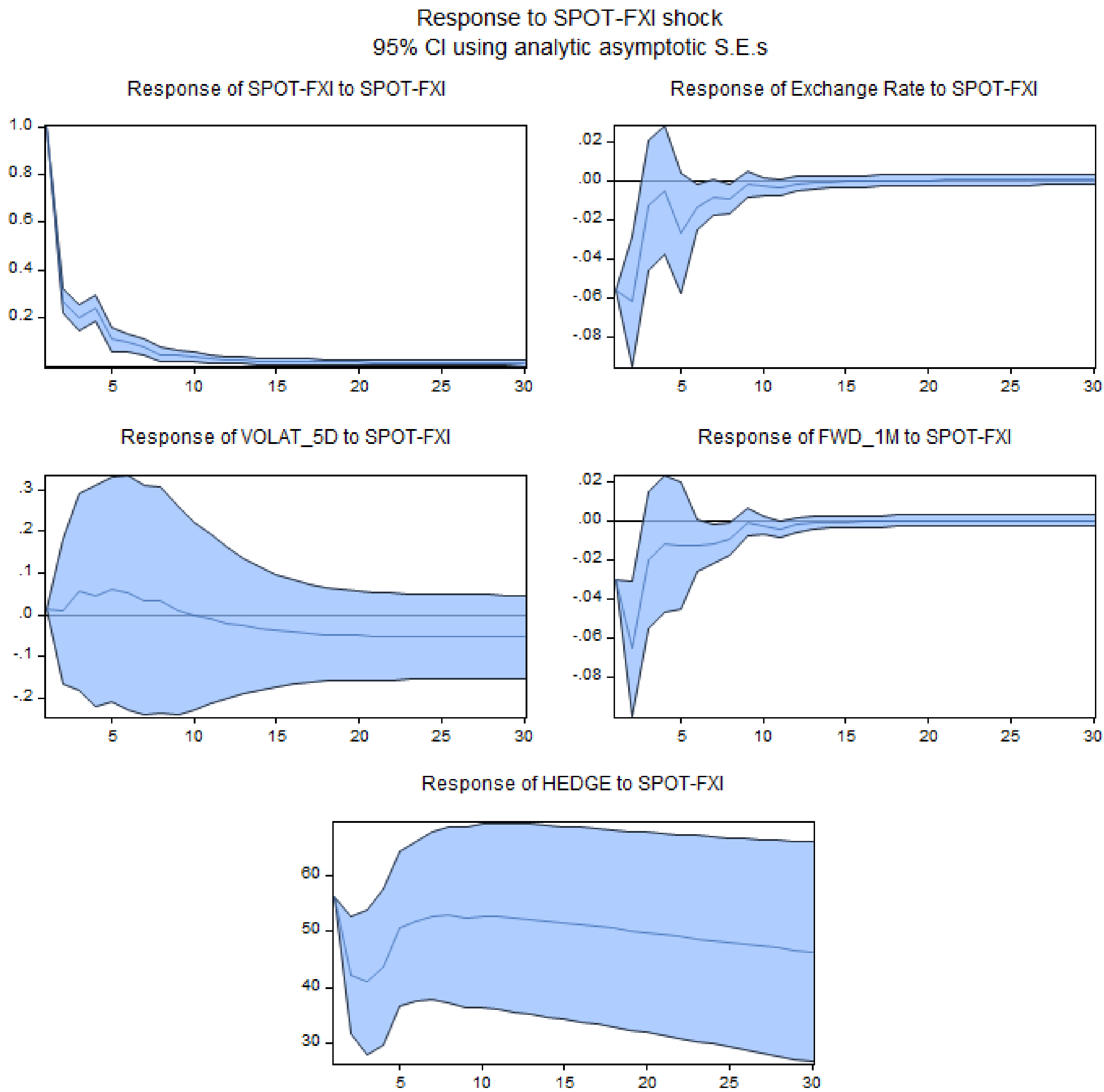


FIGURE 13: **Impulse Response Functions to an FX spot intervention shock (USD hundred millions) (2020-2023) - Level and Volatility.**

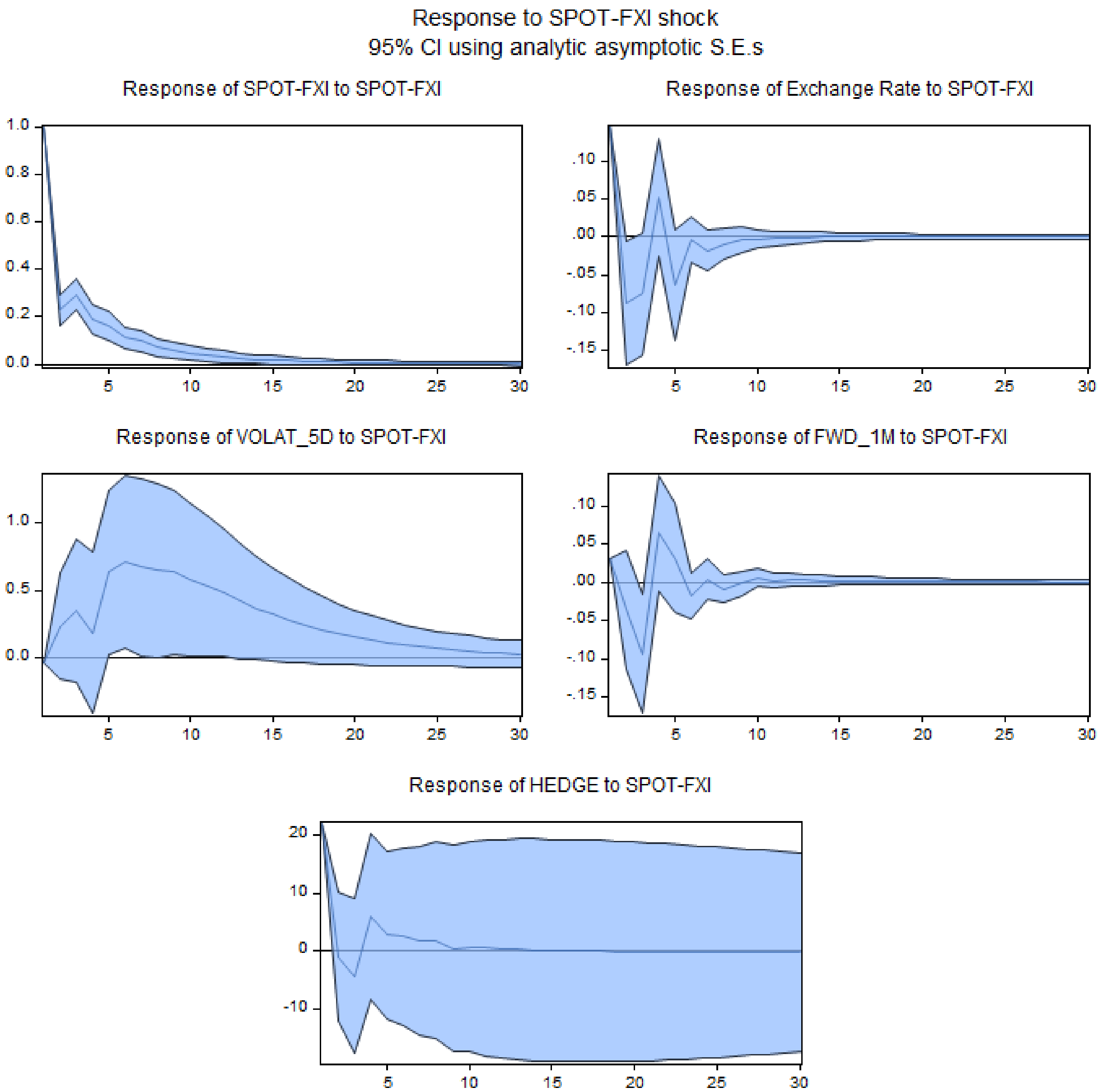
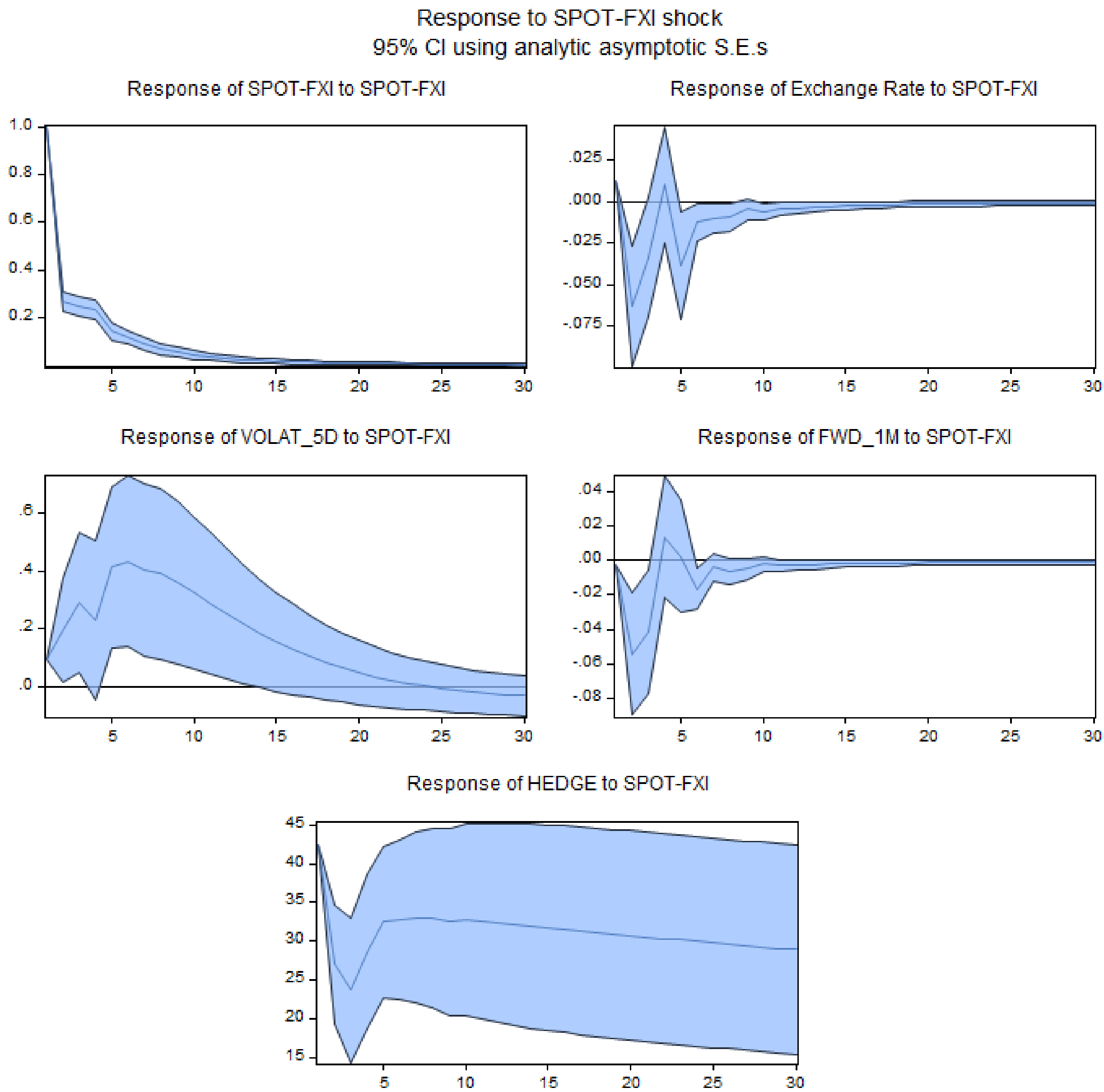


FIGURE 14: Impulse Response Functions to an FX spot intervention shock (USD hundred millions) (2014-2023) - Level and Volatility.



5.3 Event study analysis at intraday frequency

5.3.1 Methodology

In the second part of this research, I propose an alternative approach to analyze the effect of FX intervention on the exchange rate without the need to use an artificially constructed instrument. Thanks to the fact that FX interventions happen on a daily basis in Peru, it is possible to use intraday data to study the impact of these interventions. When using data of a high enough frequency, FX interventions happen with a natural delay with respect to the market conditions that triggered them. Evidently, a central bank requires some time to react to the exchange rate evolution and also to implement the actual intervention. Hence, at a frequency of 10-minute intervals, like the one used in this section, the reaction function of the BCRP would depend only on lags of the exchange rate, and not on its contemporaneous value. Therefore, the simultaneity bias normally present in a regression of the exchange rate on FX intervention is mitigated since the contemporaneous exchange rate evolution (in the last few minutes) is unlikely to determine the contemporaneous level of FX intervention.

This alternative methodology will also allow to shed some lights on the mechanisms behind the effectiveness of the FX derivatives intervention. Little to none research work has been advocated to empirically analyze the channels that make the exchange rate intervention effective in the case of Peru. The intervention through derivative instruments, in a similar fashion that the spot operations, should have a clear impact on exchange rates through the portfolio channel, which is related to the changes in the asset composition (and hence the risk faced by economic agents and banks) that generate the operations from the central bank (Sarno and Taylor, 2001). However, since these operations are usually carried out through auctions (as in the case of Peru), they provide an opportunity to investigate on the signaling and coordination channel, which refers to the information that exchange rate intervention provides about the future monetary policy and exchange rate's fundamental value. Once the auction is announced and before the instrument is officially issued, banks already know that the central bank has decided to intervene, which should be enough to activate those two channels. Therefore, it is possible to use intraday data to find out if there is an effect attributable to the signaling and coordination channel besides the effect attributable to the portfolio balance channel.

The standard event study regression with intraday data uses leads and lags of the endogenous variable (in this case FX intervention), as proposed by Lahura and Vega (2013):

$$exc_t = \delta + \sum_{i=-T0}^{T1} \beta_i.ISSUED_{t-i} + \sum_{i=1}^{p} \theta_i.exc_{t-i} + \gamma.X_t + \varepsilon_t \tag{5}$$

Where exc_t is the log change of the exchange rate and $ISSUED_t$ is the sum of the FX derivatives auctions that ended and were therefore issued at time t. X_t is a vector of additional controls, including the log change of the VIX (VIX_t), the DXY (DXY_t) and the copper price ($COPP_t$), the total amount of maturing instruments of the day ($MATUR_t$), and dummies that control for the first interval of hours 9 and 13 (first interval of the day and first interval of the last hour of the day).

However, given the way intervention is executed in Peru, it is possible to use a more precise specification in which, instead of leads of the same endogenous variable, I use the lead values of the actual information that banks had in each specific period of time:

$$exc_t = \delta + \sum_{i=-T0}^{-T1-1} \eta_i.ANNOUNCE_{t-i} + \sum_{i=-T1}^{-1} \phi_i.BID_{t-i} + \sum_{i=0}^{T2} \beta_i.ISSUED_{t-i} + \sum_{i=1}^{p} \theta_i.exc_{t-i} + \gamma.X_t + \varepsilon_t \tag{6}$$

Where exc_t is the log change of the exchange rate, $ANNOUNCE_t$ is a dummy variable that takes the value of 1 if the BCRP has announced that it will intervene, BID_t is the sum of FX derivatives auctions that started at time t, and $ISSUED_t$ is the sum of the FX derivatives auctions that ended and were therefore issued at time t.

In these equations, the values of $T0$ and $T1$ are set according to the time structure that FX interventions from the BCRP follow. Three stages can be identified when the BCRP is about to issue a derivative instrument (FX Swap): the announcement of the intervention, the bidding process (auction) and the issuance of the instrument. The announcement takes place around 10 to 20 minutes before the bidding process starts. In this moment, commercial banks become aware of the fact that the BCRP is going to intervene and issue an instrument. Only when the auction starts, banks find out the size of the intervention (the amount of the instrument that is going to be offered and potentially issued). In this process, the participants (banks) compete for a part of total amount of the instrument issued by posting the fixed interest rate in US dollars that they will be payed (aside from the depreciation of the currency). Banks that offer the lowest interest rates are awarded with a part of the total amount. The auction lasts around 30 minutes and, once it is concluded, banks find out what share of the total amount they received and how much was issued in total.

Since only the time at which the instrument is officially issued (when the auction concludes) is available, $ISSUED_t$ is the only variable precisely constructed. The other two variables ($ANNOUNCE_t$ and BID_t) are constructed based on the time-frames aforementioned. These time-frames are an approximation of the average time that usually passes between each stage. Therefore, these variables do not precisely capture the moment in which each stage begins, and are rather a proxy. This is likely to generate some noise in the estimations, so robustness and sensibility checks to these time-frames are required.

Due to the existence of a maximum interest rate set by the BCRP and because there can be moments of low demand for certain instruments at certain terms, the amount that the BCRP intends to issue (BID_t) can be higher than the amount ultimately issued ($ISSUED_t$). It is even possible that there is no demand from the market given the interest rate limit, so the issued amount is zero. Between 2014 and 2023, 1847 FX Swaps were issued. In 43% of those cases, the issued amount was lower than the amount offered, but only in 19% of them this amount was less than half of the total bid. Also, in 5% of the interventions the amount issued was null. For this reason, instead of using leads of the total amount issued ($ISSUED_t$) to assess the impact prior to the actual intervention (signaling effect), I use leads of the total amount offered in the auction (BID_t), which is the amount known by market participants prior to the actual issuance. To capture a possible effect of the announcement of the intervention, I use the leads of a dummy variable that identifies an intervention ($ANNOUNCE_t$), since the amount of the auction is unknown by then. Doing this, instead of following the standard approach of an event study regression, which uses lags and leads of the same variable, should provide a more precise estimation of the information effects of FX intervention.

Given the time structure described above and considering the data used is at 10-minute intervals, $T0$ is set to 5 and $T1$ to 3. The value of $T2$ depends on how long it takes banks to fully price in the effect of the intervention. Dominguez (2003) estimates the intraday effects of the FX interventions of the G-3 central banks and finds evidence of a significant effect up to 1 hour after the intervention. In the case of Peru, Lahura and Vega (2013) use lags for up to 25 minutes after the intervention. In this study, I follow the latter and set the value of $T2$ to 3, which considers effects up to 30 minutes after the intervention. When including more lags, their coefficients are not significant, which supports the choice of a lagged effect of a maximum of 30 minutes. Finally p is set to 1, since very little error autocorrelation is found in the residuals of the equation.

5.3.2 Results

The data used is at 10-minute intervals. As explained before, the identifying assumption behind these estimations is that the exchange rate and FX intervention are not simultaneously determined within a 10-minute window. This means that FX intervention may be determined by the exchange rate variation 20 minutes ago or later (which can be controlled by lagged components), but not by the change of the exchange rate in the last 10 minutes (which is its contemporaneous change at this frequency).

I start by following the standard event study regression and estimate equation (5). The results for the pre-pandemic sample (2014-2019), post-pandemic sample (2020-2023) and the full sample (2014-2023) are presented in Tables 2, 3 and 4, respectively. In this tables, the lags of FX intervention ($ISSUED_t$) are represented by a negative number in parenthesis and the leads are represented by a positive number in parenthesis. The lags of the exchange rate (exc_t) are represented by the AR() components.

Both in the pre-pandemic and post-pandemic period, as well as throughout the whole sample, results indicate that there is a quick impact (within the first 20 minutes) of FX derivative intervention on the exchange rate and in the expected direction (a positive intervention generates an appreciation of the currency). The highest significance is found in the coefficient of the first lag of FX intervention, which means that the strongest impact takes place between 10 and 20 minutes after the intervention. However, the signs found for the coefficients of the first three leads (up to 30 minutes before the intervention) are mostly positive and only in a few cases they are negative, but not significant. This result means that an information channel does not seem to be present in these interventions, since minutes before the actual issuance of the instruments, when banks are already aware of the fact than a derivative is going to be issued, no significant effects on the exchange rate are found. Moreover, coefficients of further leads show that an exchange rate depreciation takes place around 40 minutes and earlier prior to an FX derivative intervention. This is an expected result, since a positive amount of FX intervention is equivalent to a sale of US dollars, which should be executed when depreciative pressures are observed.

Estimations of equation (6) are shown in Tables 5, 6 and 7. Using this specification, results lead to similar conclusions. There is a significant negative effect (appreciation) of an intervention after 10 minutes of being completed. However, there is no impact on the exchange rate before the actual issuance, when the bidding process has already started and banks are participating of it, as can be seen in the coefficients of the leads of BID. The coefficients of the leads of $ANNOUNCE$ are positive, which means that interventions are related to a currency depreciation 40 or more minutes before. To confirm that these positive coefficients for the furthest leads of the intervention variable (whether it is leads of $ISSUED$

or *ANNOUNCE*) mean that interventions are triggered by a currency depreciation and not that the announce of an intervention leads to a depreciation, I estimate regressions of the FX intervention on lags of the exchange rate. These can be interpreted as reaction functions and the results for each sample are presented in Appendix C. In every sub-period, it is found that there is not a significant relationship between interventions and the exchange rate movements 30 minutes before them (the first three lags). This confirms what was being assumed based on how FX intervention operates in Peru: interventions are executed with some delay and are not caused by the most recent exchange rate movements. On the other hand, coefficients from lag 4 onward are significant and positive, which means that exchange rate variations 40 or more minutes earlier are determinants of derivatives interventions. This explains why including two many leads in equations (5) and (6) is a problem.

To make sure that the inclusion of two many leads is not biasing the estimation of the other coefficients, I estimate equation (6) excluding the *ANNOUNCE* terms and then excluding all the lead terms (see Appendix D). Results do not vary significantly when dropping the lead terms and they lead to similar conclusions. For robustness purposes, I also estimate equation (6) but reducing the sample to only days where there was an intervention, either passive (an instrument is maturing that day) or active (an instrument is issued that day). Results, which can be found in Appendix E, are qualitatively similar to the ones obtained using the entire sample.

TABLE 2: Intraday regression estimates: Pre-pandemic sample (2014-2019)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000233	0.000428	-0.544739	0.5859
ISSUED(-3)	$4.48E-06$	$7.54E-06$	0.595074	0.5518
ISSUED(-2)	$-1.01E-06$	$4.93E-06$	-0.205120	0.8375
ISSUED(-1)	$-1.42E-05$	$6.45E-06$	-2.194509	0.0282
ISSUED	$-4.54E-06$	$6.73E-06$	-0.673989	0.5003
ISSUED(1)	$4.55E-06$	$7.02E-06$	0.648093	0.5169
ISSUED(2)	$-1.33E-05$	$7.81E-06$	-1.704298	0.0883
ISSUED(3)	$-4.81E-06$	$8.16E-06$	-0.589585	0.5555
ISSUED(4)	$5.15E-06$	$7.17E-06$	0.717394	0.4731
ISSUED(5)	$4.29E-05$	$3.11E-06$	13.80652	0.0000
COPP	-0.001474	0.000240	-6.140458	0.0000
DUM9	0.012568	0.000646	19.44080	0.0000
DUM13	-0.000619	0.001816	-0.340684	0.7333
DXY	0.005056	0.000621	8.143204	0.0000
VIX	0.000211	$2.97E-05$	7.111600	0.0000
MATUR	$-8.74E-07$	$3.67E-06$	-0.238286	0.8117
AR(1)	-0.041048	0.001468	-27.96673	0.0000
SIGMASQ	0.003672	$3.87E-06$	949.4845	0.0000

R-squared	0.008243	Mean dependent var	0.000396
Adjusted R-squared	0.007844	S.D. dependent var	0.060847
S.E. of regression	0.060608	Akaike info criterion	-2.768353
Sum squared resid	155.0292	Schwarz criterion	-2.764666
Log likelihood	58460.71	Hannan-Quinn criter.	-2.767189
F-statistic	20.63480	Durbin-Watson stat	1.999785
Prob(F-statistic)	0.000000	Sample size	42215

TABLE 3: Intraday regression estimates: Post-pandemic (2020-2023)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001288	0.000904	-1.424118	0.1544
ISSUED(-3)	$-2.68E-05$	$1.44E-05$	-1.856946	0.0633
ISSUED(-2)	$-4.80E-06$	$1.00E-05$	-0.479125	0.6319
ISSUED(-1)	$-2.97E-05$	$1.16E-05$	-2.574748	0.0100
ISSUED	$-6.74E-06$	$1.66E-05$	-0.405874	0.6848
ISSUED(1)	$5.11E-06$	$1.93E-05$	0.265088	0.7909
ISSUED(2)	$8.60E-06$	$1.97E-05$	0.436288	0.6626
ISSUED(3)	$1.28E-05$	$1.49E-05$	0.863899	0.3877
ISSUED(4)	0.000106	$8.35E-06$	12.71721	0.0000
ISSUED(5)	$7.97E-05$	$1.15E-05$	6.960059	0.0000
COPP	-0.001386	0.000378	-3.669430	0.0002
DUM9	0.015750	0.001174	13.41321	0.0000
DUM13	-0.006842	0.003899	-1.754757	0.0793
DXY	0.005627	0.001193	4.717050	0.0000
VIX	0.000289	$6.53E-05$	4.427007	0.0000
MATUR	$3.46E-06$	$8.50E-06$	0.406955	0.6840
AR(1)	0.030815	0.002155	14.30142	0.0000
SIGMASQ	0.008445	$1.22E-05$	689.9799	0.0000

R-squared	0.009700	Mean dependent var	0.000393
Adjusted R-squared	0.009101	S.D. dependent var	0.092346
S.E. of regression	0.091925	Akaike info criterion	-1.935058
Sum squared resid	237.3553	Schwarz criterion	-1.929778
Log likelihood	27212.33	Hannan-Quinn criter.	-1.933358
F-statistic	16.18493	Durbin-Watson stat	2.001473
Prob(F-statistic)	0.000000	Sample size	28102

TABLE 4: Intraday regression estimates: Full sample (2014-2023)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000478	0.000435	-1.099899	0.2714
ISSUED(-3)	$-5.98E-06$	$7.42E-06$	-0.806255	0.4201
ISSUED(-2)	$-1.31E-06$	$4.85E-06$	-0.270620	0.7867
ISSUED(-1)	$-1.89E-05$	$5.91E-06$	-3.196733	0.0014
ISSUED	$-5.10E-06$	$7.29E-06$	-0.700128	0.4838
ISSUED(1)	$5.79E-06$	$8.06E-06$	0.718525	0.4724
ISSUED(2)	$-4.64E-06$	$8.55E-06$	-0.542966	0.5872
ISSUED(3)	$1.67E-06$	$7.65E-06$	0.217714	0.8277
ISSUED(4)	$4.41E-05$	$4.44E-06$	9.948546	0.0000
ISSUED(5)	$5.74E-05$	$3.72E-06$	15.41783	0.0000
COPP	-0.001474	0.000202	-7.295418	0.0000
DUM9	0.013772	0.000597	23.08343	0.0000
DUM13	-0.003267	0.001883	-1.735490	0.0827
DXY	0.005307	0.000595	8.925281	0.0000
VIX	0.000240	$3.05E-05$	7.856718	0.0000
MATUR	$-1.30E-06$	$3.81E-06$	-0.342142	0.7322
AR(1)	0.003063	0.001229	2.492362	0.0127
SIGMASQ	0.005593	$4.37E-06$	1278.568	0.0000
R-squared	0.006642	Mean dependent var		0.000395
Adjusted R-squared	0.006402	S.D. dependent var		0.075038
S.E. of regression	0.074798	Akaike info criterion		-2.347806
Sum squared resid	393.3677	Schwarz criterion		-2.345461
Log likelihood	82577.41	Hannan-Quinn criter.		-2.347083
F-statistic	27.65645	Durbin-Watson stat		2.000088
Prob(F-statistic)	0.000000	Sample size		70317

TABLE 5: Intraday regression estimates: Pre-pandemic sample (2014-2019) - Alternative Specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000253	0.000430	-0.587723	0.5567
ISSUED(-3)	$4.74E-06$	$7.55E-06$	0.627619	0.5303
ISSUED(-2)	$-9.06E-07$	$4.92E-06$	-0.183964	0.8540
ISSUED(-1)	$-1.40E-05$	$6.48E-06$	-2.162974	0.0305
ISSUED	$-5.05E-06$	$6.72E-06$	-0.751692	0.4522
BID(1)	$6.12E-06$	$3.85E-06$	1.591501	0.1115
BID(2)	$-1.06E-05$	$5.94E-06$	-1.780763	0.0750
BID(3)	$-7.63E-06$	$6.76E-06$	-1.128858	0.2590
ANNOUNCE(4)	0.001517	0.002374	0.638919	0.5229
ANNOUNCE(5)	0.011058	0.001307	8.457673	0.0000
COPP	-0.001476	0.000239	-6.163779	0.0000
DUM9	0.012709	0.000662	19.19997	0.0000
DUM13	-0.000651	0.001817	-0.358061	0.7203
DXY	0.005106	0.000622	8.206923	0.0000
VIX	0.000213	$2.98E-05$	7.143730	0.0000
MATUR	$5.34E-08$	$3.74E-06$	0.014284	0.9886
AR(1)	-0.040798	0.001473	-27.69203	0.0000
SIGMASQ	0.003673	$3.88E-06$	946.3031	0.0000
R-squared	0.007779	Mean dependent var		0.000396
Adjusted R-squared	0.007380	S.D. dependent var		0.060847
S.E. of regression	0.060622	Akaike info criterion		-2.767886
Sum squared resid	155.1017	Schwarz criterion		-2.764198
Log likelihood	58450.84	Hannan-Quinn criter.		-2.766721
F-statistic	19.46421	Durbin-Watson stat		1.999761
Prob(F-statistic)	0.000000	Sample size		42215

TABLE 6: Intraday regression estimates: Post-pandemic (2020-2023) - Alternative Specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001425	0.000909	-1.567913	0.1169
ISSUED(-3)	$-2.63E-05$	$1.45E-05$	-1.814763	0.0696
ISSUED(-2)	$-4.39E-06$	$1.00E-05$	-0.437616	0.6617
ISSUED(-1)	$-2.97E-05$	$1.16E-05$	-2.565957	0.0103
ISSUED	$-6.60E-06$	$1.66E-05$	-0.398150	0.6905
BID(1)	$-1.66E-06$	$1.49E-05$	-0.110917	0.9117
BID(2)	$-2.79E-06$	$1.64E-05$	-0.170410	0.8647
BID(3)	$1.20E-05$	$1.21E-05$	0.989807	0.3223
ANNOUNCE(4)	0.022513	0.002219	10.14576	0.0000
ANNOUNCE(5)	0.022114	0.002597	8.516341	0.0000
COPP	-0.001404	0.000376	-3.733757	0.0002
DUM9	0.015081	0.001183	12.74715	0.0000
DUM13	-0.006522	0.003898	-1.673106	0.0943
DXY	0.005654	0.001194	4.737046	0.0000
VIX	0.000295	$6.53E-05$	4.523604	0.0000
MATUR	$2.01E-06$	$8.55E-06$	0.235344	0.8139
AR(1)	0.030026	0.002158	13.91134	0.0000
SIGMASQ	0.008441	$1.21E-05$	697.9984	0.0000
R-squared	0.010080	Mean dependent var		0.000393
Adjusted R-squared	0.009481	S.D. dependent var		0.092346
S.E. of regression	0.091907	Akaike info criterion		-1.935441
Sum squared resid	237.2644	Schwarz criterion		-1.930162
Log likelihood	27217.72	Hannan-Quinn criter.		-1.933742
F-statistic	16.82465	Durbin-Watson stat		2.001423
Prob(F-statistic)	0.000000	Sample size		28102

TABLE 7: Intraday regression estimates: Full sample (2014-2023) - Alternative Specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000638	0.000435	-1.465438	0.1428
ISSUED(-3)	$-6.27E-06$	$7.42E-06$	-0.845050	0.3981
ISSUED(-2)	$-1.86E-06$	$4.89E-06$	-0.380046	0.7039
ISSUED(-1)	$-1.94E-05$	$5.91E-06$	-3.285674	0.0010
ISSUED	$-5.80E-06$	$7.27E-06$	-0.797944	0.4249
BID(1)	$3.15E-06$	$4.91E-06$	0.640503	0.5218
BID(2)	$-7.46E-06$	$6.98E-06$	-1.069015	0.2851
BID(3)	$1.23E-07$	$6.30E-06$	0.019527	0.9844
ANNOUNCE(4)	0.014277	0.001307	10.92477	0.0000
ANNOUNCE(5)	0.017843	0.001277	13.97067	0.0000
COPP	-0.001475	0.000202	-7.312941	0.0000
DUM9	0.013528	0.000604	22.39597	0.0000
DUM13	-0.002978	0.001882	-1.582228	0.1136
DXY	0.005366	0.000595	9.024178	0.0000
VIX	0.000241	$3.05E-05$	7.904402	0.0000
MATUR	$-1.70E-06$	$3.85E-06$	-0.441984	0.6585
AR(1)	0.002551	0.001229	2.076299	0.0379
SIGMASQ	0.005591	$4.38E-06$	1275.945	0.0000
R-squared	0.007127	Mean dependent var		0.000395
Adjusted R-squared	0.006887	S.D. dependent var		0.075038
S.E. of regression	0.074779	Akaike info criterion		-2.348294
Sum squared resid	393.1757	Schwarz criterion		-2.345949
Log likelihood	82594.58	Hannan-Quinn criter.		-2.347571
F-statistic	29.68991	Durbin-Watson stat		2.000067
Prob(F-statistic)	0.000000	Sample size		70317

6 Conclusions

This study empirically analized the impact of FX intervention in the derivatives market from the Central Bank of Peru (BCRP) on the peruvian exchange rate. For that purpose, I proposed two alternative approaches: a SVAR model that uses daily data and a regression framework that uses intraday data. The results using both methods support the growing use of this kind of intervention in Peru, since they show that FX derivatives intervention has a statistically significant effect on the exchange rate's level in the expected direction. According to my estimations, an FX net intervention of USD 134 million in a day, which is the average size of intervention between 2014 and 2023, generates an appreciation of around 0,044% the same day. On the other hand, the intraday analysis shows that these interventions have a quick impact on the exchange rate, since the strongest effect is seen between 10 and 20 minutes after the intervention. Moreover, estimations for FX spot intervention show that, as previously found in the literature, it is also effective to affect the level of the exchange rate in the short run, and it is slightly more effective than the interventions through derivatives instruments.

Despite these findings, the results did not allow to conclude that FX derivatives interventions have a significant effect on the exchange rate's volatility in the short-run. This could be worrisome, since the main goal behind the BCRP's FX intervention is reducing the volatility in the FX market. However, the impact of these interventions are more likely to be seen in the long-run, because it is the complete setup of having an interventionist regime what leads to a more stable currency and lower FX volatility, and not a single FX intervention shock that takes place in a day, which is the focus of this study. The empirical framework proposed in this paper, therefore, is useful to study the short-run effects of FX intervention, but it is limited when it comes to understanding more persistent and complex effects like the one it has on the volatility of a currency. In order to do that, a different identification approach or a theoretical framework would be needed.

Besides that, future research could use the empirical approach of this study to investigate heterogeneous effects between sale and purchase interventions. Also, more attention can be given to the relationship between spot and derivatives intervention. In this study, both are included as endogenous variables in the VAR model, but more analytical work is required to understand if there is a complementary or substitute relationship between them.

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Appendix A

TABLE A1: Reaction function equation: Pre-pandemic sample (2014-2019)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.133412	0.023584	5.656920	0.0000
exc_{early}	0.996384	0.130077	7.659962	0.0000
$\text{exc}_{open-close}$	-0.135542	0.131323	-1.032129	0.3022
$\text{exc}_{late-yesterday}$	0.228667	0.207980	1.099468	0.2718
COP	0.135518	0.030699	4.414366	0.0000
CLP	0.048240	0.041647	1.158289	0.2469
BRL	0.036059	0.023395	1.541333	0.1235
MXN	0.075311	0.033677	2.236248	0.0255
MATUR	0.263920	0.020833	12.66814	0.0000

R-squared	0.212453	Mean dependent var	0.002795
Adjusted R-squared	0.207963	S.D. dependent var	0.849957
S.E. of regression	0.756432	Akaike info criterion	2.285945
Sum squared resid	802.7810	Schwarz criterion	2.319425
Log likelihood	-1604.877	Hannan-Quinn criter.	2.298455
F-statistic	47.31019	Durbin-Watson stat	1.288345
Prob(F-statistic)	0.000000	Sample size	1412

FIGURE A1: Residuals and Fitted vs. Actual values comparison - FX Intervention Reaction Function - Pre pandemic sample (2014-2019)

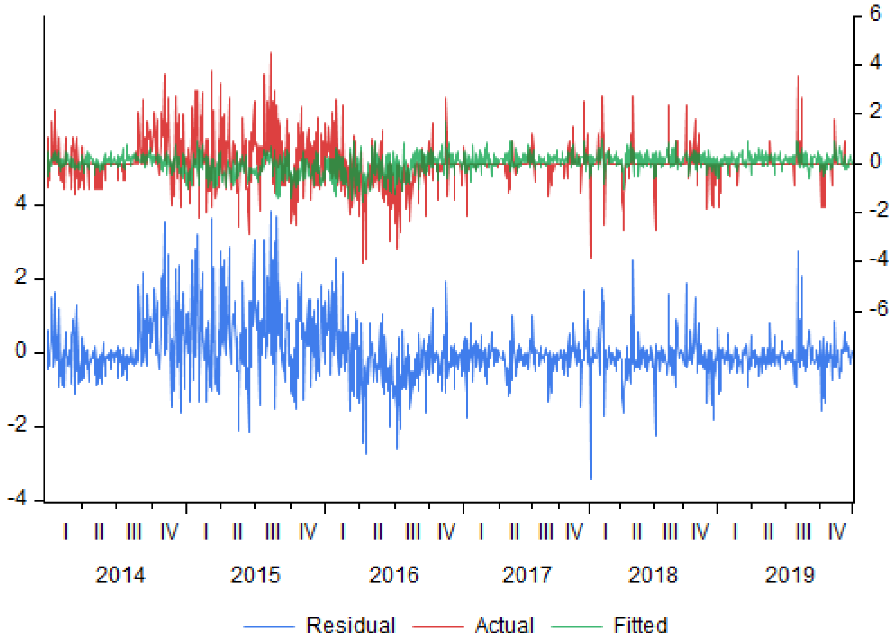


TABLE A2: Reaction function equation: Post-pandemic sample (2020-2023)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.429234	0.031638	13.56686	0.0000
exc_{early}	0.790449	0.089086	8.872899	0.0000
$exc_{open-close}$	−0.152603	0.092412	−1.651337	0.0990
$exc_{late-yesterday}$	0.028168	0.160623	0.175365	0.8608
COP	0.054444	0.032575	1.671344	0.0950
CLP	−0.001004	0.030224	−0.033216	0.9735
BRL	0.030113	0.027449	1.097031	0.2729
MXN	0.041025	0.038121	1.076189	0.2821
MATUR	0.542077	0.033384	16.23769	0.0000
R-squared	0.285027	Mean dependent var		0.125927
Adjusted R-squared	0.279118	S.D. dependent var		0.914525
S.E. of regression	0.776475	Akaike info criterion		2.341065
Sum squared resid	583.6207	Schwarz criterion		2.386061
Log likelihood	−1134.610	Hannan-Quinn criter.		2.358186
F-statistic	48.23709	Durbin-Watson stat		1.254004
Prob(F-statistic)	0.000000	Sample size		977

FIGURE A2: Residuals and Fitted vs. Actual values comparison - FX Intervention Reaction Function - Post pandemic sample (2020-2023)

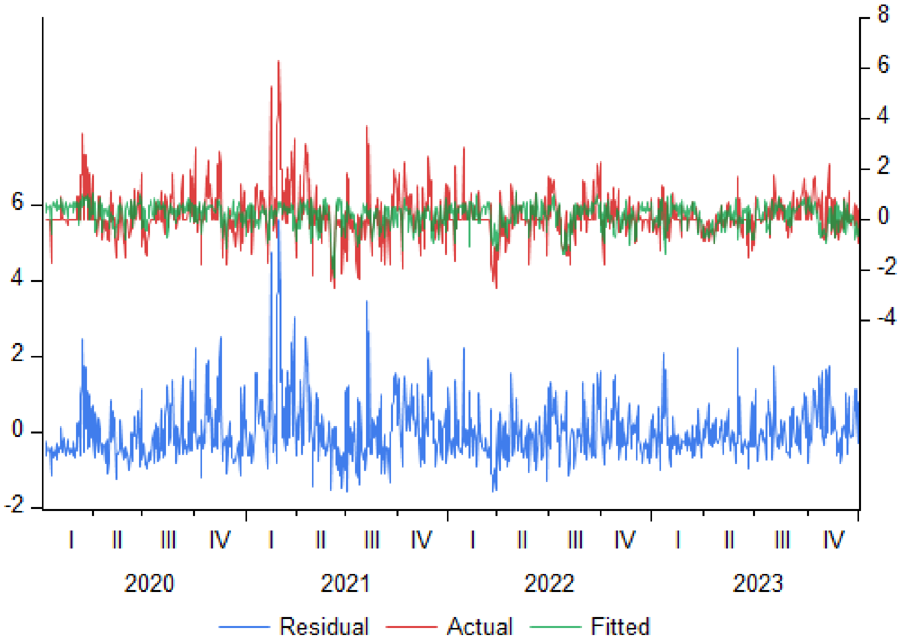
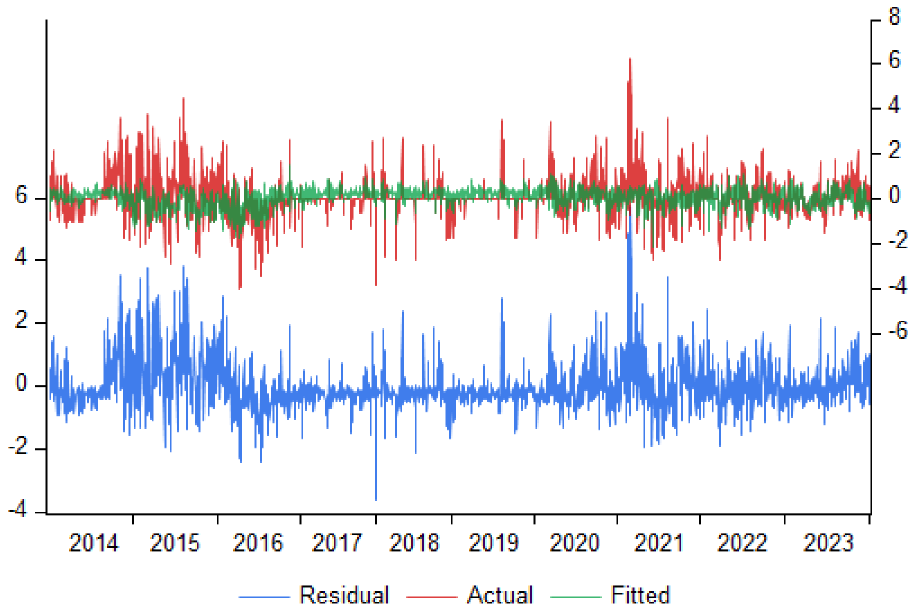


TABLE A3: Reaction function equation: Full sample (2014-2023)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.235727	0.019036	12.38352	0.0000
exc_{early}	0.848136	0.073866	11.48212	0.0000
$exc_{open-close}$	-0.077469	0.075243	-1.029579	0.3033
$exc_{late-yesterday}$	0.113136	0.128044	0.883576	0.3770
COP	0.106939	0.022398	4.774535	0.0000
CLP	0.019990	0.024602	0.812538	0.4166
BRL	0.037256	0.018047	2.064354	0.0391
MXN	0.063444	0.025412	2.496617	0.0126
MATUR	0.343507	0.017975	19.11029	0.0000
R-squared	0.222034	Mean dependent var		0.053150
Adjusted R-squared	0.219419	S.D. dependent var		0.878837
S.E. of regression	0.776457	Akaike info criterion		2.335609
Sum squared resid	1434.866	Schwarz criterion		2.357378
Log likelihood	-2780.884	Hannan-Quinn criter.		2.343530
F-statistic	84.90749	Durbin-Watson stat		1.232433
Prob(F-statistic)	0.000000	Sample size		2389

FIGURE A3: Residuals and Fitted vs. Actual values comparison - FX Intervention Reaction Function - Full sample (2014-2023)



Appendix B

FIGURE B1: Impulse Response Functions to an FX derivatives intervention shock (USD hundred millions) (2014-2023) - Stochastic Volatility Approach.

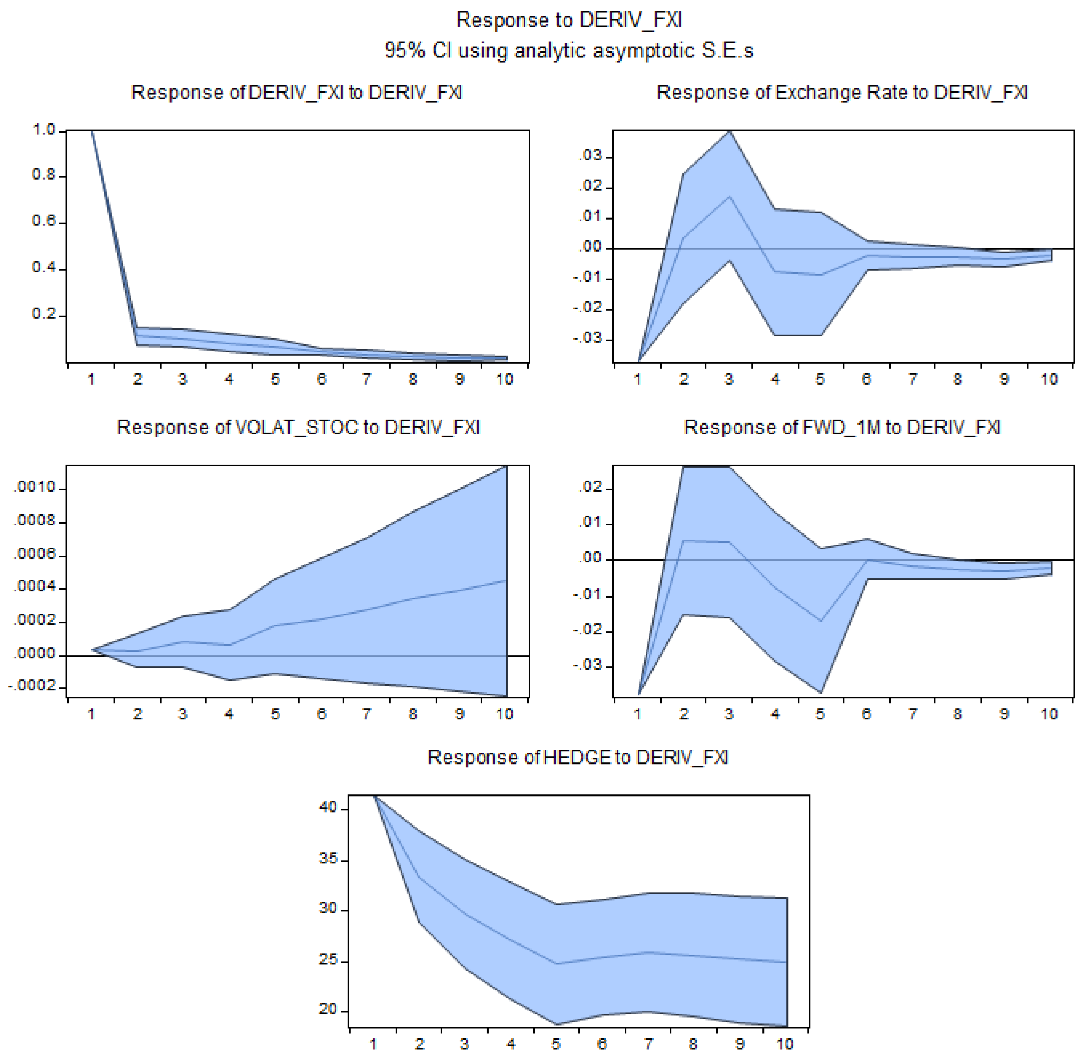


FIGURE B2: Impulse Response Functions to an accumulated FX derivatives intervention shock (USD hundred millions) (2014-2023) - Stochastic Volatility Approach.

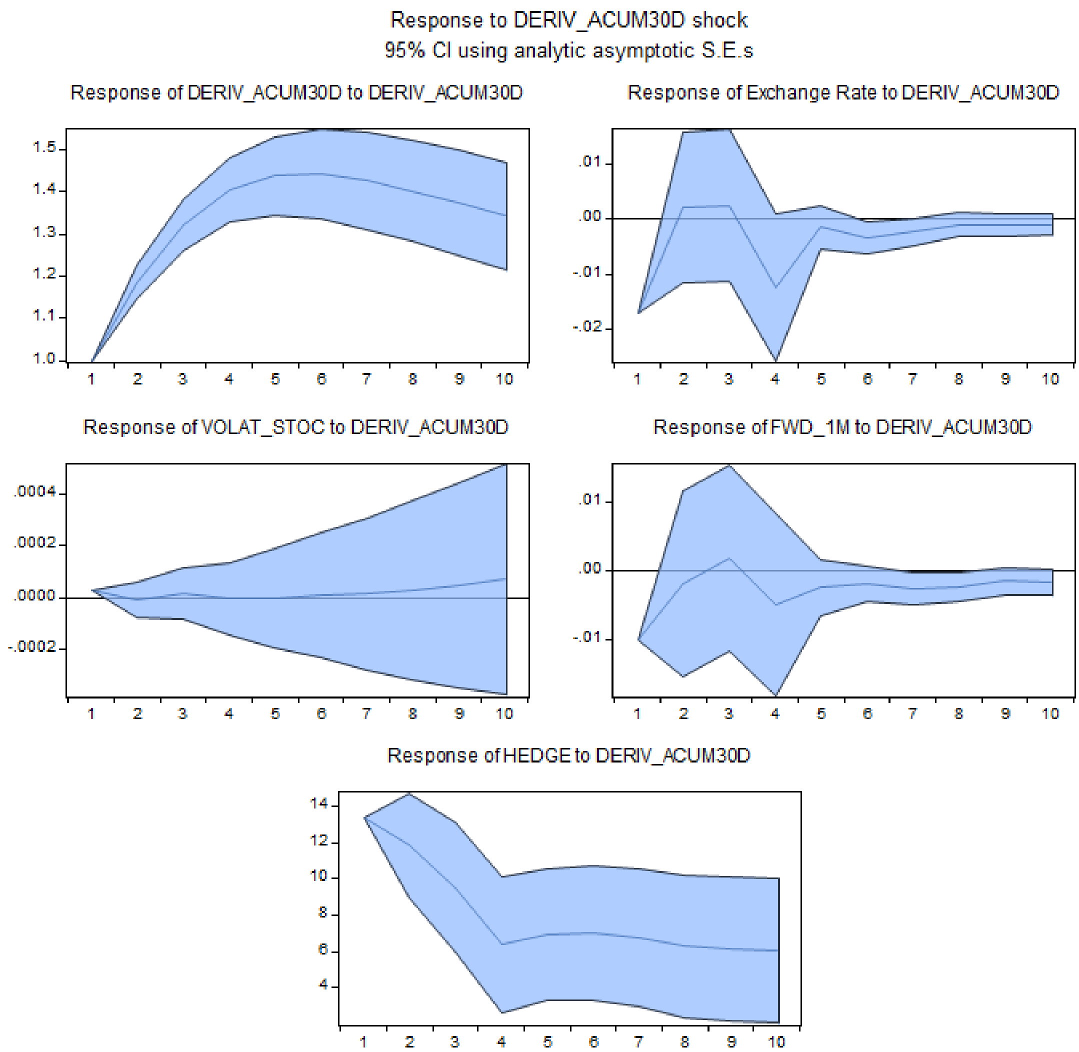


FIGURE B3: Impulse Response Functions to an FX spot intervention shock (USD hundred millions) (2014-2023) - Stochastic Volatility Approach.

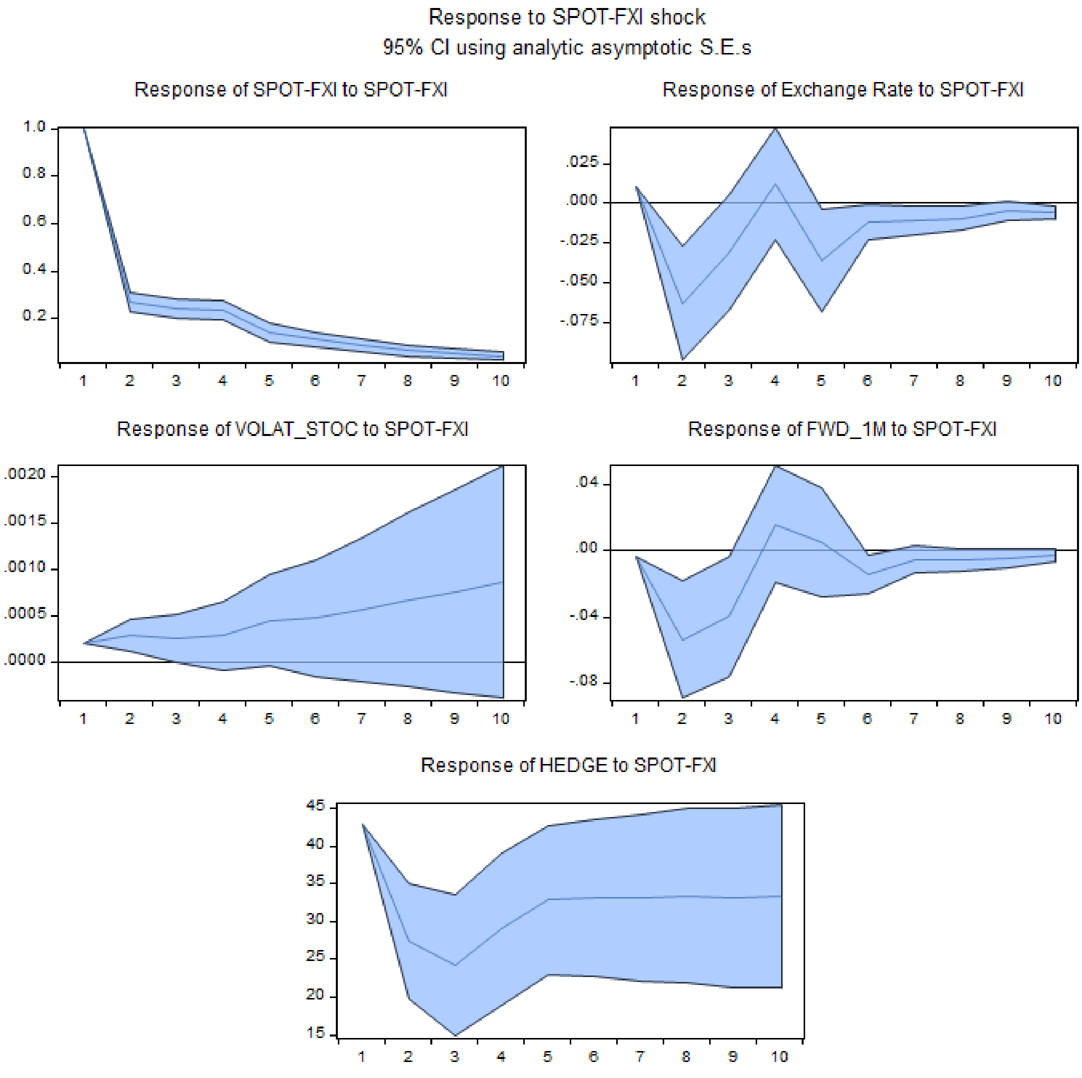
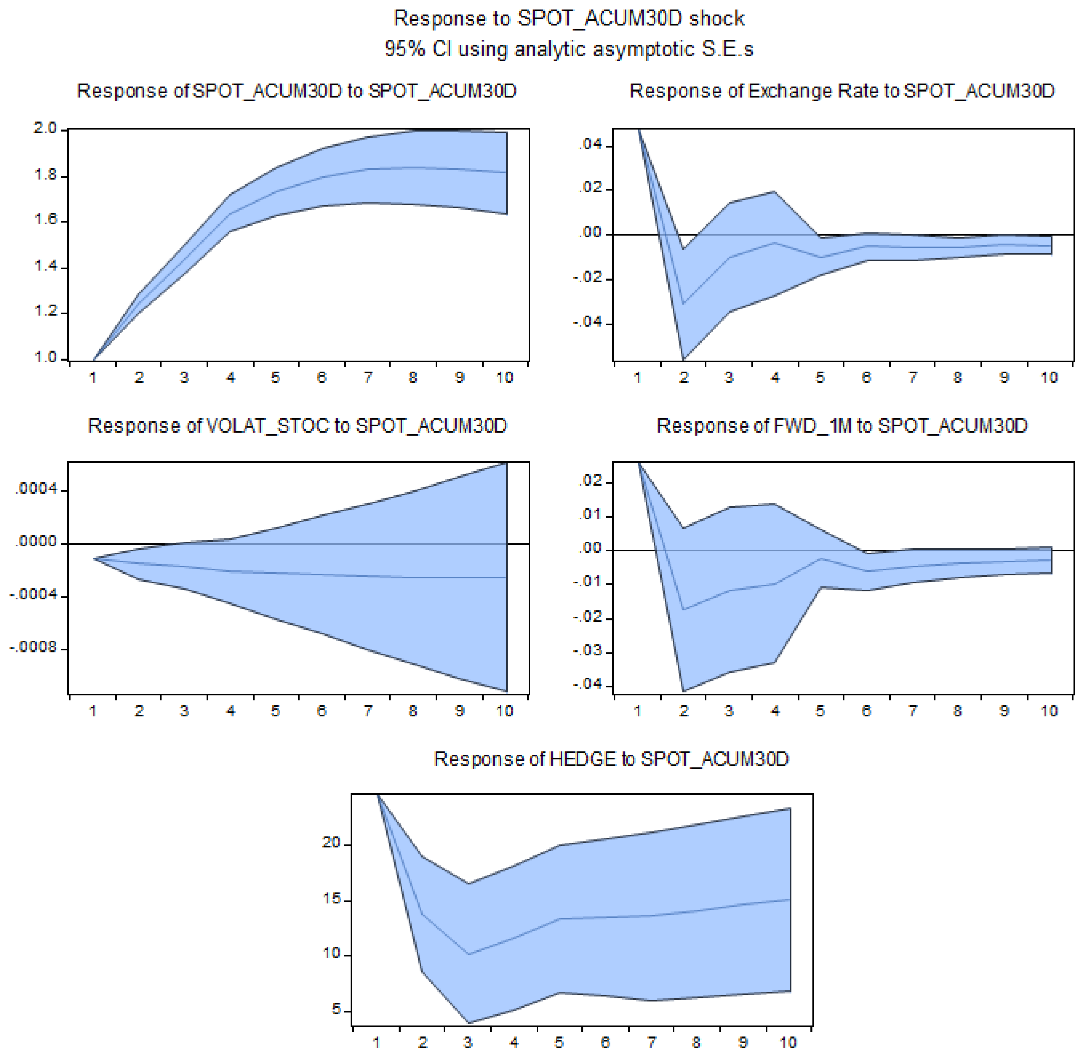


FIGURE B4: Impulse Response Functions to an accumulated accumulated FX spot intervention shock (USD hundred millions) (2014-2023) - Stochastic Volatility Approach.



Appendix C

TABLE C1: Reaction function at intraday level: Pre-pandemic sample (2014-2019)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.737027	0.221320	21.40353	0.0000
exc	−1.670986	3.642567	−0.458739	0.6464
exc(-1)	3.657302	3.645178	1.003326	0.3157
exc(-2)	−5.640484	3.645254	−1.547350	0.1218
exc(-3)	−1.144265	3.646742	−0.313777	0.7537
exc(-4)	5.670001	3.646823	1.554778	0.1200
exc(-5)	28.34154	3.647044	7.771100	0.0000
exc(-6)	20.49127	3.646829	5.618928	0.0000
exc(-7)	22.91589	3.646582	6.284211	0.0000
exc(-8)	23.66076	3.645003	6.491288	0.0000
exc(-9)	20.14243	3.644889	5.526210	0.0000
exc(-10)	8.505753	3.642325	2.335254	0.0195

R-squared	0.004665	Mean dependent var	4.786109
Adjusted R-squared	0.004406	S.D. dependent var	45.56168
S.E. of regression	45.46120	Akaike info criterion	10.47188
Sum squared resid	87221832	Schwarz criterion	10.47434
Log likelihood	−221023.2	Hannan-Quinn criter.	10.47266
F-statistic	17.98173	Durbin-Watson stat	2.017646
Prob(F-statistic)	0.000000	Sample size	42215

TABLE C2: Reaction function at intraday level: Post-pandemic sample (2020-2023)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.794049	0.262609	29.67934	0.0000
exc	−1.183411	2.847306	−0.415625	0.6777
exc(-1)	2.736251	2.848878	0.960466	0.3368
exc(-2)	1.792713	2.850349	0.628945	0.5294
exc(-3)	0.945715	2.850560	0.331765	0.7401
exc(-4)	24.17383	2.850508	8.480532	0.0000
exc(-5)	18.21824	2.850573	6.391080	0.0000
exc(-6)	11.14852	2.850503	3.911070	0.0001
exc(-7)	13.35598	2.850593	4.685335	0.0000
exc(-8)	10.06543	2.850395	3.531240	0.0004
exc(-9)	11.61499	2.848965	4.076916	0.0000
exc(-10)	8.115573	2.847371	2.850199	0.0044

R-squared	0.007303	Mean dependent var	7.835328
Adjusted R-squared	0.006915	S.D. dependent var	44.17151
S.E. of regression	44.01853	Akaike info criterion	10.40753
Sum squared resid	54428047	Schwarz criterion	10.41105
Log likelihood	−146224.1	Hannan-Quinn criter.	10.40866
F-statistic	18.78764	Durbin-Watson stat	1.987352
Prob(F-statistic)	0.000000	Sample size	28102

TABLE C3: Reaction function at intraday level: Full sample (2014-2023)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.960547	0.169420	35.18203	0.0000
exc	-1.225790	2.258621	-0.542716	0.5873
exc(-1)	3.346315	2.258706	1.481518	0.1385
exc(-2)	-1.048664	2.259269	-0.464161	0.6425
exc(-3)	0.436462	2.259600	0.193159	0.8468
exc(-4)	16.63120	2.259641	7.360107	0.0000
exc(-5)	22.26229	2.259757	9.851631	0.0000
exc(-6)	14.53542	2.259648	6.432605	0.0000
exc(-7)	16.69128	2.259748	7.386344	0.0000
exc(-8)	15.11368	2.259401	6.689243	0.0000
exc(-9)	14.51285	2.258812	6.424991	0.0000
exc(-10)	8.024134	2.258781	3.552418	0.0004

R-squared	0.005052	Mean dependent var	6.003868
Adjusted R-squared	0.004897	S.D. dependent var	45.03256
S.E. of regression	44.92218	Akaike info criterion	10.44791
Sum squared resid	$1.42E+08$	Schwarz criterion	10.44947
Log likelihood	-367373.1	Hannan-Quinn criter.	10.44839
F-statistic	32.45958	Durbin-Watson stat	2.003395
Prob(F-statistic)	0.000000	Sample size	70327

Appendix D

TABLE D1: Intraday regression estimates: Pre-pandemic sample (2014-2019) - No ANNOUNCE terms

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000189	0.000426	-0.442993	0.6578
ISSUED(-3)	$4.66E-06$	$7.54E-06$	0.617739	0.5368
ISSUED(-2)	$-1.20E-06$	$4.91E-06$	-0.243582	0.8076
ISSUED(-1)	$-1.40E-05$	$6.49E-06$	-2.154285	0.0312
ISSUED	$-5.41E-06$	$6.68E-06$	-0.810087	0.4179
BID(1)	$6.23E-06$	$3.84E-06$	1.623488	0.1045
BID(2)	$-1.11E-05$	$5.95E-06$	-1.862515	0.0625
BID(3)	$-8.15E-06$	$6.75E-06$	-1.208087	0.2270
COPP	-0.001500	0.000239	-6.262671	0.0000
DUM9	0.013347	0.000640	20.85638	0.0000
DUM13	-0.000854	0.001818	-0.469685	0.6386
DXY	0.005159	0.000621	8.303300	0.0000
VIX	0.000217	$2.98E-05$	7.279126	0.0000
MATUR	$3.48E-06$	$3.45E-06$	1.007546	0.3137
AR(1)	-0.040128	0.001474	-27.21772	0.0000
SIGMASQ	0.003675	$3.88E-06$	946.5392	0.0000

R-squared	0.007239	Mean dependent var	0.000396
Adjusted R-squared	0.006886	S.D. dependent var	0.060847
S.E. of regression	0.060637	Akaike info criterion	-2.767436
Sum squared resid	155.1862	Schwarz criterion	-2.764158
Log likelihood	58439.34	Hannan-Quinn criter.	-2.766401
F-statistic	20.51656	Durbin-Watson stat	1.999710
Prob(F-statistic)	0.000000	Sample size	42222

TABLE D2: Intraday regression estimates: Pre-pandemic sample (2014-2019) - No lead terms

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000206	0.000424	-0.486624	0.6265
ISSUED(-3)	$4.73E-06$	$7.53E-06$	0.627797	0.5301
ISSUED(-2)	$-1.05E-06$	$4.90E-06$	-0.214794	0.8299
ISSUED(-1)	$-1.38E-05$	$6.49E-06$	-2.120920	0.0339
ISSUED	$-5.02E-06$	$6.68E-06$	-0.751046	0.4526
COPP	-0.001492	0.000239	-6.233613	0.0000
DUM9	0.013416	0.000632	21.22172	0.0000
DUM13	-0.000972	0.001816	-0.535351	0.5924
DXY	0.005135	0.000621	8.274000	0.0000
VIX	0.000215	$2.98E-05$	7.226261	0.0000
MATUR	$2.01E-06$	$3.28E-06$	0.613385	0.5396
AR(1)	-0.040160	0.001458	-27.54146	0.0000
SIGMASQ	0.003676	$3.82E-06$	961.6595	0.0000

R-squared	0.007094	Mean dependent var	0.000396
Adjusted R-squared	0.006812	S.D. dependent var	0.060847
S.E. of regression	0.060640	Akaike info criterion	-2.767432
Sum squared resid	155.2088	Schwarz criterion	-2.764769
Log likelihood	58436.26	Hannan-Quinn criter.	-2.766591
F-statistic	25.13153	Durbin-Watson stat	1.999720
Prob(F-statistic)	0.000000	Sample size	42222

TABLE D3: Intraday regression estimates: Post-pandemic sample (2020-2023) - No ANNOUNCE terms

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000340	0.000913	-0.372133	0.7098
ISSUED(-3)	$-2.01E-05$	$1.46E-05$	-1.377068	0.1685
ISSUED(-2)	$5.23E-06$	$9.71E-06$	0.538882	0.5900
ISSUED(-1)	$-2.56E-05$	$1.15E-05$	-2.215489	0.0267
ISSUED	$-5.53E-06$	$1.66E-05$	-0.333501	0.7388
BID(1)	$3.37E-07$	$1.49E-05$	0.022619	0.9820
BID(2)	$-1.74E-06$	$1.66E-05$	-0.105178	0.9162
BID(3)	$9.00E-06$	$1.22E-05$	0.736936	0.4612
COPP	-0.001434	0.000375	-3.825649	0.0001
DUM9	0.016577	0.001164	14.24496	0.0000
DUM13	-0.008035	0.003904	-2.058244	0.0396
DXY	0.005863	0.001194	4.912576	0.0000
VIX	0.000304	$6.51E-05$	4.667822	0.0000
MATUR	$1.40E-05$	$8.46E-06$	1.651471	0.0987
AR(1)	0.033757	0.002156	15.65432	0.0000
SIGMASQ	0.008478	$1.14E-05$	742.8540	0.0000

R-squared	0.005824	Mean dependent var	0.000400
Adjusted R-squared	0.005293	S.D. dependent var	0.092346
S.E. of regression	0.092102	Akaike info criterion	-1.931277
Sum squared resid	238.3054	Schwarz criterion	-1.926584
Log likelihood	27159.13	Hannan-Quinn criter.	-1.929766
F-statistic	10.97115	Durbin-Watson stat	2.001722
Prob(F-statistic)	0.000000	Sample size	28109

TABLE D4: Intraday regression estimates: Post-pandemic sample (2020-2023) - No lead terms

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000313	0.000899	-0.348140	0.7277
ISSUED(-3)	$-1.95E-05$	$1.45E-05$	-1.342604	0.1794
ISSUED(-2)	$5.31E-06$	$9.62E-06$	0.551443	0.5813
ISSUED(-1)	$-2.55E-05$	$1.15E-05$	-2.218039	0.0266
ISSUED	$-5.19E-06$	$1.65E-05$	-0.313846	0.7536
COPP	-0.001433	0.000374	-3.829637	0.0001
DUM9	0.016598	0.001146	14.48607	0.0000
DUM13	-0.007686	0.003899	-1.971292	0.0487
DXY	0.005874	0.001190	4.934795	0.0000
VIX	0.000304	$6.50E-05$	4.679270	0.0000
MATUR	$1.44E-05$	$8.41E-06$	1.713066	0.0867
AR(1)	0.034060	0.002152	15.82677	0.0000
SIGMASQ	0.008478	$1.14E-05$	743.5464	0.0000

R-squared	0.005798	Mean dependent var	0.000395
Adjusted R-squared	0.005374	S.D. dependent var	0.092345
S.E. of regression	0.092097	Akaike info criterion	-1.931489
Sum squared resid	238.3312	Schwarz criterion	-1.927676
Log likelihood	27162.00	Hannan-Quinn criter.	-1.930262
F-statistic	13.65609	Durbin-Watson stat	2.001749
Prob(F-statistic)	0.000000	Sample size	28112

TABLE D5: Intraday regression estimates: Full sample (2014-2023) - No ANNOUNCE terms

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000202	0.000435	-0.464595	0.6422
ISSUED(-3)	$-4.57E-06$	$7.47E-06$	-0.612265	0.5404
ISSUED(-2)	$9.70E-07$	$4.73E-06$	0.205049	0.8375
ISSUED(-1)	$-1.80E-05$	$5.95E-06$	-3.022764	0.0025
ISSUED	$-5.65E-06$	$7.27E-06$	-0.777478	0.4369
BID(1)	$3.86E-06$	$4.93E-06$	0.781931	0.4343
BID(2)	$-7.51E-06$	$7.03E-06$	-1.067890	0.2856
BID(3)	$-1.06E-06$	$6.32E-06$	-0.167893	0.8667
COPP	-0.001510	0.000201	-7.510345	0.0000
DUM9	0.014565	0.000590	24.67471	0.0000
DUM13	-0.003717	0.001884	-1.973347	0.0485
DXY	0.005494	0.000595	9.237399	0.0000
VIX	0.000249	$3.05E-05$	8.185361	0.0000
MATUR	$6.76E-06$	$3.71E-06$	1.824062	0.0681
AR(1)	0.004864	0.001229	3.956913	0.0001
SIGMASQ	0.005604	$4.18E-06$	1339.357	0.0000

R-squared	0.004843	Mean dependent var	0.000397
Adjusted R-squared	0.004631	S.D. dependent var	0.075039
S.E. of regression	0.074865	Akaike info criterion	-2.346029
Sum squared resid	394.1010	Schwarz criterion	-2.343944
Log likelihood	82515.27	Hannan-Quinn criter.	-2.345386
F-statistic	22.81466	Durbin-Watson stat	2.000126
Prob(F-statistic)	0.000000	Sample size	70331

TABLE D6: Intraday regression estimates: Full sample (2014-2023) - No lead terms

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000217	0.000432	-0.503699	0.6145
ISSUED(-3)	$-4.55E-06$	$7.46E-06$	-0.609590	0.5421
ISSUED(-2)	$1.00E-06$	$4.72E-06$	0.212737	0.8315
ISSUED(-1)	$-1.80E-05$	$5.94E-06$	-3.038191	0.0024
ISSUED	$-5.67E-06$	$7.26E-06$	-0.780083	0.4353
COPP	-0.001507	0.000201	-7.500312	0.0000
DUM9	0.014596	0.000584	25.00623	0.0000
DUM13	-0.003788	0.001882	-2.012250	0.0442
DXY	0.005487	0.000594	9.232229	0.0000
VIX	0.000249	$3.05E-05$	8.176541	0.0000
MATUR	$6.30E-06$	$3.64E-06$	1.730066	0.0836
AR(1)	0.004841	0.001229	3.940192	0.0001
SIGMASQ	0.005604	$4.18E-06$	1340.166	0.0000

R-squared	0.004811	Mean dependent var	0.000396
Adjusted R-squared	0.004641	S.D. dependent var	0.075039
S.E. of regression	0.074865	Akaike info criterion	-2.346074
Sum squared resid	394.1336	Schwarz criterion	-2.344381
Log likelihood	82517.38	Hannan-Quinn criter.	-2.345552
F-statistic	28.32808	Durbin-Watson stat	2.000123
Prob(F-statistic)	0.000000	Sample size	70334

Appendix E

TABLE E1: Intraday regression estimates: Pre-pandemic sample (2014-2019) - Only days with intervention

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003051	0.001221	2.497967	0.0125
ISSUED(-3)	$-2.85E-06$	$9.21E-06$	-0.309468	0.7570
ISSUED(-2)	$1.03E-06$	$5.02E-06$	0.205664	0.8371
ISSUED(-1)	$-1.43E-05$	$7.81E-06$	-1.833843	0.0667
ISSUED	$-7.57E-06$	$8.32E-06$	-0.910039	0.3628
BID(1)	$3.96E-06$	$4.95E-06$	0.799692	0.4239
BID(2)	$-1.36E-05$	$6.97E-06$	-1.953152	0.0508
BID(3)	$-1.10E-05$	$7.79E-06$	-1.408712	0.1589
ANNOUNCE(4)	-0.000832	0.002828	-0.294362	0.7685
ANNOUNCE(5)	0.003404	0.002030	1.676738	0.0936
COPP	-0.001544	0.000427	-3.611882	0.0003
DUM9	0.049297	0.001700	28.99995	0.0000
DUM13	-0.000274	0.004106	-0.066786	0.9468
DXY	0.003212	0.001265	2.538872	0.0111
VIX	0.000199	$7.53E-05$	2.643158	0.0082
MATUR	$-9.65E-06$	$6.47E-06$	-1.491584	0.1358
AR(1)	-0.006519	0.004056	-1.606964	0.1081
SIGMASQ	0.004211	$1.43E-05$	293.6160	0.0000

R-squared	0.024578	Mean dependent var	0.003445
Adjusted R-squared	0.023069	S.D. dependent var	0.065709
S.E. of regression	0.064947	Akaike info criterion	-2.628854
Sum squared resid	46.32758	Schwarz criterion	-2.616901
Log likelihood	14478.01	Hannan-Quinn criter.	-2.624827
F-statistic	16.27918	Durbin-Watson stat	2.000163
Prob(F-statistic)	0.000000	Sample size	11001

TABLE E2: Intraday regression estimates: Post-pandemic sample (2020-2023) - Only days with intervention

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001593	0.001272	1.251803	0.2107
ISSUED(-3)	$-2.55E-05$	$1.28E-05$	-1.980814	0.0476
ISSUED(-2)	$-4.72E-06$	$8.76E-06$	-0.538252	0.5904
ISSUED(-1)	$-3.12E-05$	$1.01E-05$	-3.103973	0.0019
ISSUED	$-1.00E-05$	$1.37E-05$	-0.732452	0.4639
BID(1)	$-5.14E-06$	$1.23E-05$	-0.416446	0.6771
BID(2)	$-6.03E-06$	$1.35E-05$	-0.447742	0.6543
BID(3)	$2.39E-06$	$1.02E-05$	0.234114	0.8149
ANNOUNCE(4)	0.018363	0.002219	8.273943	0.0000
ANNOUNCE(5)	0.015924	0.002309	6.895820	0.0000
COPP	-0.000897	0.000473	-1.895539	0.0580
DUM9	0.068672	0.001605	42.78395	0.0000
DUM13	-0.008637	0.005027	-1.718062	0.0858
DXY	0.005806	0.001474	3.938630	0.0001
VIX	0.000274	$7.16E-05$	3.828562	0.0001
MATUR	$-1.17E-05$	$1.04E-05$	-1.121280	0.2622
AR(1)	0.043212	0.004278	10.10053	0.0000
SIGMASQ	0.006793	$1.53E-05$	443.4701	0.0000

R-squared	0.035972	Mean dependent var	0.004673
Adjusted R-squared	0.034863	S.D. dependent var	0.083944
S.E. of regression	0.082468	Akaike info criterion	-2.151601
Sum squared resid	100.5792	Schwarz criterion	-2.142359
Log likelihood	15947.38	Hannan-Quinn criter.	-2.148533
F-statistic	32.46084	Durbin-Watson stat	2.001198
Prob(F-statistic)	0.000000	Sample size	14807

TABLE E3: Intraday regression estimates: Full sample (2014-2023) - Only days with intervention

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002196	0.000868	2.530852	0.0114
ISSUED(-3)	$-1.04E-05$	$8.05E-06$	-1.289410	0.1973
ISSUED(-2)	$-7.53E-07$	$4.89E-06$	-0.154033	0.8776
ISSUED(-1)	$-1.85E-05$	$6.40E-06$	-2.889444	0.0039
ISSUED	$-7.98E-06$	$7.64E-06$	-1.044649	0.2962
BID(1)	$1.08E-06$	$5.22E-06$	0.206624	0.8363
BID(2)	$-9.73E-06$	$7.29E-06$	-1.335454	0.1817
BID(3)	$-4.76E-06$	$6.61E-06$	-0.720640	0.4711
ANNOUNCE(4)	0.011099	0.001609	6.898895	0.0000
ANNOUNCE(5)	0.010839	0.001494	7.254649	0.0000
COPP	-0.001211	0.000320	-3.787389	0.0002
DUM9	0.060000	0.001108	54.15787	0.0000
DUM13	-0.005039	0.003352	-1.503317	0.1328
DXY	0.004409	0.000974	4.526348	0.0000
VIX	0.000244	$5.03E-05$	4.849034	0.0000
MATUR	$-1.22E-05$	$5.65E-06$	-2.158790	0.0309
AR(1)	0.028491	0.002893	9.847023	0.0000
SIGMASQ	0.005710	$9.47E-06$	603.0106	0.0000

R-squared	0.029532	Mean dependent var	0.004149
Adjusted R-squared	0.028892	S.D. dependent var	0.076704
S.E. of regression	0.075588	Akaike info criterion	-2.326339
Sum squared resid	147.3527	Schwarz criterion	-2.320649
Log likelihood	30037.08	Hannan-Quinn criter.	-2.324500
F-statistic	46.16472	Durbin-Watson stat	2.000562
Prob(F-statistic)	0.000000	Sample size	70317