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Alejandro Jara
Marco Piña

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Exchange rate volatility and the effectiveness of FX interventions: the case of Chile*

Alejandro Jara
Central Bank of Chile

Marco Piña
Central Bank of Chile

Abstract

In this paper, we study the effectiveness of FX interventions in Chile since adopting a fully flexible exchange rate regime in the late 1990s. In particular, we ask whether these interventions have dumped excess exchange rate volatility and reduced its probability of being in a high volatility state. To do so, we rely on a high-frequency GARCH(1,1) volatility model with Markov-Switching regimes (Haas et al., 2004) and evaluate the effectiveness of FX interventions within a Local Projection setting (Jordà, 2005). We show that FX interventions in Chile tend to occur during high exchange rate volatility periods, which correlate with domestic and foreign financial factors. Moreover, we show that the FX intervention that started by the end of 2019–the latest intervention included in our study–effectively reduced the exchange rate volatility and the probability of being at a high volatility state.

Resumen

En este documento, estudiamos la efectividad de las intervenciones cambiarias en Chile desde que se adoptó un régimen de tipo de cambio completamente flexible a fines de la década de 1990. En particular, nos preguntamos si estas intervenciones han eliminado el exceso de volatilidad del tipo de cambio y reducido su probabilidad de encontrarse en un estado de alta volatilidad. Para hacerlo, nos basamos en un modelo de volatilidad de alta frecuencia con cambios de regímenes Markov-Switching-GARCH(1,1) (Haas et al., 2004) y evaluamos la efectividad de las intervenciones cambiarias dentro de un marco de Proyecciones Locales (Jordà, 2005). Mostramos que las intervenciones cambiarias en Chile tienden a ocurrir durante períodos de alta volatilidad del tipo de cambio, que se correlacionan con factores financieros internos y externos. Además, mostramos que la intervención cambiaria que comenzó a fines de 2019–la última intervención incluida en nuestro estudio–redujo de manera efectiva la volatilidad del tipo de cambio y la probabilidad de encontrarse en un estado de alta volatilidad.

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* We thank our colleagues at the Central Bank of Chile for useful discussions at different stages of this project. The opinions expressed here are those of the authors and do not necessarily represent the opinion of the Central Bank of Chile or any of its Board Members. Address: Agustinas 1180, Santiago, Chile. E-mails: ajara@bcentral.cl and mpina@bcentral.cl.

1 Introduction

Under floating exchange rates regimes, central banks occasionally intervene in the exchange rate market for many reasons. As part of its macroprudential toolkit, foreign exchange (FX) interventions are mainly used by central banks to deal with financial stability concerns associated with excess exchange rate volatility and sudden changes in capital inflows (BIS, 2019). On the same ground, FX interventions in emerging economies are sometimes justified as being consistent with international reserve accumulation programs that aim to build reserves for precautionary reasons (Arslan & Cantú, 2019). Nonetheless, historically FX interventions have also been used to respond to different objectives than pursuing financial stability. For example, depending on the direction of the exchange rate pressure, FX interventions could help central banks to support the maintenance of price stability (Patel & Cavallino, 2019) or improve export competitiveness (Aizenman et al., 2015; Cabezas & De Gregorio, 2019)[1/].

Since September 1999, when Chile adopted a fully flexible exchange rate regime, and until the last dates considered in this study in early 2020, its central bank has intervened five times in the exchange rate market. These interventions have taken different forms and directions, acting on the spot and the forward market and responding to different purposes[2/]. For example, in 2001 and 2002, the Central Bank of Chile argued excess exchange rate depreciation over and above its fundamentals to justify the intervention at that time (De Gregorio et al., 2005; Tapia et al., 2004). In 2008 and 2011, on the other hand, the FX interventions were motivated by the need to accumulate international reserves without any explicit considerations about the exchange rate's level or its volatility, even though the Chilean peso was considered strong before the interventions began (Claro & Soto, 2013; Vial, 2019). Finally, in 2019, the Central Bank of Chile intervened the exchange rate in response to what was perceived as an excessive degree of exchange rate volatility (Central Bank of Chile, 2019, 2020).

An issue often addressed in the literature is how effective FX interventions are in attaining their goals. Fratzscher et al. (2019), for example, finds that FX interventions are effective, especially when announced and accompanied by a verbal intervention. On the other hand, Menkhoff (2010) and Adler & Tovar (2011) highlight that FX interventions can effectively curb the exchange rate and its volatility in emerging market economies, but less so in advanced economies. As for some country-specific studies, Durán-Vanegas et al. (2016) shows that FX interventions effectively reduce the exchange rate volatility in Peru. Echavarría et al. (2018), analyzing the case of Colombia, emphasize that FX interventions are more effective when they are previously announced. Kuersteiner et al. (2018), on the other hand, looking at the same country's experience, find that the FX interventions'

[1/] Nevertheless, it is well recognized that using FX interventions to control price stability could potentially undermine the credibility of the inflation target framework (Hofman et al., 2020).

[2/] The Chilean experience regarding FX interventions, both in terms of the frequency and directions, is not significantly different from the experience observed in other emerging economies with a floating exchange regime (Fratzscher et al., 2019).

effects on the exchange rate are short live and tend to last between 2 to 3 weeks. Also, Viola et al. (2019) obtain mixed results when studying daily or accumulated interventions in the case of Brazil, increasing and reducing volatility at different quantiles. In contrast, Janot & Macedo (2016) finds that unanticipated interventions in Brazil affect the exchange rate level but finds no evidence on its effect on the volatility. Similarly, when looking at the case of Mexico, García-Verdú & Zerecero (2013) find mixed results and emphasize that reducing exchange rate volatility may depend on the design of the intervention. Finally, Disyatat & Galati (2007) find no evidence of a short-term impact on volatility in the case of FX interventions conducted by the Czech National Bank.

This lack of a unified conclusion regarding the effectiveness of FX interventions reflects, among other issues, the wide variety of success criteria used in these empirical studies. Fatum & M. Hutchison (2003), Durán-Vanegas et al. (2016), Fratzscher (2008) and Fratzscher et al. (2019), for example, look at the direction and smoothness of the exchange rate level after an intervention. On the other hand, several studies focus on how the interventions affect the volatility of the exchange rate (Echavarría et al., 2018; Gamboa-Estrada, 2019; Viola et al., 2019). Apart from providing alternative ways to measure exchange rate volatility, these studies emphasize different properties and characteristics of exchange rate volatility. For example, Viola et al. (2019) implements a quantile regressions approach to account for potential asymmetric effects on volatility. In contrast, Gamboa-Estrada (2019) estimates an extension of the GARCH model to study regime changes in volatility and the effectiveness of Latin American interventions, an approach similar to the one proposed in this article.

In Chile, the empirical evidence regarding the effectiveness of FX interventions is also inconclusive. In particular, it depends on whether the effectiveness is measured on the impact over the exchange rate level or its volatility and whether it is concerned about the announcement or the intervention itself. Tapia et al. (2004), focusing on the interventions that occurred during 1998-2003, find that the public announcements had significant effects on the exchange rate level, but the intervention itself had a relatively small impact. Similarly, Broto (2013) suggests that the interventions of 2008 and 2011 not only were ineffective in altering the exchange rate level but also increased its volatility. Additionally, Fuentes et al. (2014), focusing on the interventions of 2008 and 2011, shows that pre-announced interventions have significant–although transitory–effects on volatility, while the announcements have a significant and persistent effect on the exchange rate level. Finally, Gamboa-Estrada (2019) emphasizes that the FX interventions in Chile have a less stabilizing role because they occur only exceptionally.

This paper considers all five FX interventions in Chile since establishing a fully flexible exchange rate regime in September 1999 until the last dates included in our analysis in early 2020. In doing so, we add to the existing empirical evidence by including the 2019 intervention in the analysis. In addition, we propose an alternative methodological approach to evaluate the effectiveness of interventions, based on a regime-switching volatility analysis, similar to Beine et al. (2003), but using high-frequency data and including a Local Projection approach (Jordà, 2005) to account for the dynamic impact of FX interventions.

Therefore, the novelty of our empirical strategy is twofold. On the one hand, in addition to the standard exchange rate's return and volatility as a metric to measure the effectiveness of FX interventions, we look at the probability of being at a high and low exchange rate volatility state. We do so by estimating a Markov-Switching GARCH model of the exchange rate volatility with regime changes (Haas et al., 2004). Secondly, to address how FX interventions affect these different metrics, we implement a Local Projection setting (Jordà, 2005), accounting for a wide range of domestic and foreign financial factors as control variables. This particular approach allows us to address the impact's effect of the interventions, as well as their persistence over time.

We emphasize that during the fully flexible exchange rate regime, the exchange rate volatility in Chile can be characterized by a model of regime changes with two states (low and high volatility). Also, we show that FX interventions in Chile occur during different states of volatility—not only states of high volatility—, showing that the central bank's motives to intervene have been different over time, consistent with the literature. Finally, we emphasize that the 2019 interventions effectively reduced the exchange rate volatility for more than 20 days after the intervention, also reducing the probability of being in a high volatility state and the level of the exchange rate.

The article is organized as follows. Section 2, after examining the high-frequency properties of the nominal exchange rate returns in Chile, proposes a model for the exchange rate volatility and studies the suitability of a switching regime in the exchange rate volatility behavior. Section 3 assesses the role of FX interventions in understanding the dynamics of exchange rate returns and their volatility following two approaches. First, by adding a set of financial variables in the mean equation and the variance equation of the exchange rate returns. Then, by analyzing the role of FX interventions within a Local Projection framework. Finally, Section 4 concludes.

2 Modeling the exchange rate volatility

As a starting point, we examine the high-frequency properties of the nominal exchange rate in Chile. In particular, we compute the exchange rate daily returns at time t (e_t) during the January 4th, 2000 and February 21st, 2020 sample period[3/]. In doing so, we propose the most suitable specification to model exchange rate returns' conditional mean and variance by testing the order of an ARMA(p,q) in the mean and a GARCH(p,q) specification to assess the returns' variance. We conclude that with an ARMA(0,1)-EGARCH(1,1), we obtain a good fit to the data relative to other models while maintaining some desirable features such as parsimony and the capacity to account for asymmetric effects.

Figure 1 shows the evolution of the nominal exchange rate (E_t) and its daily returns (e_t) in the upper and lower panel, respectively. It also highlights the foreign exchange

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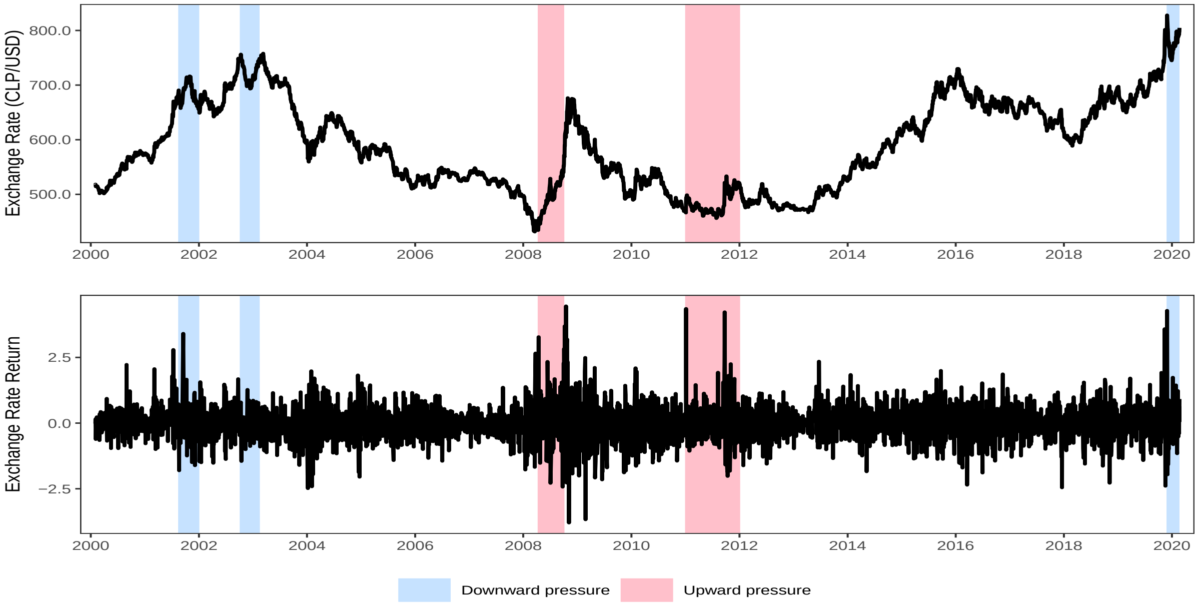
[3/] Here $e_t = 100 * \log(E_t/E_{t-1})$, where E_t is the observed Chilean peso to the US dollar (CLP/USD) exchange rate weighted by the spot transactions conducted in the Formal Exchange Market (FEM) during the immediately preceding business day.

Figure 1. The exchange rate level and the exchange rate daily returns



Notes: Downwards and upwards FX pressures are intervention pressures towards appreciation and depreciation, respectively.

intervention periods from January 4th, 2000 to February 21st, 2020[4/]. By simple observation, we see that the variance of the daily returns is not constant over time and presents volatility clusters as periods of high and low volatility tend to be highly persistent. More formally, column 1 in Table 1 summarizes the main descriptive statistics of daily returns, as well as a set of tests to study the normality, autocorrelation, heteroscedasticity, and the stationarity properties of e_t[5/]. As can be seen, the null hypotheses that test for normality, no autocorrelation, homoscedasticity, and non-stationarity, are all rejected at 0.1%, consistently with our observation of Figure 1.

Therefore, we eliminate the autocorrelation of e_t by adjusting an ARMA(0,1) model to the mean returns, so that $e_t = c + \phi\epsilon_{t-1} + \epsilon_t$[6/]. Once the model is adjusted for its mean, the series of residuals ($\hat{\epsilon_t}$) no longer presents autocorrelation (see the second column of Table 1 and the ACF and PACF plots in Figure A2). However, these residuals still present

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[4/] As we explain later, some interventions can be associated with downward pressures on the exchange rate (blue area), while others with upward pressures (red area).

[5/] To test for the normality of e_t, we use Jarque Bera (JB) (1980) and Lobato Velasco (LV) (2004). To test for autocorrelation, we use Ljung-Box (LB) (1978) and Box-Pierce (BP) (1970). Finally, we implement the Lagrange Multiplier (LM) (Engle, 1982) and Breusch-Pagan (BrP) (1979) to test for heteroscedasticity, and ADF (Dickey, 1997) for stationarity.

[6/] The order of the ARMA(p,q) model was determined by the ACF and PACF tests, which indicate that the most appropriate model for the mean is an ARMA(0,1). See Figure A1.

heteroscedasticity and are still characterized by a non-Gaussian distribution[7/]. Then, we test for ARCH effects on the ARMA(0,1)'s squared residuals, $(\hat{e_t})^2$. In the third column of Table 1 we observe that squared residuals present autocorrelation. Therefore, we finally estimate a GARCH(p, q) model in the variance equation of e_t as a way to address both the autocorrelation and the heteroscedasticity[8/]. Moreover, we assume a more flexible, non-Gaussian distribution, such as Student's t distribution for the residuals, because, as highlighted by the JB and LV tests in Table 1), the normality in the residuals is strongly rejected.

Table 1. Summary statistics of the exchange rate daily residuals

	e_t	$\hat{e_t}$	$(\hat{e_t})^2$
Mean	0.0088	0.0000	0.3751
Std	0.6198	0.6125	0.9672
Min	-3.7992	-3.7455	0.0000
Max	4.4585	4.8034	23.0728
Skew	0.4213	0.3904	
Kurt	7.4863	7.6469	
Normality			
JB	4200.5***	4475.9***	
LV	4194.3***	4475.3***	
Autocorrelation			
LB(5)	111.72***	2.4301	984.64***
BP(5)	111.65***	2.4265	983.33***
Heteroscedasticity			
LM(5)	11418***	11768***	253038***
BrP(5)	70.468***	65.11***	125.84***
Stationarity			
ADF	-17.116***	-17.243***	-10.752***

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Null hypotheses: (i) JB and LV (H_0: is Gaussian), (ii) BL and BP (H_0: no autocorrelation), (iii) LM and BrP (H_0: is homoscedastic) and (iv) ADF(H_0: not stationary). LB(Q), BP(Q), LM(Q) and BrP(Q) tests were performed considering 5 lags (Q=5).

To summarize and properly model the Chilean exchange rate daily return and its volatility, we assume: (i) an ARMA (0,1) in the mean equation of e_t, (ii) innovations z_t that follow a Student's t distribution, with ν degrees of freedom, and (iii) a GARCH model in the variance equation σ_t^2, such that:

$$e_t = c + \phi\epsilon_{t-1} + \epsilon_t \tag{1}$$

$$\epsilon_t = \sqrt{\sigma_t} z_t, \qquad z_t \sim t(\nu), \qquad \nu > 2 \tag{2}$$

[7/] See also the QQ-plot in Figure A3.

[8/] See also the ACF and PACF tests for the square of the residuals in Figure A4.

2.1 The variance equation

We now turn to the performance of five alternative GARCH specifications to select the GARCH model in the variance equation that better fits the data. In particular, we estimate a: (i) ARCH (Engle, 1982), (ii) GARCH (Bollerslev, 1986), (iii) EGARCH (Nelson, 1991), (iv) TGARCH (Zakoian, 1994), and (v) GJR-GARCH (Glosten et al., 1993) model, so that[9/]:

$$ARCH: \quad \sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \epsilon_{t-j}^2 \tag{3}$$

$$GARCH: \quad \sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \epsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{4}$$

$$EGARCH: \quad \log(\sigma_t^2) = \omega + \sum_{j=1}^{q} (\alpha_j z_{t-j} + \gamma_j (|z_{t-j}| - \mathbb{E}|z_{t-j}|)) + \sum_{j=1}^{p} \beta_j \log(\sigma_{t-j}^2) \tag{5}$$

$$TGARCH: \quad \sigma_t = \omega + \sum_{j=1}^{q} \alpha_j (|z_{t-j}| - \gamma_j z_{t-j}) + \sum_{j=1}^{p} \beta_j \sigma_{t-j} \tag{6}$$

$$GJR-GARCH: \quad \sigma_t^2 = \omega + \sum_{j=1}^{q} (\alpha_j \epsilon_{t-j}^2 + \gamma_j \mathbb{1}\{\epsilon_{t-j} \leq 0\}_{t-j} \epsilon_{t-j}^2) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{7}$$

Table 2 summarizes the estimation of all these different model specifications. Additionally, Table 2 shows different performance metrics used in the literature to select the GARCH model that best fits the data. In particular, following Pagan & Schwert (1990), Bollerslev et al. (1994), and P. R. Hansen & Lunde (2005), we focus on the following loss functions and information criteria to select the most suitable model[10/]:

$$MSE2 \equiv T^{-1} \sum_{t=1}^{T} (\sigma_t - \epsilon_t)^2 \qquad R2log \equiv T^{-1} \sum_{t=1}^{T} (\log(\sigma_t^2 / \epsilon_t^{-2}))^2$$

$$MSE1 \equiv T^{-1} \sum_{t=1}^{T} (\sigma_t^2 - \epsilon_t^2)^2 \qquad MAD2 \equiv T^{-1} \sum_{t=1}^{T} |\sigma_t^2 - \epsilon_t^2|$$

$$PSE \equiv T^{-1} \sum_{t=1}^{T} (\sigma_t^2 - \epsilon_t^2)^2 / \sigma_t^4 \qquad MAD1 \equiv T^{-1} \sum_{t=1}^{T} |\sigma_t - \epsilon_t|$$

From the EGARCH (5), TGARCH (6) and GJR-GARCH (7) estimate in Table 2, it is clear that a nonnegligible asymmetric effect is present in the variance of the exchange rate returns[11/]. Therefore, we discard the standard ARCH (3) and GARCH (4) models

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[9/] Notice that some of these specifications use standardized residuals z_t, instead of the residuals ϵ_t.

[10/] Since our main goal is to analyze past events of the exchange rate dynamic, we do not select criteria like forecasting performance.

[11/] Notice, however, that the parameters associated with asymmetric effects are not directly comparable across these specifications.

as a suitable model specification. Also, the EGARCH(1,1) model obtained the best performance in almost every metric except for PSE and R2log measures, which shows that the model is more penalized when the estimated variance is close to zero. Nonetheless, the EGARCH(1,1) obtains the best results in the metrics that directly penalize the distance between the estimated variance and the one realized. For this reason, we choose the EGARCH(1,1) model as a baseline model for further analyses[12/].

Table 2. Alternative variance model specifications

	ARCH(1)	GARCH(1,1)	EGARCH(1,1)	TGARCH(1,1)	GJR-GARCH(1,1)
Mean equation					
c	0.0006	−0.0028	0.0011	0.0007	0.0003
	(0.0088)	(0.0080)	(0.0073)	(0.0081)	(0.0081)
ϕ	0.1689^{***}	0.1483^{***}	0.1534^{***}	0.1547^{***}	0.1497^{***}
	(0.0158)	(0.0146)	(0.0152)	(0.0146)	(0.0146)
Variance equation					
ω	0.2925^{***}	0.0041^{**}	-0.0270^{***}	0.0114^{***}	0.0046^{**}
	(0.0119)	(0.0013)	(0.0064)	(0.0028)	(0.0014)
α	0.2308^{***}	0.0806^{***}	0.0297^{***}	0.0944^{***}	0.0991^{***}
	(0.0311)	(0.0104)	(0.0090)	(0.0103)	(0.0139)
ν	5.2831^{***}	7.8191^{***}	7.8996^{***}	7.8957^{***}	7.9222^{***}
	(0.3874)	(0.7734)	(0.7818)	(0.7780)	(0.7914)
β		0.9116^{***}	0.9775^{***}	0.9081^{***}	0.9091^{***}
		(0.0114)	(0.0051)	(0.0111)	(0.0117)
γ			0.1788^{***}	-0.1867^{***}	-0.0352^{**}
			(0.0180)	(0.0533)	(0.0132)
Log-like	−4173.2860	−3969.9497	−3951.6000	−3951.8238	−3966.0205
AIC	1.7273	1.6436	1.6365	1.6366	1.6424
BIC	1.7340	1.6517	1.6458	1.6459	1.6518
MSE2	0.9273	0.8559	0.8448	0.8458	0.8537
MSE1	0.7453	0.7505	0.7384	0.7425	0.7559
PSE	6.1282	6.4870	6.7464	6.9499	6.9067
R2log	7.9930	7.2002	7.2417	7.2235	7.2385
MAD2	0.4126	0.3986	0.3878	0.3896	0.3992
MAD1	0.6999	0.6773	0.6741	0.6743	0.6789

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

[12/] We also considered different orders for each of the models presented in Table 2. These results are presented in Appendix B.

2.2 Testing structural changes

We now analyze if there is any evidence of parameters instability in the mean and the variance equation. First, we test the stability in individual parameters following Hansen's test (B. E. Hansen, 1992). Then, we look at Nyblom's test (Nyblom, 1989), which allows us to test the stability in all the parameters at once. Table 3 reports these results.

The performed tests show that the parameters in the mean equation are statistically stable[13/]. On the other hand, the parameters in the variance equation are also relatively stable. However, the parameter γ is statistically unstable at a level of confidence of 5%, which suggests that the asymmetric effects characterizing the variance may result in more than one volatility state. Finally, Nyblom's test shows statistically significant instability in all parameters when tested jointly[14/].

Table 3. Parameters' stability

	Hansen	Nyblom
Mean equation		
c	0.266	
ϕ	0.058	
Variance equation		
ω	0.203	
α	0.345	
β	0.166	
γ	0.516^{**}	
ν	0.087	
Joint parameters		1.897^{*}

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The second column shows the Hansen's statistic for individual parameters, whose critical values are 0.35 ($\alpha = 10\%$), 0.47 ($\alpha = 5\%$), 0.75 ($\alpha = 1\%$). The last row shows the Nyblom's statistic for joint stability of the parameters, whose critical values are 1.69 ($\alpha = 10\%$), 1.90 ($\alpha = 5\%$) and 2.35 ($\alpha = 1\%$). The null hypothesis in both cases is H_0: Parameter is stable.

2.3 Modeling the regime switching volatility

Following the previous analysis, first we decided to keep all the parameters in the mean equation and the ν parameter as constant. Then, we analyze the suitability of modeling the variance equation assuming two volatility states, given the evidence of instability in the asymmetry parameter and the aggregate instability when all parameters are tested jointly[15/]. Thus, we extend the model to allow regime-switching in the volatility equation

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[13/] Notice that we have to consider that c is statistically zero in all these estimates.

[14/] When testing the stability of the parameter ν, it results to be highly stable, similarly to ϕ.

[15/] In the Appendix, we analyze models where ν can also present a regime-switching over time. When comparing these models against models with fixed ν, we conclude that keeping ν constant allows us to better identify the volatility states (See Appendix C).

assuming that the EGARCH(1,1) model—i.e., the model that better fits the data when no regime-switching is assumed —governs at each state[16/]. Therefore, we establish the following Markov-Switching model with two volatile states, allowing the volatility to vary over time and change across different states:

$$e_t = c + \phi\epsilon_{t-1} + \epsilon_t \tag{8}$$

$$\epsilon_t|(s_t = k) = \sqrt{\sigma_{k,t}}z_t, \qquad z_t \sim t(\nu), \qquad \nu > 2 \tag{9}$$

$$\log(\sigma^2_{k,t}) = \omega_{0,k} + \alpha_k z_{t-1} + \gamma_k(|z_{t-1}| + \mathbb{E}[z_{t-1}]) + \beta_k \log(\sigma^2_{k,t-1}) \tag{10}$$

Table 4 summarizes the estimation of equations (8) to (10), when e_t is assumed to have zero mean and volatility $\sigma_{k,t}$ varies over time t and changes across states k, and the dynamic of exchange rate volatility follows an EGARCH(1,1) model. These results emphasize that the asymmetry effect presented before has vanished in the second—high volatility state —regime, consistent with the parameter instability tested in the previous section, especially for the γ parameter.

Table 4 also shows the transition probability across different states, highlighting the fact that the low-volatility state is more persistent than the high-volatility state, as $\pi_{1,1} = 0.993$ is greater than $\pi_{2,2} = 0.852$. This stylized fact is also observed in Figure 2, where we present the exchange rate volatility resulting from the MS(2)-EGARCH(1,1) model (upper panel), as well as the unconditional probability of remaining at the low-volatility and high volatility state (middle and lower panel, respectively).

3 The exchange rate volatility and the effectiveness of FX interventions

In this section, we turn to the role of FX interventions in understanding the dynamics of exchange rate returns and their volatility. First, we briefly characterize the FX interventions that occurred in Chile between January 4th, 2000, to February 21st, 2020, and discuss the behavior of the exchange rate around these events, including the exchange rate return, volatility, and the probability of being at a low/high volatility state. Then, we introduce a set of domestic and external financial conditions that, in combination with the FX interventions, act as potential determinants of the exchange rate dynamic. Finally, we take all these elements together and assess the significance of FX interventions following two approaches.

In the first approach, we re-estimate the model for the exchange-rate returns previously discussed in section 2 (i.e., the ARMA(0,1)-EGARCH(1,1) model), but this time, we add the set of financial variables, including the FX interventions, as potential determinants in the mean equation and the variance equation. Then, we implement a Local

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[16/] We are well aware that the dynamics of the volatility model could differ across volatility states, needing potentially different specifications for each state. We keep this issue for future research.

Table 4. Regime switching volatility: MS(2)-EGARCH(1,1)

Parameter	Regime 1	Regime 2
ω	-0.0374^{***}	0.0548^{*}
	(0.0054)	(0.0296)
γ	0.1413^{***}	0.0301
	(0.0178)	(0.0865)
α	0.0259^{**}	0.1477^{**}
	(0.0094)	(0.0600)
β	0.9747^{***}	0.8988^{***}
	(0.0038)	(0.0104)
ν	13.0980^{***}	
	(3.1941)	
$\pi_{1,1}$	0.9930^{***}	
	(0.0884)	
$\pi_{2,1}$		0.1480^{***}
		(0.0060)
Stable Prob	0.9549%	0.0451%
Log-like	−3944.4238	
AIC	1.6351	
BIC	1.6499	

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Projections analysis with a special focus on the role of FX interventions. Following this approach, after controlling by the whole set of potential determinants, we can assess the contemporary impact of FX interventions and how persistent these effects are.

3.1 FX interventions and financial determinants of the exchange rate dynamic

Table 5 shows the five episodes of FX interventions that occurred in Chile between January 4th, 2000, to February 21st, 2020[17/]. This table shows the length of the interventions, highlighting that they tend to last for at least several weeks but that the actual number of days that they are in place differs across episodes.

Then, interventions are classified depending on the conditions characterizing the exchange rate around the day of the announcement[18/]. See Figure 1 and 2, when the exchange rate returns, volatility, and the probability of being at a low/high volatility state

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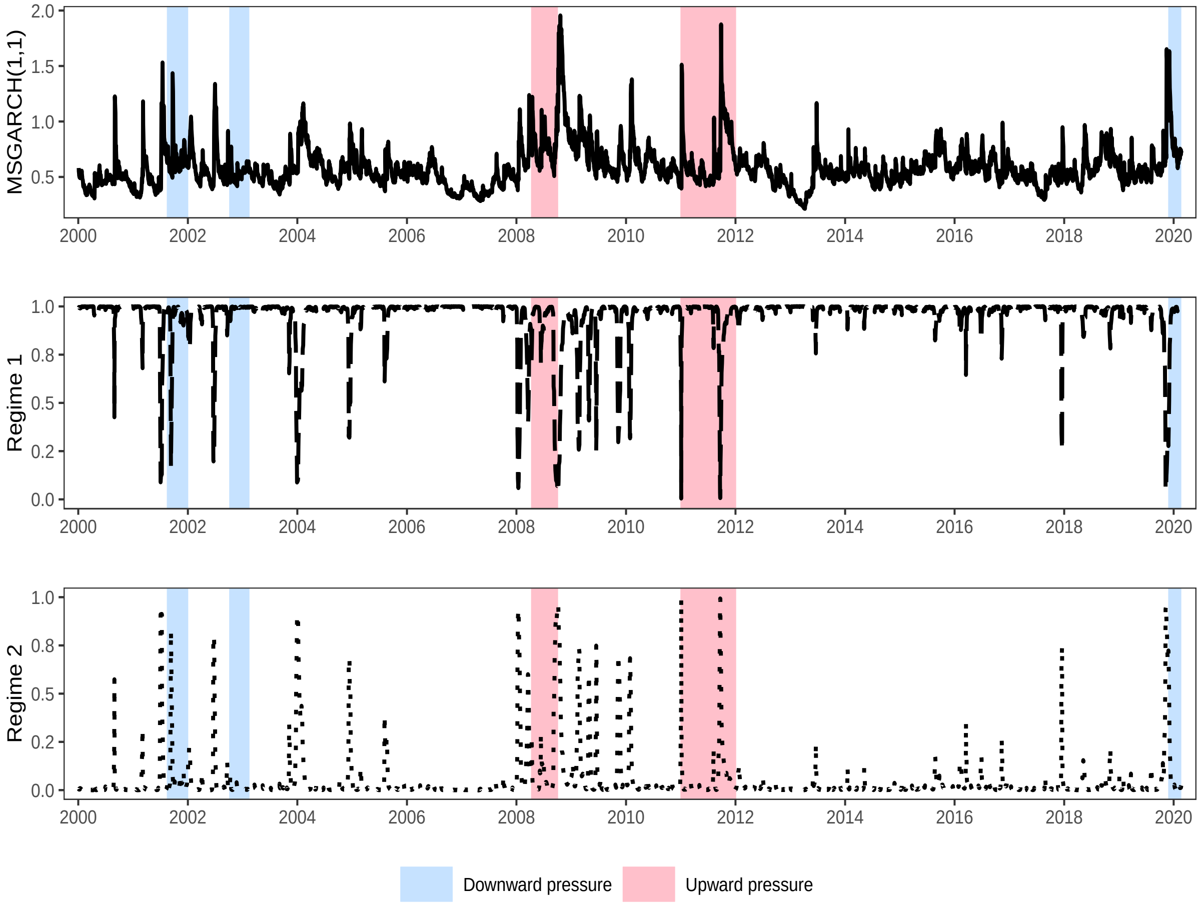
[17/] We define an intervention day when a sale or purchase of foreign currency occurs either in the spot or forward markets.

[18/] Notice that the day of the announcement coincides or it is very close to the actual day of the intervention.

Figure 2. Exchange rate volatility and the unconditional probability of the exchange rate volatility at different states



Notes: Based on the estimations presented in Table 4.

are displayed along with the intervention events. As can be seen, the starting day in the intervention events of 2001, 2002, and 2019 follows a period of exchange rate devaluation, while the starting day in the intervention events of 2008 and 2019, follows a period of exchange rate appreciation (Figure 1). On the other hand, the exchange rate volatility, as well as the probability of being at a high volatility state, increased before the announcements of almost all interventions, with the exception of the intervention of 2011, which followed a period of low exchange rate volatility. With the intervention of 2011 though, the exchange rate volatility jumped upright with the starting of this intervention period (Figure 2). Based on this evidence, and only for informative purposes, we classify the FX interventions in 2001, 2002, and 2019 as interventions whose aim was to generate downward pressures—either in the exchange rate return or its volatility[19/]. Contrary, the 2008 and

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[19/] A higher exchange rate misalignment—due to international events, such as the Argentinian currency

2011 interventions were conceived within a context where the local currency was perceived as overvalued, without any particular consideration about the exchange rate volatility.

Table 5. FX intervention events

Episode	FXI Pressure	Intervention period	Announcement	Days in sample
Episode 1	Downward	Aug 16, 2001 - Dec 31, 2001	Aug 16, 2001	78
Episode 2	Downward	Oct 10, 2002 - Feb 10, 2003	Oct 10, 2002	77
Episode 3	Upward	Apr 14, 2008 - Sep 29, 2008	Apr 10, 2008	110
Episode 4	Upward	Jan 05, 2011 - Dec 30, 2011	Jan 03, 2011	239
Episode 5	Downward	Dec 02, 2019 - Feb 21, 2020	Nov 28, 2019	54

Note: The sample period runs from January 4th, 2000, to February 21st, 2020. Announcement dates were obtained from Central Bank's Annual Reports (2001, 2002, 2008, 2011 and 2019). Downwards and upwards FX pressures are intervention pressures towards appreciation and depreciation, respectively.

Now, let's consider a set of high-frequency domestic and external financial factors—along with the dummy variables that capture the FX interventions described above—that can potentially be associated with the dynamic of the exchange rates, including its returns and volatility[20/].

The domestic factors considered are: (i) the copper price, (ii) the stock market index (IPSA), (iii) the Chilean emerging markets bond index (EMBI CL), (iv) the short-term interest rate spreads vis-a-vis the U.S. monetary policy and (v) an uncertainty measure that captures the global disagreement in topics such as the economy, economic policies, uncertainty about particular events, and the current economic situation in Chile developed by Becerra et al. (2020)[21/]. On the other hand, the set of external factors includes: (i) the Cboe volatility index (VIX), as a measure of foreign investors' risk, and (ii) the U.S. dollar index (USDX), as a measure of the value of the U.S. dollar relative to the value of a basket of currencies. Finally, we include an aggregate dummy of FX interventions (FXI), a separate set of dummies for downward and upward FX pressures (FX_d and FX_u, respectively), and individual dummies for each intervention episode separately (FX_{2001}, FX_{2002}, FX_{2008}, FX_{2011}, and FX_{2019}).

Table 6 summarizes the correlations between these different factors[22/]. Overall, the correlations appear to be relatively low. However, we observe a non-negligible correlation between ΔCOPPER and ΔIPSA (28%), ΔCOPPER and ΔUSDX (-25%), ΔEMBI and ΔIPSA (-21%), and VIX with the aggregate intervention dummy FXI (20%).

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crisis of 2001 and the sharp increase in the Brazilian country risk in 2002—explains the interventions of 2001 and 2002. On the other hand, the intervention of 2019 responded to the exchange rate misalignment due to domestic events associated with the social unrest that started in October 2019.

[20/] See E. Hansen & Morales (2019) for a similar discussion.

[21/] These last two factors are only available for a shorter time span.

[22/] All indexes are expressed in daily percentage changes, i.e., $\Delta COPPER$, $\Delta IPSA$, $\Delta EMBI$, $\Delta USDX$.

Table 6. Correlation matrix of external determinants

	$\Delta COPPER$	$\Delta IPSA$	$\Delta EMBI$	$\Delta USDX$	VIX	FXI
$\Delta COPPER$	1.00	-	-	-	-	-
$\Delta IPSA$	0.28	1.00	-	-	-	-
$\Delta EMBI$	-0.13	-0.21	1.00	-	-	-
$\Delta USDX$	-0.25	-0.10	0.01	1.00	-	-
VIX	-0.08	-0.08	0.06	0.02	1.00	-
FXI	-0.02	-0.02	0.00	0.01	0.20	1.00

3.2 FX interventions in the mean and variance equation of the variance model

Now, we take a first look at the significance of FX interventions in explaining the exchange rate dynamic. To do so, we first assess the statistical significance of domestic and external factors within the mean equation and the variance equation of the variance model specification ARMA(0,1)-EGARCH(1,1) in Table 2. Columns (1) and (2) of Table 7 evaluate the separated impact of these two groups of factors (domestic and external)[23/]. In comparison, column (3) keeps only those factors that are statistically significant. In the mean equation, the copper price, the EMBI spread, and the VIX are all positively correlated to the exchange rate return and statistically significant at 1%. In the variance equation instead, the stock price index (IPSA) showed a negative and statistically significant effect, while the VIX correlates positively, but its statistical significance is much lower[24/].

From columns (4) to (6), we keep the same specification as in column (3), and we add different measures of the FX intervention dummies[25/]. First, column (4) includes the aggregate measure of FX interventions, which does not appear to be significant in the mean or variance equation. Then, in column (5), we look at the differentiated impact of downward and upward FX pressures. Again, we find no statistically significant effect in either equation. Finally, in column (6), we identify the impact of each FX intervention separately. In this case, only the 2008 intervention shows a statistically significant effect in the mean equation, while no intervention seems to affect the variance equation in our volatility model specification.

We conclude that a set of domestic and external factors are relevant in explaining the exchange rate returns and variance. Moreover, their sign and statistical significance are very stable across different specifications. However, at first glance, FX interventions have a negligible impact on the exchange rate return and variance when taken as a contemporary average effect. In our last section, we move one step forward by looking at the persistence

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[23/] We only show the coefficients associated with these variables for simplicity. The other parameters associated with the variance model specification are available upon request.

[24/] Table E4 shows the estimation results of this variance model specification when including the interest rate spreads and DEPU as determinants, which both resulted in being none statistically significant.

[25/] For the effect of FX interventions, we look at the impact of interventions at time $t-1$.

Table 7. Variance model: role of the determinants

	(1)	(2)	(3)	(4)	(5)	(6)
Mean equation						
$\Delta Copper$	0.0196^{***}		0.0195^{***}	0.0195^{***}	0.0195^{***}	0.0197^{***}
$\Delta IPSA$	-0.0023					
$\Delta EMBI$	0.9644^{***}		0.9480^{***}	0.9567^{**}	0.9452^{***}	0.9497^{***}
$\Delta USDX$		-0.0155				
VIX		0.0034^{***}	0.0031^{***}	0.0033^{**}	0.0034^{***}	0.0036
FXI				-0.0187		
FXI_u					0.0016	
FXI_d					-0.0573	
FXI_{2001}						-0.0914
FXI_{2002}						-0.0620
FXI_{2008m}						0.1845^{**}
FXI_{2011}						-0.0443
FXI_{2019}						0.0454
Variance equation						
$\Delta Copper$	-0.0031					
$\Delta IPSA$	-0.0254^{*}		-0.0320^{***}	-0.0318^{***}	-0.0318^{***}	-0.0333^{***}
$\Delta EMBI$	0.8181					
$\Delta USDX$		-0.0225				
VIX		0.0008^{*}	0.0006^{*}	0.0006	0.0006	0.0007
FXI				0.0024		
FXI_u					0.0032	
FXI_d					0.0015	
FXI_{2001}						0.0084
FXI_{2002}						-0.0054
FXI_{2008}						0.0210
FXI_{2011}						-0.0052
FXI_{2019}						-0.0007
Log-like	−3929.6913	−3946.8667	−3926.9740	−3926.7338	−3926.3183	−3921.8560
AIC	1.6295	1.6357	1.6279	1.6287	1.6293	1.6300
BIC	1.6456	1.6491	1.6427	1.6461	1.6494	1.6581

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

response to FX interventions on the return and variable of the exchange rate to assess the effectiveness of FX interventions better.

3.3 FXI effectiveness in a Local Projections approach

Finally, we discuss the effectiveness of FX interventions from the application of an analysis of local projections on the set of metrics that capture the dynamics of the exchange rate described above. In particular, we implement this approach over a set of high-frequency variables (y_t^i), such as (i) the daily return of the exchange rate (e_t), (ii) the volatility of the exchange rate (σ_t^2), (iii) the daily change in the volatility of the exchange rate ($\Delta\sigma_t^2$), and (iv) the probability of being at a high/low volatility state (p_t^{high} and p_t^{low}).

For the volatility of the exchange rate we use three measures. First, as our baseline measure, we use the estimated volatility from the ARCH(0,1)-EGARCH(1,1) model described above (σ_t^2, EGARCH(1,1)). Secondly, as a robustness exercise, we use the intra-day volatility of the exchange rate measure à la Parkinson (1980) (σ_t^2, à la Parkinson)[26/]. Third, we use the exponentially weighted moving average (EWMA) volatility, in which more recent returns have greater weight on the variance[27/]. Finally, the probabilities of being at a high/low volatility state are those estimated in section 2.3 and presented in Figure 2.

We implement a Local Projections methodology described in Jordà (2005) to measure structural changes in the dynamic of the exchange rate before and after the FX intervention occurs. The advantage of this non-parametric methodology is that it is model-free, not restricted to the invertibility condition, as in the case of vector autoregressive models (VAR). This characteristic enables estimation even when there is no vector moving average (VMA) representation of the system, making it less sensitive to specification errors (Brugnolini, 2018; Jordà, 2005).

In particular, we assess the impact of the FX intervention "j" on the set of metrix y_t^i described above, over an horizon $h \geq 0$. In other words, we estimate the following equation[28/]:

$$\Delta y_{i,t+h} = \beta_h FXI_t^j + \delta_h FXI_{l,t}^{-j} + \alpha_{i,h} + \sum_{m=1}^{M} \lambda_{m,h} y_{i,t-m} + \sum_{n=0}^{N} \phi_{n,h} X_{t-n} + \gamma_0 t + \gamma_1 t^2 + \mu_{i,t,h} \quad (11)$$

X_t corresponds to the broad set of domestic and external factors discussed previously that can potentially affect the dynamic of the exchange rate, such as the EMBI CL, VIX, USDX, copper price, IPSA, interest rate spread, and DEPU[29/]. We also include a linear and quadratic trend to control by other variables that capture market developments that could be affecting exchange rate dynamics and that are not observable. Finally, M and N represent the maximum lagging span of the dependent and independent variables, which can differ among them, but that we keep equal to 6 for simplicity.

Figures 3, 4, and 5 summarize our main findings. As can be seen in Figure 3, the 2019 FX intervention is associated with a short-lived drop in the daily exchange rate return. On the other hand, consistently with the authority's main goal, the exchange rate volatility, measured by the EGARCH or the EWMA, is reduced. In particular, this reduction lasts more than 20 days after this intervention. Although the Parkinson's volatility is also reduced, the duration of this fall is less than that observed in the other two measures due to the short impact that the FX intervention had on the daily return. Overall, this intervention had a significant impact on the exchange rate dynamic, which is also reflected in the drop in the daily change in volatility and the resulting impact on the probability of being in a high volatility state, which is reduced more permanently.

[26/] σ_t^2, (à la Parkinson) $= (h-l)^2$. Where h and l are the higher and lower intra-day exchange rate quotes.

[27/] In particular, we define the EWMA model as $\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)e_{t-1}^2$, where $\lambda = 0.94$ as it is common in the literature (Zumbach, 2007).

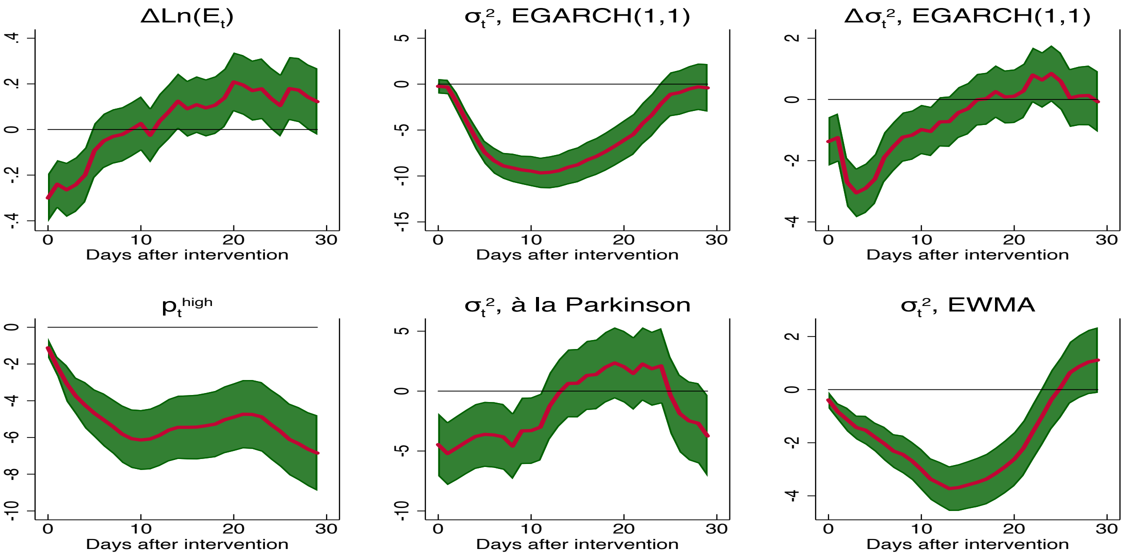
[28/] Where "j" represents each interventions that occurred in 2001, 2002, 2008, 2011, and 2019. In each case, we include the others interventions (-j) as a control variable.

[29/] In particular—wherever possible—we include these variables as measured in logarithms and in changes of the logarithms.

Figure 4 shows the joint impact on the dynamics of the exchange rate of the 2008 and 2011 interventions. As mentioned above, these interventions had as their main objective the accumulation of international reserves, without an explicit concern about the level or volatility of the exchange rate. While the combined effect shows an insignificant impact on the daily return of the exchange rate, Figures F3 and F4 show that both interventions did not generate the same impact, despite responding to similar objectives by the authority. In particular, the 2008 intervention is associated with an increase in the exchange rate daily return, while the 2011 intervention has a negligible impact on it. Concerning the exchange rate volatility, the collective impact shows that these interventions are associated with a drop in exchange rate volatility, although this drop is short-lived. Furthermore, the probability of being in a state of high exchange rate volatility increases after these interventions. This transitory drop in exchange rate volatility and subsequent increase in the probability of being in a high volatility state is particularly evident after the 2011 intervention.

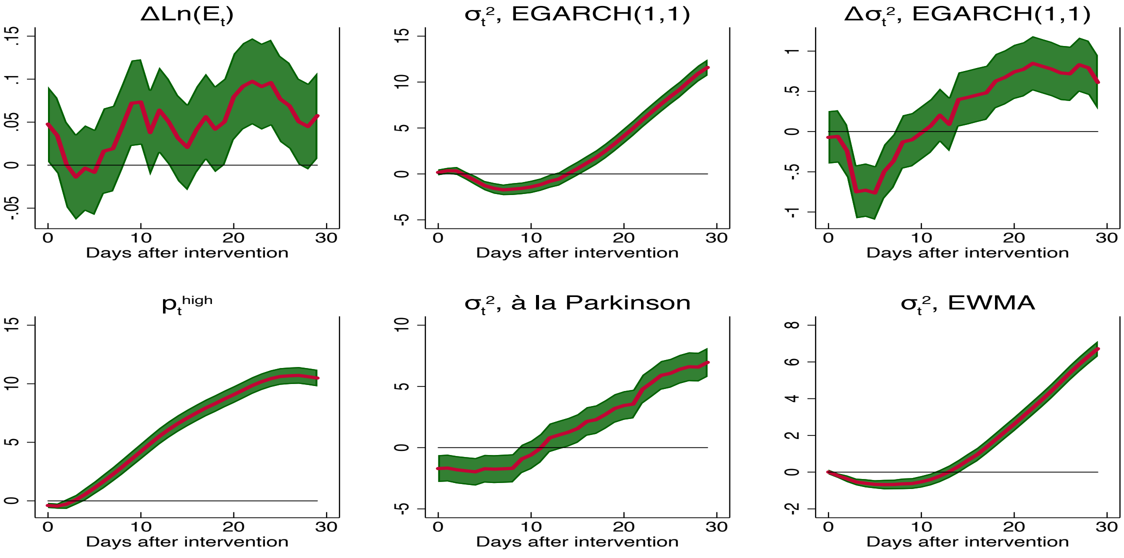
Finally, the joint impact of the 2001 and 2002 interventions on the dynamics of the exchange rate is analyzed in Figure 5, since the main motivations for these interventions were associated with the high exchange rate misalignment due to external financial spillovers. The separate impact of the 2001 and 2002 interventions can be seen in Figures F1 and F2. Unlike the 2008 and 2011 interventions, the dynamics of the daily return of the exchange rate do not differ substantially among the 2001 and 2002 FX interventions. On the other hand, the exchange rate volatility increased after the 2001 intervention and decreased after 2002. Nonetheless, it is important to notice that the assessment of the 2001 and 2002 interventions are less robust compared to the other interventions discussed previously, mainly because some of the control variables used in our assessment, such as the interest rate spread, and the DEPU, are not available for the early 2000s.

Figure 3. Effectiveness of 2019 FXI



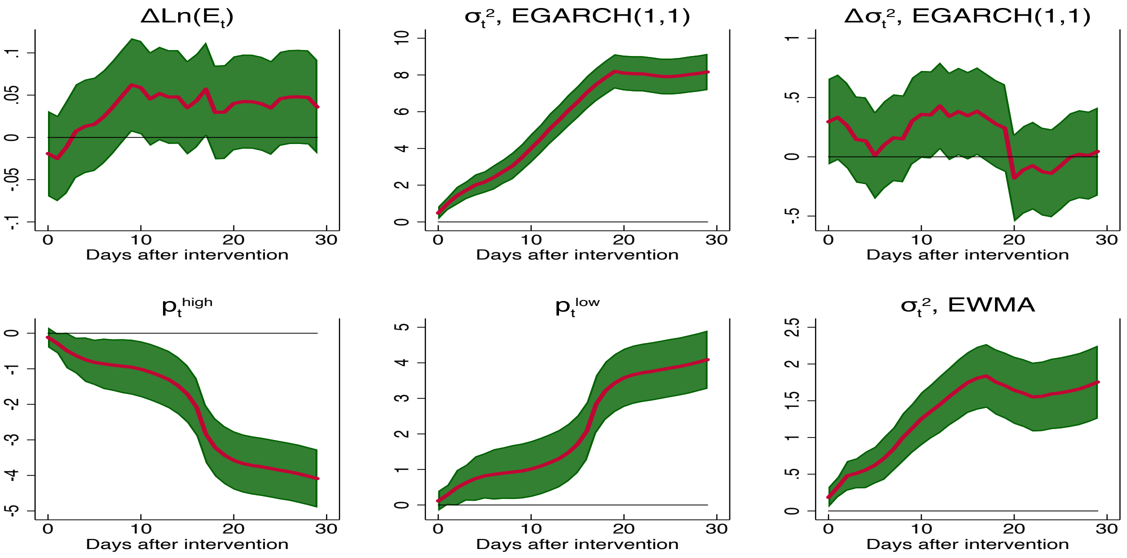
Notes: Authors' estimations based on equation 11.

Figure 4. Effectiveness of 2008 & 2011 FX interventions



Notes: Authors' estimations based on equation 11.

Figure 5. Effectiveness of 2001 & 2002 FX interventions



Notes: Authors' estimations based on equation 11.

4 Conclusions

In this article, after examining the high-frequency properties of the nominal exchange rate returns in Chile, we estimate the exchange rate volatility during January 4th, 2000 and February 21st, 2020 sample period. We conclude that a switching regime in the exchange rate volatility behavior, based on an ARMA (0,1)-EGARCH(1,1) model and characterized by a persistent low-volatility state, is the most suitable model to analyze the exchange rate volatility in Chile. Then, we study the role of FX interventions in understanding the dynamics of exchange rate returns and their volatility by first discussing the significance of a set of domestic and external factors that explain the exchange rate returns and variance. We show that periods of high exchange rate volatility tend to correspond to local and foreign financial factors and traditionally have resulted in some form of FX intervention by the Central Bank of Chile. However, when taken as a average effect, FX interventions have a negligible impact on the exchange rate returns and variance.

In our last section, within a Local Projection setting, we move one step forward by looking at the persistence response to FX interventions on the returns and variable of the exchange rate to assess the effectiveness of FX interventions better. We show that the FX intervention of 2019 had a significant impact on the exchange rate dynamic, which is also reflected in the drop in the daily change in volatility and the resulting impact on the probability of being in a high volatility state, consistently with the authority's main goal when starting the intervention. Regarding the interventions of 2008 and 2011, whose purpose was to build international reserves for precautionary reasons, did not generate the same impact on the exchange rate returns and volatility, despite responding to similar objectives by the authority. In particular, the 2008 intervention is associated with an increase in the exchange rate daily return, consistent with what has been emphasized by Gamboa-Estrada (2019) and the idea that this intervention occurred during a period when the Chilean peso was internationally strong (Claro & Soto, 2013). However, the 2011 intervention has a negligible impact on the exchange rate returns. Moreover, the probability of being in a state of high exchange rate volatility increases after these interventions. This transitory drop in exchange rate volatility and subsequent increase in the probability of being in a high volatility state is particularly evident after the 2011 intervention.

Overall, our main findings are consistent with the existing literature that emphasizes that the impact of FX interventions on the exchange rate dynamic depends on the design of the intervention (Disyatat & Galati, 2007; García-Verdú & Zerecero, 2013; Janot & Macedo, 2016). Moreover, we provide a novel evidence regarding the 2019 FX intervention in Chile, and show that this intervention was effective in attending the authority's main goal. Concerning further research on this topic, we suggest measuring the non-linear effects of FX intervention (Viola et al. (2019)), and explore more in depth the role of different FX intervention designs, such as those focused on the spot versus forward FX market.

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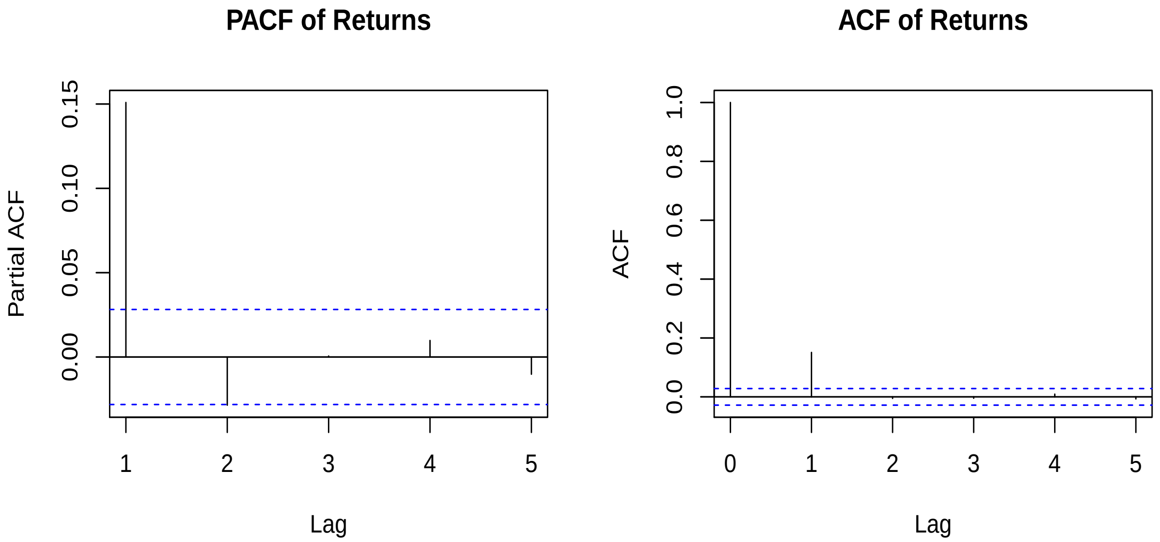
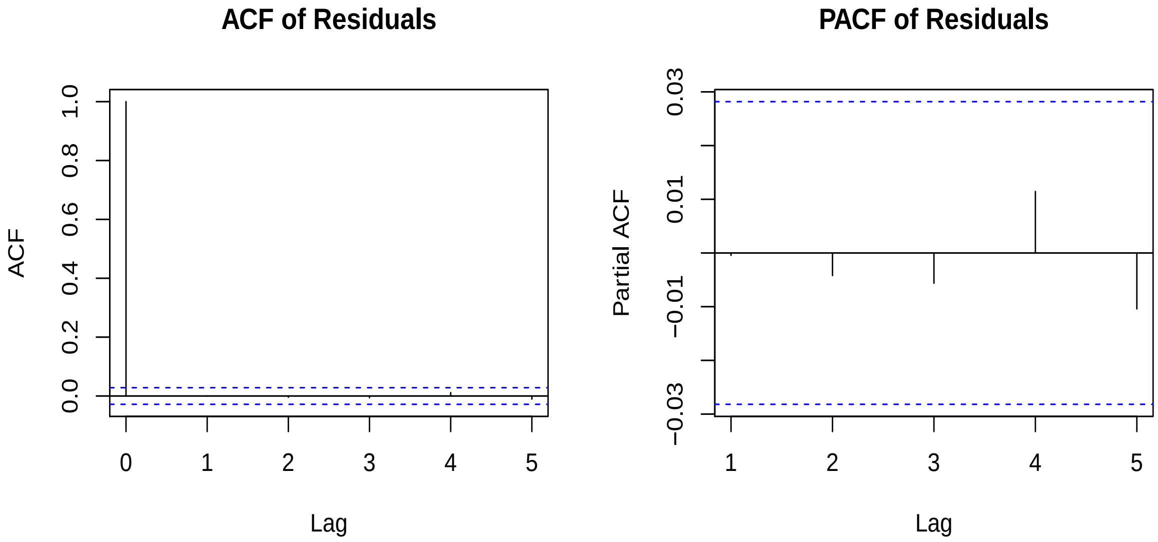
A Model selection

Figure A1. ACF and PACF on exchange rate returns



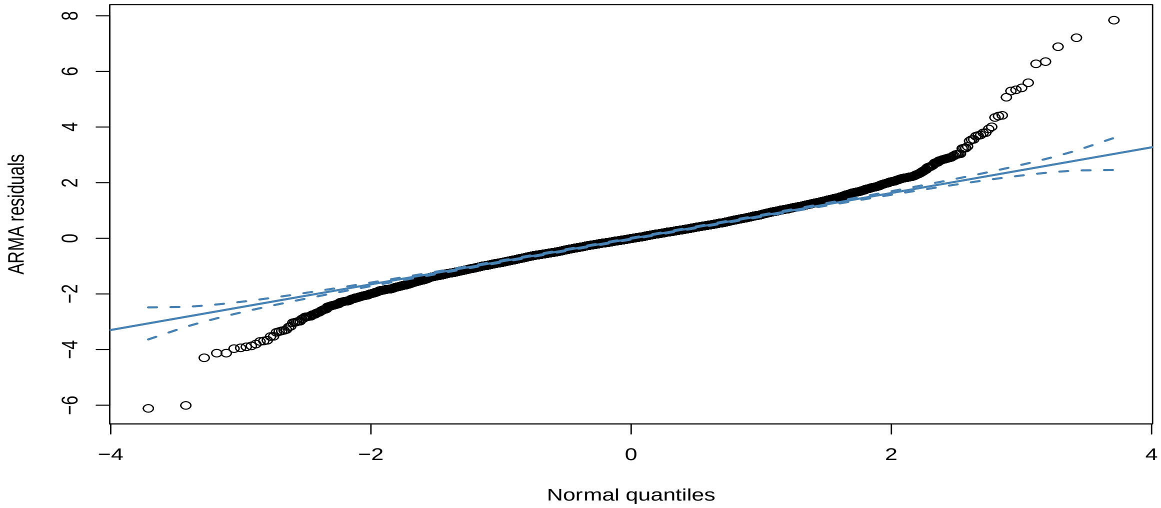
Notes: Autocorrelation functions suggest an ARMA(0,1) specification in the mean equation.

Figure A2. ACF and PACF on ARMA(0,1)'s residuals



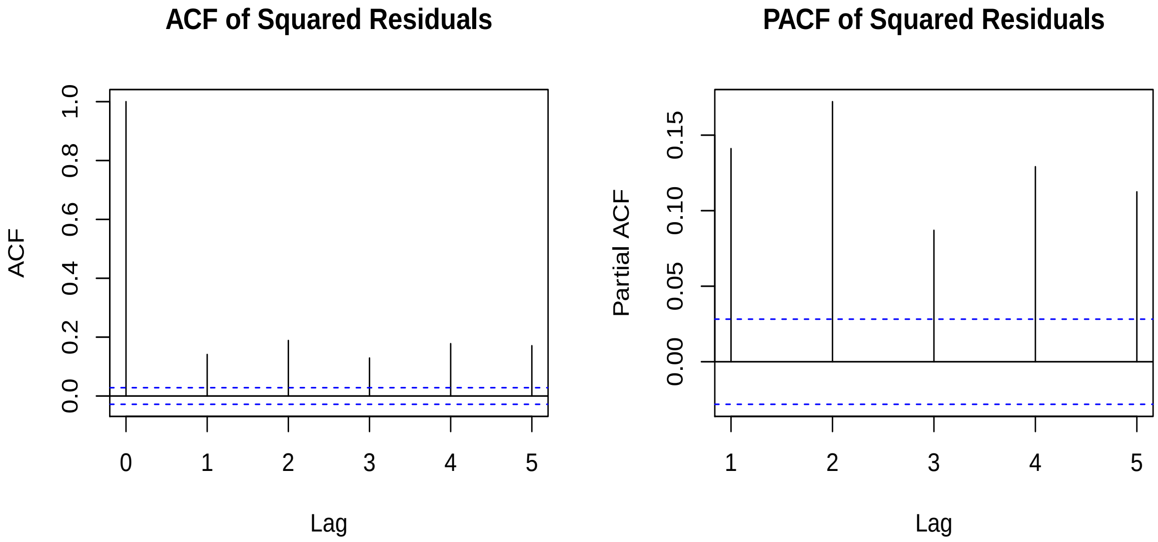
Notes: Autocorrelation functions on residuals suggest that the ARMA(0,1) specification has removed the autocorrelation.

Figure A3. QQ-plot on ARMA(0,1)'s residuals



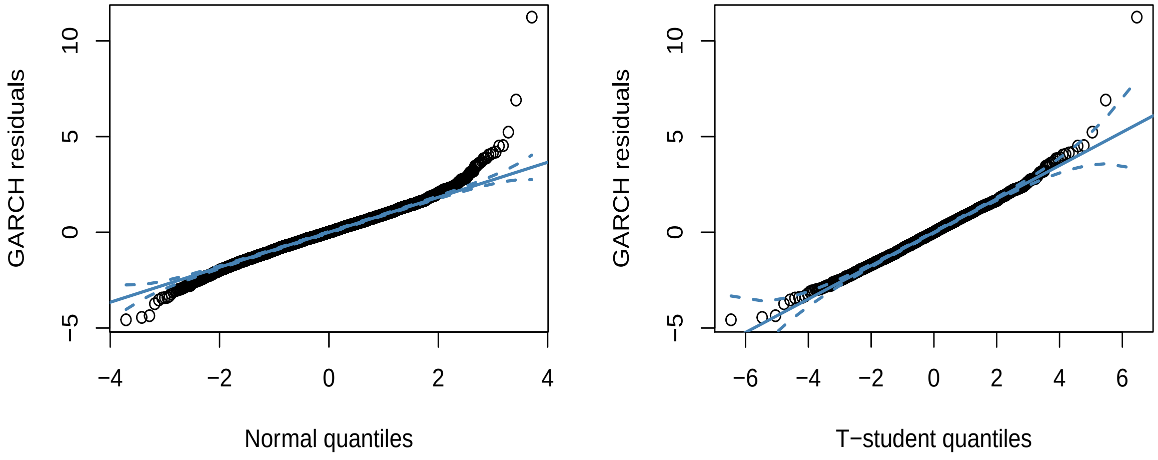
Notes: Figure shows that the residuals of the ARMA(0,1) doesn't match the normal distribution quantiles, specially on tails.

Figure A4. ACF and PACF on squared ARMA(0,1)'s residuals



Notes: Autocorrelation functions on ARMA(0,1) squared residuals suggest the existence of ARCH effects.

Figure A5. E-GARCH(1,1) residuals



Notes: Figure shows how well the t-Student distribution (right panel) can fit the residuals of the E-GARCH(1,1) estimates in comparison with the normal distribution (left panel).

B GARCH order

The Table B1 shows that the information criteria decrease as the order of the ARCH specification increases, which means that a GARCH(p,q) model should be more appropriate for estimating.

Table B1. ARCH

	ARCH(1)	ARCH(2)	ARCH(3)	ARCH(4)
c	0.0006	−0.0016	0.0003	−0.0022
	(0.0088)	(0.0086)	(0.0085)	(0.0084)
ϕ	0.1689^{***}	0.1566^{***}	0.1549^{***}	0.1562^{***}
	(0.0158)	(0.0153)	(0.0150)	(0.0147)
ω	0.2925^{***}	0.2351^{***}	0.2016^{***}	0.1810^{***}
	(0.0119)	(0.0106)	(0.0101)	(0.0102)
α_1	0.2308^{***}	0.1677^{***}	0.1347^{***}	0.1179^{***}
	(0.0311)	(0.0267)	(0.0251)	(0.0248)
α_2		0.2103^{***}	0.1678^{***}	0.1438^{***}
		(0.0282)	(0.0260)	(0.0253)
α_3			0.1647^{***}	0.1554^{***}
			(0.0258)	(0.0249)
α_4				0.1078^{***}
				(0.0231)
ν	5.2831^{***}	6.1449^{***}	6.5400^{***}	6.6820^{***}
	(0.3874)	(0.5129)	(0.5638)	(0.5828)
Log likelihood	−4173.2860	−4118.4681	−4080.7515	−4061.5246
AIC	1.7273	1.7050	1.6899	1.6823
BIC	1.7340	1.7131	1.6992	1.6930

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Information criteria in Table B2 indicates that the best order for the GARCH model is GARCH(1,1).

Table B2. GARCH

	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)
c	-0.0028	-0.0028	-0.0028	-0.0027
	(0.0080)	(0.0080)	(0.0080)	(0.0080)
ϕ	0.1483^{***}	0.1486^{***}	0.1483^{***}	0.1485^{***}
	(0.0146)	(0.0148)	(0.0146)	(0.0147)
ω	0.0041^{**}	0.0047^{**}	0.0041^{**}	0.0076^{**}
	(0.0013)	(0.0015)	(0.0014)	(0.0025)
α_1	0.0806^{***}	0.0961^{***}	0.0808^{***}	0.0892^{***}
	(0.0104)	(0.0142)	(0.0212)	(0.0141)
β_1	0.9116^{***}	0.6741^{***}	0.9115^{***}	0.0000
	(0.0114)	(0.1311)	(0.0137)	(0.1373)
β_2		0.2211		0.8340^{***}
		(0.1224)		(0.1243)
α_2			0.0000	0.0630^{**}
			(0.0250)	(0.0220)
ν	7.8191^{***}	7.8215^{***}	7.8138^{***}	7.8402^{***}
	(0.7734)	(0.7746)	(0.7734)	(0.7789)
Log likelihood	-3969.9497	-3969.7445	-3970.0510	-3969.3213
AIC	1.6436	1.6440	1.6441	1.6442
BIC	1.6517	1.6533	1.6535	1.6549

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Information criteria in Table B3 indicates that the best order for the EGARCH model is EGARCH(1,1).

Table B3. EGARCH

	eGARCH(1,1)	eGARCH(1,2)	eGARCH(2,1)	eGARCH(2,2)
c	0.0011	0.0010	0.0011	0.0010
	(0.0073)	(0.0081)	(0.0080)	(0.0080)
ϕ	0.1534^{***}	0.1533^{***}	0.1517^{***}	0.1520^{***}
	(0.0152)	(0.0151)	(0.0143)	(0.0143)
ω	-0.0270^{***}	-0.0276^{***}	-0.0263^{***}	-0.0391^{*}
	(0.0064)	(0.0063)	(0.0067)	(0.0175)
α_1	0.0297^{***}	0.0306^{***}	0.0681^{**}	0.0597^{***}
	(0.0090)	(0.0092)	(0.0241)	(0.0148)
β_1	0.9775^{***}	0.9463^{***}	0.9781^{***}	0.4633
	(0.0051)	(0.0201)	(0.0054)	(0.7931)
γ_1	0.1788^{***}	0.1833^{***}	0.1630^{***}	0.1862^{***}
	(0.0180)	(0.0175)	(0.0377)	(0.0269)
β_2		0.0307		0.5042
		(0.0191)		(0.7766)
α_2			−0.0417	−0.0180
			(0.0245)	(0.0466)
γ_2			0.0145	0.0801
			(0.0399)	(0.0871)
ν	7.8996^{***}	7.9000^{***}	7.9739^{***}	7.9717^{***}
	(0.7818)	(0.7822)	(0.7955)	(0.7949)
Log likelihood	−3951.6000	−3951.6331	−3950.1246	−3950.2878
AIC	1.6365	1.6369	1.6367	1.6372
BIC	1.6458	1.6476	1.6487	1.6506

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Information criteria in Table B4 indicates that the best order for the GJR-GARCH model is GJR-GARCH(1,1).

Table B4. GJR-GARCH

	gjrGARCH(1,1)	gjrGARCH(1,2)	gjrGARCH(2,1)	gjrGARCH(2,2)
c	0.0003	0.0003	0.0004	0.0003
	(0.0081)	(0.0081)	(0.0081)	(0.0081)
ϕ	0.1497^{***}	0.1500^{***}	0.1484^{***}	0.1486^{***}
	(0.0146)	(0.0148)	(0.0145)	(0.0147)
ω	0.0046^{**}	0.0054^{**}	0.0050^{**}	0.0058^{*}
	(0.0014)	(0.0017)	(0.0017)	(0.0027)
α_1	0.0991^{***}	0.1226^{***}	0.1026^{***}	0.1288^{***}
	(0.0139)	(0.0219)	(0.0288)	(0.0309)
β_1	0.9091^{***}	0.6178^{***}	0.9045^{***}	0.5791
	(0.0117)	(0.1855)	(0.0145)	(0.4098)
γ_1	-0.0352^{**}	-0.0446^{**}	-0.0745^{*}	-0.0866^{*}
	(0.0132)	(0.0172)	(0.0333)	(0.0407)
β_2		0.2710		0.3021
		(0.1732)		(0.3713)
α_2			0.0000	0.0000
			(0.0335)	(0.0604)
γ_2			0.0397	0.0431
			(0.0344)	(0.0519)
ν	7.9222^{***}	7.9331^{***}	7.9715^{***}	8.0112^{***}
	(0.7914)	(0.7944)	(0.8039)	(0.8101)
Log likelihood	−3966.0205	−3965.6420	−3964.8285	−3964.1343
AIC	1.6424	1.6427	1.6428	1.6429
BIC	1.6518	1.6534	1.6548	1.6563

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

BIC information criteria in Table B5 indicates that the best order for the TGARCH model is TGARCH(1,1), while AIC criteria indicates TGARCH(2,1) could better fit the data. However, we select model TGARCH(1,1) in order to facilitate the comparision with the other models.

Table B5. TGARCH

	tGARCH(1,1)	tGARCH(1,2)	tGARCH(2,1)	tGARCH(2,2)
c	0.0007	0.0007	0.0005	0.0005
	(0.0081)	(0.0081)	(0.0079)	(0.0079)
ϕ	0.1547^{***}	0.1548^{***}	0.1528^{***}	0.1528^{***}
	(0.0146)	(0.0148)	(0.0146)	(0.0146)
ω	0.0114^{***}	0.0127^{***}	0.0112^{**}	0.0119^{***}
	(0.0028)	(0.0031)	(0.0041)	(0.0033)
α_1	0.0944^{***}	0.1098^{***}	0.0872^{***}	0.0930^{***}
	(0.0103)	(0.0133)	(0.0178)	(0.0125)
β_1	0.9081^{***}	0.6898^{***}	0.8806^{***}	0.7868^{***}
	(0.0111)	(0.1024)	(0.0163)	(0.0134)
γ_1	-0.1867^{***}	-0.1912^{***}	-0.4668^{***}	-0.4292^{**}
	(0.0533)	(0.0537)	(0.1385)	(0.1604)
β_2		0.2042^{*}		0.0887^{***}
		(0.0961)		(0.0125)
α_2			0.0173^{**}	0.0201^{*}
			(0.0055)	(0.0090)
γ_2			0.7681	0.4592
			(0.5664)	(0.8144)
ν	7.8957^{***}	7.9128^{***}	8.0331^{***}	8.0412^{***}
	(0.7780)	(0.7816)	(0.8041)	(0.8056)
Log likelihood	−3951.8238	−3951.5068	−3949.1392	−3949.0902
AIC	1.6366	1.6368	1.6363	1.6367
BIC	1.6459	1.6476	1.6483	1.6501

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

C Regime switching model

Table C1. Regime switching volatility: MS(2)-EGARCH(1,1)

	MS(2)-EGARCH(1,1)	
Parameter	Regime 1	Regime 2
ω	-0.0259^{***}	0.0340^{*}
	(0.0066)	(0.0152)
γ	0.1123^{***}	0.1152^{*}
	(0.0212)	(0.0536)
α	0.0200^{*}	0.0551^{*}
	(0.0095)	(0.0320)
β	0.9850^{***}	0.9837^{***}
	(0.0048)	(0.0149)
ν	18.1324^{*}	6.6422^{**}
	(8.5593)	(2.6008)
$\pi_{1,1}$	0.9844^{***}	
	(0.0884)	
$\pi_{2,1}$	0.1555^{***}	
	(0.0060)	
Stable Prob	90.91%	9.09%
Log-like	-3942.1441	
AIC	1.6346	
BIC	1.6507	

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

$$\Pi = \begin{bmatrix} \pi_{1,1} = 0.9844 & \pi_{1,2} = 0.0156 \\ \pi_{2,1} = 0.1555 & \pi_{2,2} = 0.8445 \end{bmatrix} \tag{12}$$

In order to measure the quality of regime classification we use the regime classification measure (RCM) introduced by Ang & Bekaert (2002) and generalized by Baele (2005). It is defined as follows:

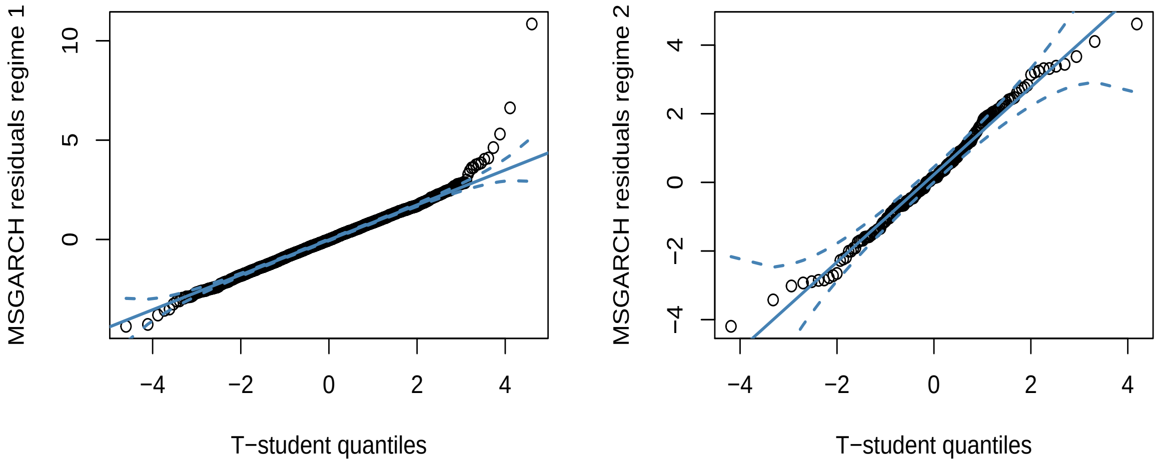
$$\text{RCM}(K) = 100 * \left(1 - \frac{K}{K-1}\frac{1}{T}\sum_{t=1}^{T}\sum_{k=1}^{K}\left(P(\sigma_{s,t} = \sigma_{k,t}|s = k) - \frac{1}{K}\right)^2\right)$$

Where K is the number of states, T is the length of the time series, $s \in K$ is the state indicator, and $k \in K$ is the current state. The RCM lies between 0 and 100, which value close to zero indicate a good measure for the underlying state of volatility.

Table C2. Regime classification

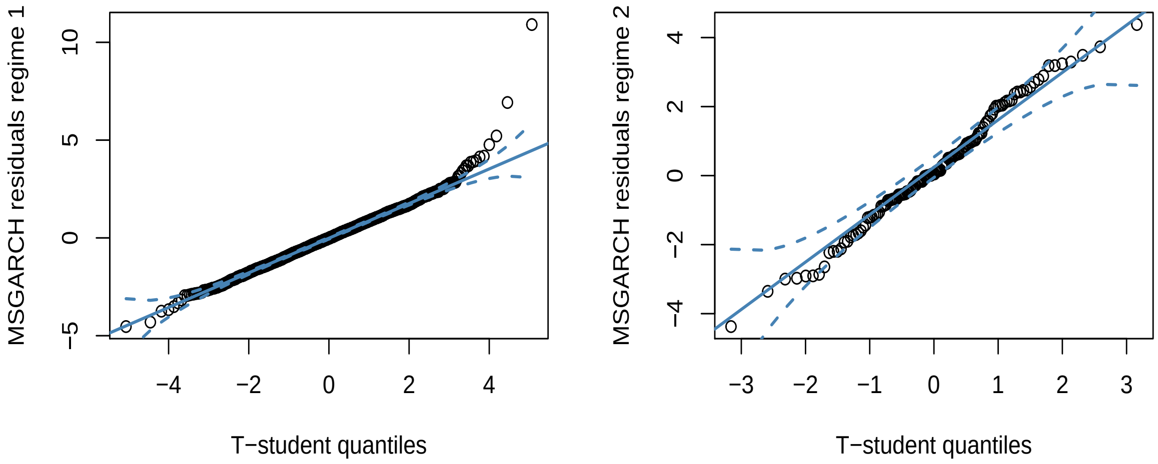
	MS-EGARCH (fixed ν)	MS-EGARCH (shifting ν)
RCM	10.0341	22.2029

Figure C1. MS(2)-EGARCH(1,1) (shifting ν)



Notes: Figure shows how well the t-Student distribution can fit the residuals of the MS-EGARCH(1,1) when ν is allowed to change between states.

Figure C2. MS(2)-EGARCH(1,1) (fixed ν)



Notes: Figure shows how well the t-Student distribution can fit the residuals of the MS-EGARCH(1,1) when ν is constant between states.

D Data

Table D1. Determinants of the exchange rate volatility

Factor	Variable	Description and source
Domestic	IPSA	The Selective Stock Price Index (IPSA) measures the price of the 40 most liquid stocks listed on the Santiago Stock Exchange. (Source: CBCh's website)
	DEPU	Uncertainty measure that captures the global disagreement in topics such as the economy, economic policies, uncertainty about particular events, and the current economic situation in Chile. (Source: Becerra et al. (2020))
	PCU	Copper price. In a copper-exporting country, such as Chile, the price of copper is a measure of external conditions. (Source: CBCh's website)
	EMBI Chile	Emerging Market Bond Index (EMBI) measures the spread between the return rates paid by Chilean's government bonds and US T-bills. (Source: CBCh's website)
External	Spread	Spread between Fixed-for-floating interest rate swaps that use the interest rate derived from the *Índice Cámara Promedio* called *Swaps Promedio Cámara* (SPC) and the overnight indexed swap (OIS) for the US. (Source: Bloomberg)
	USDX	The U.S. Dollar Index is a geometrically-averaged calculation of six currencies weighted against the US dollar. The U.S. Dollar Index contains six component currencies: the euro, Japanese yen, British pound, Canadian dollar, Swedish krona and Swiss franc. (Source: Bloomberg)
	VIX	The CBOE Volatility Index as a measure of global volatility derived from S&P 500 options. (Source: Bloomberg)

*Note.*The DEPU variable was kindly provided by the authors and covers the period Jan 12, 2012 to Jan 02, 2020 in daily frequency. The rest of the variables are available from January 4, 2000 to February 21, 2020.

E Volatility with external determinants

Table E1. Correlation matrix (2003-2020)

	ΔCOPPER	ΔIPSA	ΔEMBI	ΔUSDX	VIX	ΔSPREAD	FXI
ΔCOBRE	1.000	0.291	-0.161	-0.293	-0.079	-0.078	-0.029
ΔIPSA	0.291	1.000	-0.249	-0.137	-0.076	-0.096	-0.031
ΔEMBI	-0.161	-0.249	1.000	0.050	0.079	0.104	0.016
ΔUSDX	-0.293	-0.137	0.050	1.000	0.030	-0.097	0.014
VIX	-0.079	-0.076	0.079	0.030	1.000	0.008	0.162
ΔSPREAD	-0.078	-0.096	0.104	-0.097	0.008	1.000	0.005
FXI	-0.029	-0.031	0.016	0.014	0.162	0.005	1.000

Table E2. Volatility with external determinants

	(1)	(2)	(3)	(4)	(5)	(6)
Mean equation						
c	-0.0033	-0.0537^{***}	-0.0565^{***}	-0.0583^{**}	-0.0605^{***}	-0.0630
	(0.0087)	(0.0149)	(0.0125)	(0.0223)	(0.0131)	(0.0396)
ϕ	0.1612^{***}	0.1546^{***}	0.1602^{***}	0.1601^{***}	0.1595^{***}	0.1587^{***}
	(0.0160)	(0.0155)	(0.0137)	(0.0154)	(0.0148)	(0.0146)
Variance equation						
α	0.0138	0.0347^{***}	0.0222^{*}	0.0221^{*}	0.0221^{*}	0.0209^{*}
	(0.0101)	(0.0102)	(0.0097)	(0.0098)	(0.0098)	(0.0099)
β	0.9807^{***}	0.9748^{***}	0.9766^{***}	0.9765^{***}	0.9765^{***}	0.9758^{***}
	(0.0046)	(0.0055)	(0.0052)	(0.0052)	(0.0052)	(0.0054)
γ	0.1726^{***}	0.1844^{***}	0.1751^{***}	0.1748^{***}	0.1745^{***}	0.1749^{***}
	(0.0179)	(0.0180)	(0.0175)	(0.0176)	(0.0176)	(0.0177)
ν	7.9861^{***}	7.6535^{***}	8.0068^{***}	7.9941^{***}	7.9683^{***}	7.9841^{***}
	(0.8464)	(0.7851)	(0.8585)	(0.8568)	(0.8524)	(0.8568)
Log-like	-3929.6913	-3946.8667	-3926.9740	-3926.7338	-3926.3183	-3921.8560
AIC	1.6295	1.6357	1.6279	1.6287	1.6293	1.6300
BIC	1.6456	1.6491	1.6427	1.6461	1.6494	1.6581

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table E4 shows the estimates when considering the $SPREAD$ variable. It should be noted that the $SPREAD$ series is shorter and for that it is not considered in the main analysis. Also, the first column indicates that the variable is not statistically significant neither the mean or the variance equation. We consider dropping the VIX variable (given there is some correlation between these 2 variables) and estimate the regression again. We get the same result.

Table E3. Correlation matrix (2007-2020)

	ΔCOPPER	ΔIPSA	ΔEMBI	ΔUSDX	VIX	ΔSPREAD	FXI	DEPU
ΔCOBRE	1.000	0.337	-0.207	-0.323	-0.079	-0.123	-0.026	-0.025
ΔIPSA	0.337	1.000	-0.289	-0.166	-0.069	-0.167	-0.027	-0.026
ΔEMBI	-0.207	-0.289	1.000	0.067	0.089	0.192	0.016	0.032
ΔUSDX	-0.323	-0.166	0.067	1.000	0.030	-0.069	0.013	-0.002
VIX	-0.079	-0.069	0.089	0.030	1.000	0.003	0.124	0.277
ΔSPREAD	-0.123	-0.167	0.192	-0.069	0.003	1.000	0.004	0.002
FXI	-0.026	-0.027	0.016	0.013	0.124	0.004	1.000	0.378
DEPU	-0.025	-0.026	0.032	-0.002	0.277	0.002	0.378	1.000

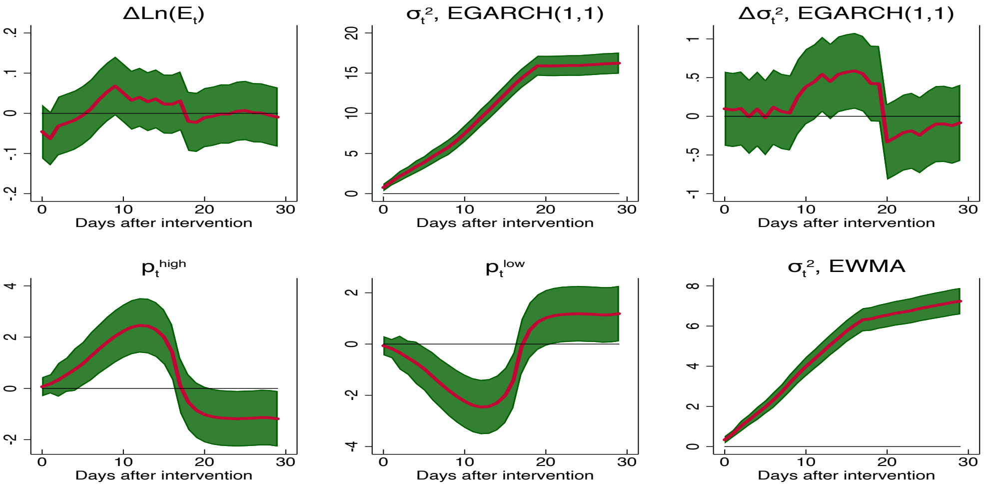
Table E4. Volatility with external determinants (including the interest rate spread and DEPU)

	Foreign variables (2003-2020)	Domestic variables (2007-2020)
Mean equation		
c	−0.0379	0.0068
	(0.0196)	(0.0120)
ϕ	0.1553***	0.1763***
	(0.0167)	(0.0190)
$\Delta USDX_m$	−0.0279	
	(0.0180)	
VIX_m	0.0025*	
	(0.0012)	
$SPREAD_m$	−4.1715	
	(8.5085)	
$\Delta Copper_m$		0.0311***
		(0.0065)
$\Delta IPSA_m$		−0.0145
		(0.0116)
$\Delta EMBI_m$		1.0818*
		(0.4439)
DEPU_m		−0.0244
		(0.0269)
Variance equation		
α	0.0345***	0.0223
	(0.0104)	(0.0122)
β	0.9745***	0.9830***
	(0.0052)	(0.0067)
γ	0.1677***	0.1507***
	(0.0168)	(0.0241)
$\Delta USDX_v$	−0.0121	
	(0.0236)	
VIX_v	0.0012**	
	(0.0004)	
$SPREAD_v$	10.0392	
	(15.3494)	
$\Delta Copper_v$		−0.0008
		(0.0088)
$\Delta IPSA_v$		−0.0184
		(0.0122)
$\Delta EMBI_v$		1.2956*
		(0.5421)
DEPU_v		0.0037
		(0.0074)
ν	7.6467***	7.4980***
	(0.8842)	(0.9569)
ω	−0.0448	−0.0153
Log likelihood	−3353.4033	−2678.2799
AIC	1.7031	1.7454
BIC	1.7222	1.7728

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

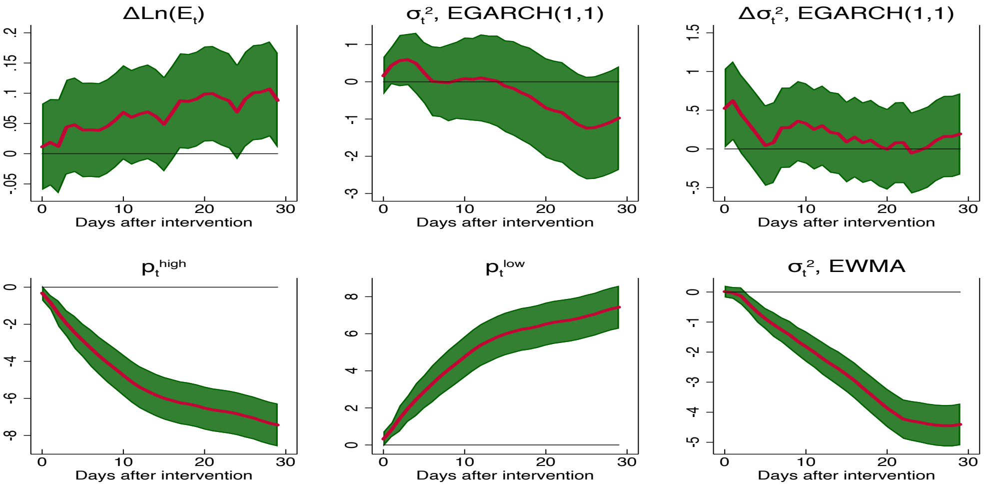
F Local Projections for alternative FX intervention events

Figure F1. Effectiveness of 2001 FX intervention



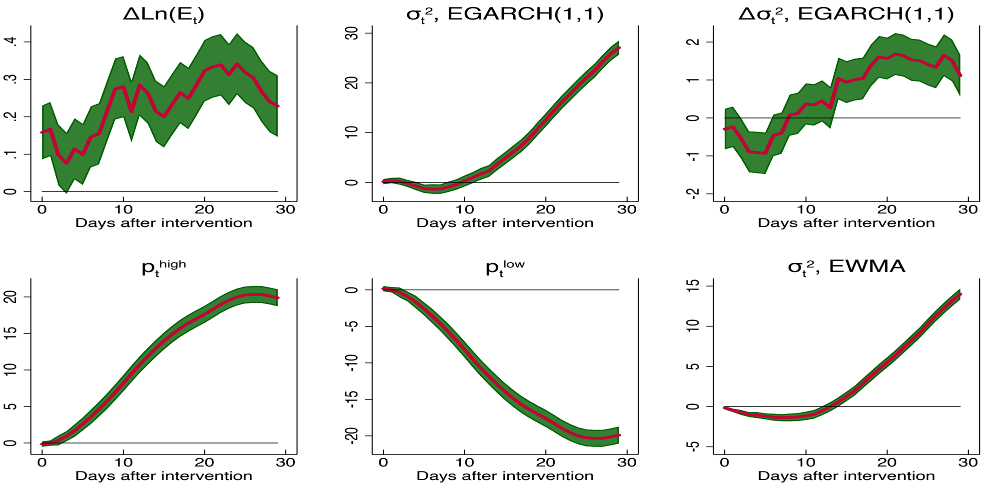
Notes: Authors' estimations based on equation 11.

Figure F2. Effectiveness of 2002 FX intervention



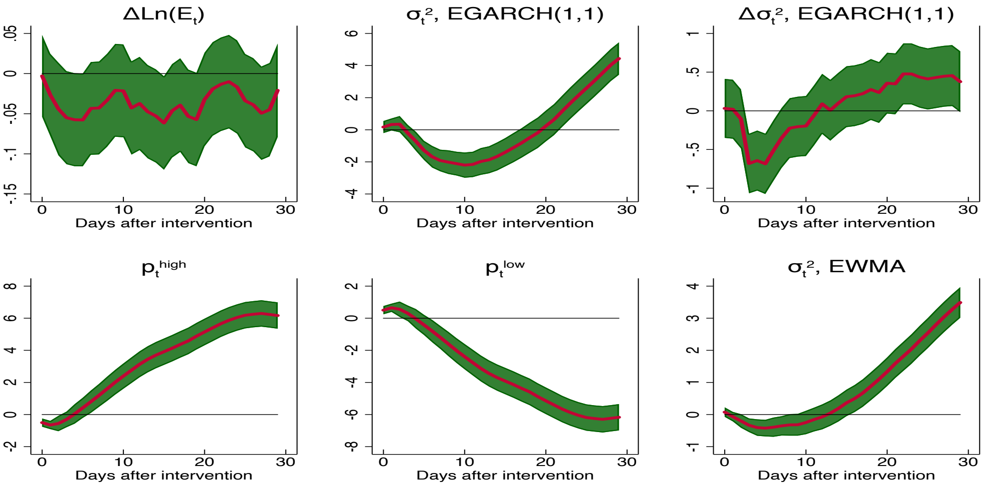
Notes: Authors' estimations based on equation 11.

Figure F3. Effectiveness of 2008 FX intervention



Notes: Authors' estimations based on equation 11.

Figure F4. Effectiveness of 2011 FX intervention



Notes: Authors' estimations based on equation 11.

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