HOW SENSITIVE IS VOLATILITY TO EXCHANGE RATE REGIMES?

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Abstract

It is usually conjectured that the nominal exchange rate should be more volatile under a free float than under a dirty float regime. This paper examines this issue for the Chilean economy. Specifically, in September 1999 the Central Bank of Chile eliminated the floating band for the nominal exchange rate, which operated since 1984, and established a free float. This lasted until the burst of the last Argentinean economic crisis in July 2001. Since then, the Central Bank has smoothed out the exchange rate path by selling US dollars and/or issuing US dollar-denominated bonds. We examine the free float period by assessing whether the increase in exchange rate volatility was as sharp as expected. We show that volatility went up, but only slightly.

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I Introduction

From August 1984 to September 1999, the exchange rate policy in Chile consisted of a floating band, whose center was the so-called reference exchange rate (*dolar acuerdo*). The value of the reference exchange rate was recalculated daily according to the fluctuations in the parities of a currency reference basket—comprised by the US dollar, the Japanese yen, and the Deutsche mark, and adjusted by the difference between domestic and foreign inflation. Even though the dirty float lasted for 15 years, the level and the rule for adjusting the reference exchange rate, as well as the width of the floating band, experienced many changes through time.[2] The floating band was finally eliminated on September 2, 1999.

Economic agents conjectured that the volatility of the nominal exchange would dramatically increase after eliminating the floating band. As a matter of fact, during the dirty float the Central Bank of Chile played an active role in the exchange rate market by buying or selling US dollars, whenever the exchange rate was either approaching the bottom or the upper bound of the band, respectively. Such policy implicitly provided exchange rate hedging to economic agents, and prevented the nominal exchange rate from experiencing sharper fluctuations.

However, a quick inspection of the evolution of the nominal exchange rate suggests that the increase in volatility was not as evident as predicted. For example, the period of greatest volatility between January 1995 and December 2000 was January 1998, when the domestic financial system became extremely illiquid due to the interest rate policy of the Central Bank of Chile. The exchange rate was also highly volatile around June 1999, that is, two months prior to eliminating the floating band.

During the free float period, August 2000 stood out for its high volatility, which might have been a consequence of an increasing oil price. (Around that time, the oil price reached a peak of US$37.4 per barrel). In mid-July 2001, the exchange market experienced extreme volatility due to the burst of the Argentinean economic crisis. Since then the Central Bank of Chile has intervened in the exchange rate market by issuing dollar-denominated bonds and by selling dollars in the spot market. Therefore, the free float was actually at work between September 1999 and mid-July 2001. This is the focus of this study.

II Evolution of the Chilean nominal exchange rate over the last decade

In this section, we analyze the evolution of the Chilean peso/US dollar exchange over the last 10 years. Table 1 gives account of the Central Bank of Chile’s exchange rate policy, which was briefly described in the Introduction, from the 1970’s to date. Some summary statistics for the daily figures of the observed market exchange rate are shown in Table 2. This is an average of the nominal exchange rate for all purchases and sales

[2] A dirty float is a type of floating exchange rate that is not completely free because Central Banks interfere occasionally to alter the rate from its free-market level.

transactions carried out by commercial banks and money exchanges with third parties the previous business day. Over our sample period, September 1991-September 2001, the nominal exchange rate reached a minimum of Ch$337.74 per US dollar, and a maximum of Ch$ 695.21 per US dollar. The sample mean was Ch$ 446.82 per US dollar. Approximately, 78 percent of the observations fell into the [300, 500) interval, whereas only 4.2 percent were between Ch$600 and Ch$700 per US dollar. The graphical representation of the data is in Figure 1.

[**Tables 1 and 2; Figure 1 about here**]

Three different estimates of daily volatility of the 'real' exchange rate (S_t) are shown in Table 3. This series is obtained by deflating the nominal exchange rate by a proxy of daily inflation (UF)[3]. The exponentially weighted moving average (EWMA) estimator is defined as:

$$\sigma_{ewma} = \sqrt{\sum_{t=1}^{T} \frac{\lambda^{t-1}}{\sum_{j=1}^{T} \lambda^{j-1}} (S_t - \bar{S})^2} \tag{1}$$

where λ is obtained by minimizing the (daily) root mean squared prediction error ($RMSE_v$):

$$RMSE_v = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (S_{t+1} - \hat{S}_{t+1|t}(\lambda))^2} \tag{2}$$

The one-day real exchange rate forecast, given the data available at time t (that is, one day earlier), is given by:

$$\hat{S}_{t+1|t} = \lambda \hat{S}_{t|t-1} + (1-\lambda) S_t \tag{3}$$

with the initial condition $\hat{S}_{2|1} = S_1$.

In order to estimate the optimal λ, we carried out a grid search over the interval [0.01, 0.99], with a step of 0.01. By using the data from the whole sample period, we found an estimate of λ equal to 0.51. The volatility series was constructed from equation (1) by taking T=20 (the average number of business days in a month), and plugging in the estimate of λ. $\bar{S}$ is the sample mean of the 20 observations taken each time.[4]

The equally weighted (EW) estimate of the volatility is calculated from equation (1) by setting λ=1. That is to say,

[3] *Unidad de Fomento* (UF) is an inflation-indexed accounting unit, which was created in August 1977. Its value is daily adjusted according to the previous month inflation, expressed in a daily basis.

[4] In order to find λ and construct the volatility series, we use the statistical package S-Plus 6.0.

$$\sigma_{ew} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(S_t - \bar{S})^2} \qquad (4)$$

Finally, the naïve estimate is calculated as the absolute value of the daily change in the real exchange rate:

$$\sigma_{naïve} = |S_t - S_{t-1}| \qquad (5)$$

[Table 3 about here]

As we see, one interesting feature of the EWMA estimator is that it is able to better capture periods of high volatility. For example, in January 1998, as a consequence of the Asian crisis, the domestic banking sector experienced extreme illiquidity, which translated into over-night lending rates around 100 percent, in real terms. On the other hand, by July 2001 it became clear that Argentina would sooner or later default, and probably devaluate its currency against the US dollar. As a consequence, not only Chilean economic agents took larger positions in the US dollar, but also Argentinean companies fled to Chile to find shelter in the US currency. Figure 2 illustrates the three series described above.

[Figure 2 about here]

In practice, the level of nominal exchange rate appears to be highly correlated with the price of copper (one of Chile's most important export products), and with the currency risk of other Latin American economies, such as Argentina's. However, such correlations do not show a consistent pattern through time. For instance, for February 1999-October 2001, the correlation coefficient between the price of copper and the nominal exchange rate was –0.12. However, this negative value heavily depended on the period June-October 2001, for which the sample correlation reached –0.93. If one looks at a moving average estimate of the correlation coefficient of both series finds that the mean is only –0.005, while the skewness of the sample distribution is 0.108.

In turn the sample correlation coefficient between the nominal exchange rate and Argentina's EMBI is about 85.6 percent for the sampling period August 1999-mid October 2001. Such large figure was mostly influenced by the observations of the period June-mid October 2001, which covered the beginning of the Argentinean crisis. Indeed, the sample correlation coefficient drops to 54.5 percent when calculated for August 1999-May 2001.

Nevertheless, in neither case does the correlation coefficient show a predictable pattern. This is depicted in Figure 3, panels (a) and (b). We calculated equally weighted moving averages correlations coefficients between the price of copper and the exchange rate, and between Argentina's EMBI and the exchange rate, by taking moving blocks of 20 observations. This finding is not surprising, given that we would expect the behavior of the nominal exchange rate—like that of any other financial series—to be rather unpredictable. We did the same exercise for the moving average correlation coefficient between the Chilean and Brazilian exchanges rates against the US dollar (Figure 3, panel (c)), and reached to a similar conclusion.

[Figure 3 about here]

Given the above evidence, in the following sections we model the dynamics of the nominal exchange rate as a function of itself, without resorting to other macroeconomic variables. In particular, we will try to answer the question about whether the nominal exchange became more volatile during the free float.

III Alternative Methods to Measure Volatility

3.1 Intraday Data

In order to have a better grasp of the dynamics of the exchange rate, we resorted to intraday data available from OTC trade. This is an electronic system that began to operate in Chile in January 2001. Unlike Bloomberg, OTC provides with information on the daily trading volume. The volume traded on the system accounts for about a fifth of all spot transactions within a day. The users of OTC trade are commercial banks. Electronic transactions usually start at 9:00 AM and end at 5:00 PM. The trading volume fluctuates sharply from day to day, and transactions take place at irregular time intervals. For instance, they may be spaced by one, five minutes, or sometimes even by an hour.

The trading volume was relatively small when OTC trade began to operate. The largest amount traded in January 2001 was US$189 million while the minimum reached US$3 million (purchases and sales are equally treated). From February 2001 onwards, however, the trading volume was much higher, reaching an average of US$322.1 million per day during 2001. The trading volume peak—about US$700 million—took place at the beginning of July 2001, when the Argentinean crisis set off a period of turbulence in the domestic exchange rate market.

The evolution of electronic trading is depicted in Figure 4, Panel (a). The figure also shows the daily turnover of forwards traded domestically (Chilean peso/US dollar and *Unidad de Fomento*/US dollar). The maximum daily turnover was reached at the beginning of October 2001, a highly volatile period. Monthly electronic trading of the US$/Ch$ exchange rate averaged 23 percent of the total spot transactions over January-September 2001. In turn Panel (b) shows monthly data of total trading in the domestic forward market, as a percentage of the spot market, for the period January 1993-December 2001. A peak is observed over 1997, which coincides with the outburst of the Asian crisis. At present, forwards trading amounts to approximately 40 percent of the spot market.

[Figure 4 about here]

We next looked at three different measures of volatility for the intraday data of the nominal exchange rate: the range, the interquartile range, and the standard deviation. As we pointed out, transactions on the electronic system take place at irregular times. Therefore, our volatility measures were computed for the prices observed on a particular day, regardless of how many transactions took place and of what the trading volume was on that day.

The price range on day t is defined as:

$$range_t = S_{max,t} – S_{min,t}, \quad (6)$$

where $S_{max,t}$ and $S_{min,t}$ are the maximum and the minimum exchange rate observed on day t, respectively.

The interquartile range on day t is in turn defined as:

$$IQ\ range_t = Q_{3t} – Q_{1t}, \quad (7)$$

where Q_{3t} and Q_{1t} are the third and first quartile of the sample on day t, respectively.

Finally, the standard deviation is defined as usual:

$$\sqrt{Stdev_t = \frac{1}{n-1}\sum_{i=1}^{n}(S_{it} - \bar{S})^2}\ . \quad (8)$$

For the sample period January-December 2001, we computed the three volatility measures described above for every day. They are depicted in Figure 5. As we see, the standard deviation and interquartile range move relatively close to one another, while the range displays a much higher magnitude of fluctuation per day. Table 5 presents some summary statistics for the three volatility estimates.

[Figure 5; Table 4 about here]

Our computations show that the mean of the range, IQ range, and of the standard deviation were Ch$4.59, 1.38, and 0.99, respectively, while the maxima were Ch$26.00, 11.41, and 8.01, respectively. The three estimates presented much lower dispersion when it came to the minima: 0.2, 0.13, and 0.1, respectively.

But, which estimate should we rely upon? In a recent article, Alizadeh, Brandt, and Diebold (2001) show, based upon results by Feller (1951) and Karatzas and Shreve (1991), that the price range is a highly efficient volatility proxy, and that the natural logarithm of the price range (log range) is approximately Gaussian.

In order to have more information about the evolution of the price range, we relied on data on the maximum and the minimum price (Ch$/US$) from Bloomberg, which is available on a daily basis from November 1996 to December 2001. As a matter of comparison between the price range and the estimates of the previous section, we computed the absolute value of the difference between the EWMA estimate and the price range, and the absolute value of the difference between the naïve and the EWMA estimates.

Table 5 shows one-way tabulations for both series. Most observations of the absolute distance between the EWMA estimate and the price range fell into the [0, 5) interval. In addition, the EWMA estimate moved closer to the price range than did to the naïve estimate. As we know, the naïve estimate measures the absolute difference between the average exchange rate observed today and on the previous business day. Therefore, it does not capture the fluctuation in the exchange rate for horizons longer than one day, and it does not capture how volatile the exchange rate might have been within one day either. So, it is not surprising that the naïve estimate appears to be a poorer proxy of volatility.

[Table 5 about here]

3.2 Daily Data

In this section we will resort to daily data to model volatility because that allows us to analyze a longer time period. As mentioned earlier, we have intraday data only for 2001, and electronic transactions occur at rather irregular points in time. This makes it hard to construct return series (e.g., five-minute returns) as it is customary in the literature of intraday volatility. However, we will use intraday measures of volatility, such as the price range, to assess the forecasting performance of each model proposed in the next section.

3.2.1 GARCH-type Models

In what follows, we will fit alternative volatility models to the data in order to have a better grasp of which one might be best in terms of forecast ability. We consider a subset of the models estimated by Bali (2000) in a paper on stochastic models of the short-term interest rate, and also resort to alternative functional forms suggested by other authors. Using our notation Bali's two-factor discrete time stochastic volatility model becomes:

$$S_t - S_{t-1} = \alpha_0 + \alpha_1^+ S_{t-1}^+ + \alpha_1^- S_{t-1}^- + \sqrt{h_t}\, z_t\,,\ \varepsilon_t = \sqrt{h_t}\, z_t\,, \text{ and } z_t \overset{iid}{\sim} N(0,1)\,, \qquad (9)$$

where $S_t^+ = \begin{cases} S_t & \text{if } \Delta S_t > 0 \text{ or } S_t > S_{t-1} \\ 0 & \text{if } \Delta S_t \le 0 \text{ or } S_t \le S_{t-1} \end{cases}$

and $S_t^- = \begin{cases} S_t & \text{if } \Delta S_t \le 0 \text{ or } S_t \le S_{t-1} \\ 0 & \text{if } \Delta S_t > 0 \text{ or } S_t > S_{t-1} \end{cases}$

From equation (9), the conditional distribution of the change in the exchange rate ΔS_t is normal, and given by $\Delta S_t | S_{t-1} \sim N(\alpha_0 + \alpha_1^+ S_{t-1}^+ + \alpha_1^- S_{t-1}^-,\ h_t)$. In addition, the drift of the diffusion function of the exchange rate is asymmetric, given that the conditional mean of ΔS_t depends on the sign of ΔS_t when $\alpha_1^+ \neq \alpha_1^-$. When $\alpha_1^+ = \alpha_1^-$, the exchange rate follows a linear mean-reverting drift. Different functional forms for h_t can be considered. For example, Bali estimates models 1 through 8. Alternative functional forms are models 9 through 12. For further discussion of these and other volatility models, see Franses and van Dijk (2000), Ball and Torous (1999), and Mills (1999):

Model 1 (GARCH): Linear symmetric generalized ARCH(1,1) due to Bollerslev (1986) and Taylor (1986),

$$h_t = \beta_0 + \beta_1\varepsilon_{t-1}^2 + \beta_2 h_{t-1}, \qquad (10)$$

where $\beta_0>0$, $0\leq\beta_1<1$, $0\leq\beta_2<1$, and $\beta_1+\beta_2<1$.

In this case, the conditional variance h_t is defined as a linear function of last period's unexpected news, ε_{t-1} and last period's volatility, h_{t-1}. Moreover, the model implies that the impact of an exchange rate shock on current volatility declines geometrically over time.

Model 2 (NGARCH): nonlinear asymmetric GARCH,

$$h_t = \beta_0 + \beta_1(\varepsilon_{t-1} + \theta\sqrt{h_{t-1}})^2 + \beta_2 h_{t-1}, \qquad (11)$$

where $\beta_0>0$, $0\leq\beta_1<1$, $0\leq\beta_2<1$, $\beta_1+\beta_2<1$, and $\theta>0$.

Under this functional form, the conditional variance is a nonlinear asymmetric function of unexpected shocks to the exchange rate. Given that $\theta>0$, a positive shock on the exchange rate causes more volatility than a negative shock of the same size.

Model 3 (VGARCH). This model also defines the conditional variance as a nonlinear asymmetric function of unexpected news in the exchange rate market,

$$h_t = \beta_0 + \beta_1(\varepsilon_{t-1}/\sqrt{h_{t-1}} + \theta)^2 + \beta_2 h_{t-1}, \qquad (12)$$

where $\beta_0>0$, $0\leq\beta_1<1$, $0\leq\beta_2<1$, $\beta_1+\beta_2<1$, and $\theta>0$. The parameter θ allows for asymmetric volatility response to past positive and negative exchange rate shocks. Specifically, given that $\theta>0$, positive shocks ($\varepsilon_{t-1}>0$) are followed by greater increases in variance than equally large negative shocks ($\varepsilon_{t-1}<0$).

Both the NGARCH and VGARCH models were proposed by Engle and Ng (1993).

Model 4 (AGARCH): Engle (1990)'s Asymmetric GARCH model,

$$h_t = \beta_0 + \beta_1(\varepsilon_{t-1} + \theta)^2 + \beta_2 h_{t-1}, \qquad (13)$$

where $\beta_0>0$, $0\leq\beta_1<1$, $0\leq\beta_2<1$, $\beta_1+\beta_2<1$, and $\theta>0$. It is similar in nature to the VGARCH model. Given that $\theta>0$, a positive shock is followed by a greater increase in variance than an unexpected negative shock of similar magnitude.

Model 5 (QGARCH): Quadratic GARCH of Sentana (1995),

$$h_t = \beta_0 + \beta_1\varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \theta\varepsilon_{t-1}, \qquad (14)$$

where $\beta_0>0$, $0\leq\beta_1<1$, $0\leq\beta_2<1$, $\beta_1+\beta_2<1$, and $\theta>0$.

This model ensures positivity of the conditional variance because it corresponds with a second-order Taylor approximation to h_t. Like in the AGARCH model, positive shocks have greater impact on h_t than negative shocks.

Model 6 (GJR-GARCH): Threshold GARCH model of Glosten, Jagannathan, and Runkle (1993),

$$h_t = \beta_0 + \beta_1\varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \theta S_{t-1}^{+}\varepsilon_{t-1}^2, \qquad (15)$$

$S_{t-1}^{+} = 1$ if $\varepsilon_{t-1}>0$, and $S_{t-1}^{+} = 0$ otherwise

where $\beta_0>0$, $0\leq\beta_1<1$, $0\leq\beta_2<1$, and $\theta>0$.

This model allows positive and negative shocks to have different impacts on conditional variance. In particular, positive (negative) innovations increase (decrease) the variance of changes in the exchange rate.

Model 7 (TGARCH): Threshold GARCH model of Zakoian (1994),

$$\sqrt{h_t} = \beta_0 + \beta_1^{+}\varepsilon_{t-1}^{+} - \beta_1^{-}\varepsilon_{t-1}^{-} + \beta_2\sqrt{h_{t-1}}, \qquad (16)$$

$\varepsilon_{t-1}^{+} = \max(0, \varepsilon_{t-1})$ and $\varepsilon_{t-1}^{-} = \min(0, \varepsilon_{t-1})$.

where $\beta_0>0$, $\beta_1^{+} \geq 0$, $\beta_1^{-} \geq 0$, and $0\leq\beta_2<1$. In this model, the conditional standard deviation or volatility, $\sqrt{h_t}$, is parameterized as a linear function of past positive and negative shocks of the nominal exchange rate as well as lagged standard deviations. In particular, the conditional standard deviation is allowed to respond asymmetrically to past and negative innovations. If, for example, $\beta_1^{+} > \beta_1^{-}$, both negative and positive shocks increase volatility, but positive shocks have a greater impact.

Negative shocks having a positive effect on volatility is known as the leverage effect (e.g. Black (1972), Christie (1982)). The intuition goes as follows: a decline in stock prices (in relation to bond prices) leads to an increase of firms leverage, and consequently to an increase of stock returns volatility (see French, Schwert, and Stambaugh (1987) for a discussion).

Model 8 (TS GARCH): Taylor (1986) and Schwert (1989)'s GARCH model,

$$\sqrt{h_t} = \beta_0 + \beta_1|\varepsilon_{t-1}| + \beta_2\sqrt{h_{t-1}}, \qquad (17)$$

where $\beta_0>0$, $0\leq\beta_1<1$, $0\leq\beta_2<1$, $\beta_1+\beta_2<1$, and $|\varepsilon_{t-1}|$ is the absolute value of the lagged residual. This functional form is a particular case of the TGARCH model, in which $\beta_1^+=\beta_1^-$. One feature of this model is that it does not allow asymmetric responses to positive and negative shocks.

Model 9 (EGARCH): The Exponential GARCH (EGARCH), proposed by Nelson (1990), is the earliest variant of the GARCH model. The EGARCH(1,1) is given by:

$$\ln(h_t) = \beta_0 + \beta_1 \ln(h_{t-1}) + \theta_1 \left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \theta_2 \frac{\varepsilon_{t-1}}{h_{t-1}}, \qquad (18)$$

$$\Leftrightarrow \qquad h_t = \exp\left(\beta_0 + \beta_1 \ln(h_{t-1}) + \theta_1 \left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \theta_2 \frac{\varepsilon_{t-1}}{h_{t-1}}\right).$$

Under this specification, the conditional variance is guaranteed to be non-negative. The news impact is asymmetric if $\theta \neq 0$. Specifically, negative shocks have an impact of $\theta-\beta_2$, while for positive shocks the impact is $\theta+\beta_2$.

In particular, we fit an EGARCH (2,1) model to our data:

$$\ln(h_t) = \beta_0 + \beta_1 \ln(h_{t-1}) + \beta_2 \ln(h_{t-2}) + \theta_1 \left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \theta_2 \frac{\varepsilon_{t-1}}{h_{t-1}}. \qquad (19)$$

Model 10 (ESTGARCH): Gonzalez-Rivera (1998) is one the earliest references on the Smooth Transition GARCH models (STGARCH). Under the GJR-GARCH model, the coefficient on the lagged squared innovation changes abruptly from β_2 to $\beta_2+\theta$ at $\varepsilon_{t-1}=0$. The STGARCH model by contrast allows a more gradual change of the coefficient on ε_{t-1}^2. For example, the Exponential STGARCH (ESTGARCH) is given by:

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 (1 - F(\varepsilon_{t-1})) + \beta_2 \varepsilon_{t-1}^2 F(\varepsilon_{t-1}) + \beta_3 h_{t-1} \qquad (20)$$

where $\beta_0>0$, $(\beta_1+\beta_2)/2 \geq 0$, $\beta_3>0$, $(\beta_1+\beta_2)/2 + \beta_3<1$, and $F(\varepsilon_{t-1}) = 1 - \exp(-\theta\,\varepsilon_{t-1}^2)$, $\theta>0$, is the exponential function.

The function F(.) changes from 1 for large negative values of ε_{t-1} to 0 for $\varepsilon_{t-1}=0$, and increases back again to 1 for large positive values of ε_{t-1}. This implies that the coefficient on ε_{t-1}^2 changes from β_2 to β_1, and then goes back to β_2. This functional form allows to model asymmetric effects of large and small shocks on conditional volatility.

Model 11 (Component GARCH): As described by Mills (1999), the Component GARCH states that in the GARCH(1,1) model the conditional variance h_t shows mean reversion to some constant level η,

$$h_t = \overline{\eta} + \beta_1(\varepsilon_{t-1}^2 - \overline{\eta}) + \beta_2(h_t - \overline{\eta}).$$

By contrast, the component model allows mean reversion to a varying level q_t, which is given by:

$$h_t - q_t = \beta_1(\varepsilon_{t-1}^2 - \eta) + \beta_2(h_t - \eta) \quad (21a)$$

$$q_t = \eta + \rho(q_{t-1} - \eta) + \phi(\varepsilon_{t-1}^2 - h_{t-1}) \quad (21b)$$

Under this specification, q_t is the time varying long-run volatility. Equation (21a) describes the transitory component, $h_t – q_t$, which converges to zero with powers of $\beta_1+\beta_2$. Equation (21b) describes the long-run component q_t, which converges to η with powers of ρ. In practical applications, ρ is between 0.99 and 1, so convergence to the long run volatility is slow.

From equation (21a), we get that $q_t = h_t - \beta_1(\varepsilon_{t-1}^2 - \eta) - \beta_2(h_t - \eta)$. Then, we can substitute q_t and its first lag into equation (21b) to obtain the following expression:

$$h_t = (1-\beta_1-\beta_2)(1-\rho)\eta + (\beta_1+\phi)\varepsilon_{t-1}^2 - (\beta_1\rho + (\beta_1+\beta_2)\phi)\varepsilon_{t-2}^2 + (\beta_2-\phi)h_{t-1}$$

$$-(\beta_2\rho-(\beta_1+\beta_2)\phi)h_{t-2}. \quad (22)$$

Equation (22) shows that the component model is a nonlinear restricted GARCH(2,2) model.

The estimation results are shown in Table 6, panels (a) and (b). Except for the EGARCH and GARCH-component, and Kalman-filter models, which were estimated with E-Views 4.0, all other functional forms were fitted to the data by the maximum likelihood procedure of TSP 4.5. As the estimation results show, almost all coefficients of the different models are statistically significant at conventional significance levels. In addition, there is enough support for the hypothesis of an asymmetric drift of the diffusion function.

By combining our previous approach and Ball and Torous (1999)'s, we next assume the following functional form for the exchange rate dynamics:

<u>Model 12 (the Kalman filter approach)</u>:

$$S_t - S_{t-1} = \alpha_0 + \alpha_1^+ S_{t-1}^+ + \alpha_1^- S_{t-1}^- + S_{t-1}^{\gamma}\sqrt{h_t}\, z_{1,t} \quad (23a)$$

$$\ln(h_t) - \mu = \beta(\ln(h_{t-1}) - \mu) + \xi\, z_{2t} \quad (23b)$$

where z_{1t} and z_{2t} are i.i.d standard normal. As before, the parameters α_0, α_1^+ and α_1^- characterize the exchange rate drift, and the parameter γ allows volatility of ΔS to depend on the lagged level of the exchange rate. Equation (24b) states that $\ln(h_t)$ follows an AR(1) process, which reverts to its unconditional mean μ at rate β, and that $Var(\ln(h_t)|\ln(h_{t-1}))=\xi^2$.

Ball and Torous propose to estimate equations (23a) and (23b) by a two-step procedure. In the first step, we run a regression of $\Delta S_t \equiv S_t - S_{t-1}$ on a constant, S^{+}_{t-1}, and S^{-}_{t-1}. The error term $\upsilon_t \equiv S^{\gamma}_{t-1}\sqrt{h_t}\, z_{1,t}$ has expectation zero. Therefore, the least square estimates of α_0, α^{+}_1, and α^{-}_1 are consistent, although not fully efficient. In the second step, we define $x_t=\ln(h_t)$, and construct $\hat{\upsilon}_t = \Delta S_t - \hat{\alpha}_0 - \hat{\alpha}^{+}_1 S^{+}_{t-1} - \hat{\alpha}^{-}_1 S^{-}_{t-1}$. Consequently, equation (23a) can be written as:

$$\hat{\upsilon} = S^{\gamma}_{t-1}\sqrt{h_t}\, z_{1,t} \qquad (23a')$$

If we square both sides of (23a') and take logs, we get:

$$\ln(\hat{\upsilon}) = x_t + 2\gamma \ln(S_{t-1}) + \ln(z^2_{1t}) \qquad (24a)$$

In turn equation (23b) becomes:

$$x_t - \mu = \beta(x_{t-1} - \mu) + \xi\, z_{2t} \qquad (24b)$$

The error term of equation (24a) is not normally distributed, but chi-square with one degree of freedom. Still, equations (24a) and (24b) can be estimated by the Kalman filter, using quasi-maximum likelihood, as suggested by Harvey, Ruiz, and Shepard (1994). The bottom of Table 6, panel (b), summarizes our results. The functional forms (2) and (3) have almost identical Akaike information criterion, but (3) exhibits higher correlation with the EWMA, naïve, and price range volatility estimates. So this is the one we report in Tables 7 and 8, which are shown below.

[Table 6 about here]

Table 7 shows descriptive statistics for in-sample volatility forecasts of the different models. They look fairly similar in terms of both mean and median. Sharper differences arise in extreme values. For example, the greatest maxima are those of the QJR GARCH, EGARCH, and the Kalman-filter models, whereas the smallest minimum is exhibited by the Component GARCH and the Kalman-filter estimates. In addition, the models exhibit different kurtosis and skewness. For example, the TS GARCH, EGARCH, ESTGARCH and the component-GARCH models have lower kurtosis. Meanwhile, the component GARCH and GJR-GARCH have the lowest and highest kurtosis, respectively.

[Table 7 about here]

Table 8 shows measures of forecast performance for the models of Table 6. $R^2_{volatility}$ (1) is the R^2 of a regression of the EWMA estimate on the volatility estimate of each corresponding model. Similarly, $R^2_{volatility}$ (2) and $R^2_{volatility}$ (3) are, respectively, the R^2 of a regression of the naïve estimate on the volatility estimate of each corresponding model; and the R^2 of a regression of the price range on the volatility estimate of each corresponding model. According to all R^2 measures, the top-three models are the component GARCH, the EST GARCH, and the EGARCH.

[Table 8 about here]

Volatility estimates provided by the component GARCH, the EST GARCH, and the EGARCH models are depicted in Figure 6. Only for illustration purposes, we have split the sample in two periods: May 1997-May 1999 (dirty float) and June 1999-June 2001 (free float). From the pictures, it is not evident that the conditional variance showed a different pattern over the free float. However, as discussed in the next section, what we need is to detect changes in the unconditional variance.

One approach usually utilized in the literature to detect structural breaks in volatility is by including dummy variables in the conditional variance equation. Nevertheless, such an approach is not free from arbitrariness. In particular, the dates picked to define the dummy variables depend on the researcher's viewpoint. A more rigorous way to tackle structural breaks is by the Inclan and Tiao (1994)'s Iterative Cumulative Sums of Squares (ICSS) algorithm.

[Figure 6 about here]

IV How much did volatility change over September 1999-June 2001?

Sudden changes in volatility can be detected by the ICSS algorithm, which is implemented in the TSM GAUSS module and described in the Appendix. Figure 7 shows daily changes of the (deflated) nominal exchange rate for January 1993-September 2001. The three episodes of greatest volatility were November 1994 (revaluation of the exchange rate, as Table 1 shows), January 1998 (liquidity crisis), and July 2001 (outbreak of the Argentinean crisis).

[Figure 7 about here]

The analysis behind the ICSS algorithm is that the time series of interest has a stationary unconditional variance over an initial time period until a sudden break takes place, possibly motivated by some special event in financial markets. The unconditional variance is then stationary until the next sudden change occurs. This process repeats through time, giving a time series of observations with a number of M breakpoints in the unconditional variance in T observations:

$$\sigma_t^2 = \begin{cases} \tau_0^2 & 1 < t < \iota_1 \\ \tau_1^2 & \iota_1 < t < \iota_2 \\ & .... \\ \tau_M^2 & \iota_M < t < T \end{cases} \qquad (25)$$

In order to estimate the number of changes and the point in time of variance shifts, a cumulative sum of square residuals is used, $C_K = \sum_{t=1}^{k} \varepsilon_t^2$, k=1, 2, .., T, where $\{\varepsilon_t\}$ is a series of uncorrelated random variables with zero mean and unconditional variance σ_t^2, as in (25). Inclan and Tiao define the statistic:

$$D_k = \frac{C_k}{C_T} - \frac{k}{T} \qquad k=1, 2,.., T, \qquad D_0=D_T=0.$$

If there are no changes in variance over the whole sample period, D_k will oscillate around zero. In contrast, if there are one or more shifts in variance, D_k departures from zero. The ICSS algorithm systematically looks for breaks in variance at different points in the series.

Table 9 shows the shifts in variance over January 1993-September 2001 for daily frequency data. Out of the 29 shifts in variance, about 17 percent of them took place over the free float. That is to say, about three breaks in variance per year. Meanwhile, between January 1993 and August 1999, twenty four changes in variance took place, which amounted to approximately 4 breaks per year. On the other hand, except for June 1999 and September 2001, the unconditional standard deviation of the exchange rate over the free float shows a similar pattern to that of low volatility periods over the dirty float. This is depicted in Figure 8.

[Table 9 and Figure 8 about here]

We also investigated whether the volatility of the Ch$/US$ exchange rate was high or not during the free float, when compared with currencies of other countries with free/dirty float regimes. Table 10 shows evidence about volatility of exchange rates for 12 countries, including Chile, for the period 1998-2001. We divided the sample into two groups: 1998-August 1999 (floating band) and September 1999-2001 (free float with occasional intervention of the Central Bank of Chile). As previously discussed, the Ch$/US$ exchange rate shows a similar pattern between the two periods. The standard deviation and the interquartile change of daily returns slightly increased over the second period. Now, when compared with other economies, Chile was not the most volatile. For example, the currencies of Australia, New Zealand and Brazil had a higher standard deviation and interquartile range over September 1999-2001. It is interesting to notice that, out of the twelve countries, only Canada and Peru had less volatile exchange rates than Chile over the two time periods.

[Table 10 about here]

V Conclusions

From the mid-1980's to September 1999, the exchange rate policy in Chile consisted of a floating band, whose center was a reference exchange rate (*dolar acuerdo*). The floating band was finally eliminated at the beginning of September 1999, and a free float was established. This lasted for about two years, until the burst of the last Argentinean economic crisis in July 2001.

The market conjectured that the exchange rate would become noticeably more volatile after eliminating the floating band. Indeed, during the dirty float the Central Bank of Chile played an active role in the exchange rate market whenever the exchange rate was either approaching the bottom or the upper bound of the band. Such policy reduced currency risk by preventing the nominal exchange rate from experiencing sharper fluctuations than otherwise.

This paper examined the free float period by assessing whether the increase in exchange rate volatility was as sharp as expected. By resorting to several stochastic volatility models (e.g., asymmetric GARCH, Exponential Smooth Transition GARCH, EGARCH models, and the Kalman Filter approach), and by detecting sudden breaks in volatility by the ICSS algorithm, we showed that volatility has not increased considerably.

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Appendix: The ICSS Algorithm

Let C_k be a sequence defined as $C_K = \sum_{t=1}^{k} \varepsilon_t^2$, k=1, 2, .., T, where $\{\varepsilon_t\}$ is a series of uncorrelated random variables with zero mean and unconditional variance σ_t^2. This sequence is centered and normalized:

$$D_k = \frac{C_k}{C_T} - \frac{k}{T} \qquad k=1, 2,.., T, \qquad D_0=D_T=0,$$

If the variance of each term of the sequence $\{\varepsilon_t\}$ remains constant, D_k fluctuates around 0 under the null hypothesis of homogeneous variance. The asymptotic distribution of *k D* is tabulated in Inclan and Tiao (1994). The breakpoint is determined as the $\max_k|D_k|$, let k^* be this point. If D_{k^*} lies outside the confidence interval, k* is an estimate of the breakpoint. Let $\varepsilon[t_1:t_2]$ be the sequence ε_{t_1}, .., ε_{t_2}, where $t_1<t_2$. The partial sums $D_k(\varepsilon[t_1:t_2])$ are computed over the interval $\varepsilon[t_1:t_2]$.

<u>Step 1</u>: Let $t_1=1$

<u>Step 2</u>: Calculate $D_k(\varepsilon[t_1:T])$. Let $k^*(\varepsilon[t_1:T])$ be the point at which $\max_k |D_k(\varepsilon[t_1:T])|$ is obtained , and let $M(t_1:T) = \max_{t_1 \le k \le T} \sqrt{(T - t_1 + 1)/2}\, |D_k(\varepsilon[t_1:T])|$. If $M(t_1:T)>D^*$, where D^* is the critical value for a given confidence level, there is a breakpoint at $k^*(\varepsilon[t_1:T])$, and proceed to step 3a. Otherwise, there is no evidence of change in variance, and the algorithm stops.

<u>Step 3a:</u> Let $t_2=k^*(\varepsilon[t_1:T])$, and calculate $D_k(\varepsilon[t_1:t_2])$. If $M(t_1:t_2)>D^*$, there is a new breakpoint, and step 3a must be iterated until $M(t_1:t_2)<D^*$. When this occurs, there is no evidence of change in variance in $t=t_1, \ldots, t_2$, and, therefore, the first breakpoint is $k_{first}=t_2$.

<u>Step 3b</u>: Now do a similar search starting from the first breakpoint found in step 2 up to the end of the series. Let $t_1=k^*(\varepsilon[t_1:T])+1$. Compute $D_k(\varepsilon[t_1:T])$, and repeat step 3b to modify t_1 until $M(t_1:T)<D^*$. Let $k_{last}=t_1-1$ be the last breakpoint.

<u>Step 3c</u>: If $k_{first}=k_{last}$, there is one breakpoint. If $k_{first}<k_{last}$, both are candidates. Steps 2, 3a, and 3b are iterated with $t_1=k_{first} + 1$ and $T=k_{last} + 1$. At each iteration, no more than two potential breakpoints are found. Let N_T be the overall number of potential breakpoints.

<u>Step 4</u>: When more than two potential breakpoints are found, the vector 'cp' of breakpoints is sorted according to time. The initial and terminal values are stacked to cp so that $cp_0=0$ and $cp_{N_T+1}=T$. For each breakpoint, $D_k(\varepsilon[cp_{j-1}+1:cp_{j+1}])$, j=1, 2,…, N_T, is computed. If $D_k(\varepsilon[cp_{j-1}+1:cp_{j+1}])>D^*$, then the point is kept; otherwise, it is eliminated. Step 4 is repeated until the number of breakpoints does not change and the new breakpoints found are close to the ones obtained in the previous iteration.

TABLES

Table 1 Chile's Foreign Exchange Rate Policy: 1970 until Today

Time Period	Exchange Rate Policy
1970	Fixed exchange rate. Devaluation took place at the authority's discretion
1973	Price controls were eliminated after Salvador Allende's overthrown, and the domestic currency was devaluated by 230 percent (September- October)
1978	A program of daily devaluation for the whole year was set up
June 1979	The exchange rate was set at $39 per US dollar
June 1982	The exchange rate was set at $43 per US dollar
March 1983	The exchange rate was adjusted daily according to the variation in the *Unidad de Fomento* (UF).
August 1984	An exchange rate floating band was introduced. Its initial width was ± 0.5 percent
September 1984	A lower price of copper, higher foreign interest rates, and lower government revenues led to a nominal devaluation of the reference exchange rate (*dolar acuerdo*) of 23.7 percent.
July 1985	The recession of the early 1980's came to an end. The floating band width was raised to ±2 percent, making room for a more active monetary policy.
January 1988	The floating band width was raised to ± 3 percent
June 1989	The floating band width was raised to ± 5 percent
January 1992	The floating band width was raised to ± 10 percent, and the value of the reference exchange rate was reduced by 5 percent.
November 1994	The composition of the currency reference basket, used to adjust the value of the reference exchange rate, was changed. [1]This translated into a nominal revaluation of the reference exchange rate of 9.7 percent.
January 1997	The floating band width was raised to ± 12.5 percent, and the US dollar was given a greater weight in the currency reference basket. The reference exchange rate was revalued by 4 percent
August 1998	An asymmetric floating band was introduced. The upper bound was 2 percent above the reference exchange rate, and the lower bound was 3.5 percent below it.
September 1998	The floating regime returned to a symmetric band (± 3.5 percent), which was widened in the following months.
Oct 1999–Jun 01	Flexible exchange rate
July 2001–	Dirty float. Discretionary intervention of the Central Bank of Chile

Source: Central Bank of Chile, press releases, and Lefort and Walker (1999). [1] The currency reference basket was made up by the US dollar, the Japanese yen, and the Deutsche mark. From August 1984 to June 1992, the weights of the Japanese yen and the Deutsche mark were set to zero. From July 1992 to November 1994, the weights given to the US dollar, the Japanese yen, and the Deutsche mark were 0.5, 0.2, and 0.3, respectively. From December 1994 to December 1996, the weights were set at 0.45, 0.25, and 0.3 respectively. From January 1997 onwards, the weights became 0.8, 0.05, and 0.15, respectively.

Table 2 Evolution of the Chilean Nominal Exchange Rate in the last 10 years

Nominal exchange rate, September 1991-September 2001 (daily figures)

Interval (Ch$)	Mean	Maximum	Minimum.	Std. Dev.	Observations
[300, 400)	365.453	399.970	333.740	20.176	495
[400, 500)	428.718	499.350	400.090	25.440	1439
[500, 600)	541.934	599.890	501.050	26.838	479
[600, 700)	642.694	695.210	600.440	32.460	106
All	**446.819**	**695.210**	**333.740**	**73.856**	**2519**

Data source: Central Bank of Chile. The nominal exchange rate corresponds with the observed market exchange rate, which is measured in Chilean pesos per US dollar.

Table 3 Three Parsimonious Estimates of the Chilean Nominal Exchange Rate: September 1991-September 2001

	Mean			Std. Dev			Number of observations		
Interval (Ch$)	Exponentially weighted	Equally weighted	Naive	Exponentially weighted	Equally weighted	Naive	Exponentially weighted	Equally weighted	Naive
[0, 5)	1.853	1.919	0.762	1.223	1.075	0.771	2239	2367	2451
[5, 10)	6.573	6.270	7.610	1.269	1.045	1.729	215	114	32
[10, 15)	11.600	11.059	11.790	1.042	0.593	1.357	34	18	16
[15, 20)	17.191	--	--	1.530	--	--	11	--	--
All	**2.459**	**2.183**	**0.921**	**2.320**	**1.595**	**1.409**	**2499**	**2499**	**2499**

Table 4 Volatility Estimates for Intraday Data

(a) Range						
Interval (Ch$)	**Mean**	**Median**	**Maximum**	**Minimum**	**Std. Dev.**	**Frequency**
[0, 5)	2.739	2.650	4.950	0.200	1.177	67.07%
[5, 10)	6.768	6.575	9.900	5.000	1.415	26.02%
[10, 15)	12.106	12.025	13.300	10.740	0.742	4.88%
[15, 30)	20.723	20.723	26.000	15.340	0.233	2.03%
All	**4.588**	**3.770**	**26.000**	**0.200**	**3.569**	**100%**

(b) Interquartile range						
Interval (Ch$)	**Mean**	**Median**	**Maximum**	**Minimum**	**Std. Dev.**	**Frequency**
[0, 5)	1.205	1.000	3.950	0.100	0.815	97.15%
[5, 10)	6.517	6.605	7.500	5.450	0.734	2.44%
[10, 15)	11.410	11.410	11.410	11.410	--	0.41%
All	**1.376**	**1.010**	**11.410**	**0.100**	**1.320**	**100%**

(c) Standard deviation						
Interval (Ch$)	**Mean**	**Median**	**Maximum**	**Minimum**	**Std. Dev.**	**Frequency**
[0, 5)	0.966	0.760	4.940	0.130	0.719	99.59%
[5, 10)	8.010	8.010	8.010	8.010	--	0.41%
All	**0.995**	**0.765**	**8.010**	**0.130**	**0.847**	**100%**

Notes: Data obtained from OTC trade. The sample period is January-December 2001, which includes 246 observations.

Table 5 The EWMA Estimate as compared with the Price Range and the Naive Estimate

	|EWMA–Price range|		|EWMA–Naive|	
Interval (Ch$)	**Count**	**Percent**	**Count**	**Percent**
[0, 5)	1234	94.41	1185	90.67
[5, 10)	63	4.82	103	7.88
[10, 15)	9	0.69	17	1.30
[15, 20)	1	0.08	2	0.15
Total	**1307**	**100.00**	**1307**	**100.00**

Notes: The data was obtained from Bloomberg. "| |" indicates absolute value. All the series were previously deflated to account for inflation. The time period covers November 1996 through December 2001, with a total number of 1307 observations.

Table 6 Stochastic Volatility Models

$$S_t - S_{t-1} = \alpha_0 + \alpha_1^+ S_{t-1}^+ + \alpha_1^- S_{t-1}^- + \sqrt{h_t}\, z_t, \ \varepsilon_t = \sqrt{h_t}\, z_t, \text{ and } z_t \overset{iid}{\sim} N(0,1)$$

GARCH: $h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}$.

NGARCH: $h_t = \beta_0 + \beta_1(\varepsilon_{t-1} + \theta\sqrt{h_{t-1}})^2 + \beta_2 h_{t-1}$.

VGARCH: $h_t = \beta_0 + \beta_1(\varepsilon_{t-1}/\sqrt{h_{t-1}} + \theta)^2 + \beta_2 h_{t-1}$.

AGARCH: $h_t = \beta_0 + \beta_1(\varepsilon_{t-1} + \theta)^2 + \beta_2 h_{t-1}$.

QGARCH: $h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \theta\varepsilon_{t-1}$.

GJR-GARCH: $h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \theta S_{t-1}^+ \varepsilon_{t-1}^2$, where $S_{t-1}^+ = 1$ if $\varepsilon_{t-1}>0$, and $S_{t-1}^+ = 0$ otherwise.

TGARCH: $\sqrt{h_t} = \beta_0 + \beta_1^+ \varepsilon_{t-1}^+ - \beta_1^- \varepsilon_{t-1}^- + \beta_2\sqrt{h_{t-1}}$, where $\varepsilon_{t-1}^+ = \max(0, \varepsilon_{t-1})$ and $\varepsilon_{t-1}^- = \min(0, \varepsilon_{t-1})$.

TS GARCH: $\sqrt{h_t} = \beta_0 + \beta_1|\varepsilon_{t-1}| + \beta_2\sqrt{h_{t-1}}$.

EGARCH: $\ln(h_t) = \beta_0 + \beta_1 \ln(h_{t-1}) + \beta_2 \ln(h_{t-2}) + \theta_1\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \theta_2 \frac{\varepsilon_{t-1}}{h_{t-1}}$

ESTGARCH: $h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2(1 - F(\varepsilon_{t-1})) + \beta_2 \varepsilon_{t-1}^2 F(\varepsilon_{t-1}) + \beta_3 h_{t-1}$, where $F(\varepsilon_{t-1}) = 1 - \exp(-\theta\varepsilon_{t-1}^2)$, $\theta>0$.

Component GARCH: $h_t - q_t = \beta_1(\varepsilon_{t-1}^2 - \eta) + \beta_2(h_t - \eta)$; $q_t = \eta + \rho(q_{t-1} - \eta) + \phi(\varepsilon_{t-1}^2 - h_{t-1})$.

(a) GARCH and Asymmetric GARCH Models

Model	α_0	α_1^+	α_1^-	β_0	β_1	β_2	θ	Log-L	Akaike info criterion
NGARCH	0.651 (4287)	0.0010 (2.271)	–0.0041 (–9.329)	1.029 (70.540)	0.732 (25.259)	0.024 (2.298)	0.239 (7.756)	–4075.45	3.245
VGARCH	0.781 (5.089)	0.0006 (1.279)	–0.0044 (–9.961)	0.943 (53.298)	0.833 (30.166)	0.072 (4.248)	0.249 (8.118)	–4066.36	3.238
AGARCH	0.578 (3.713)	0.0013 (2.790)	–0.0039 (–8.738)	0.829 (10.360)	0.764 (25.835)	0.234 (2.679)	0.215 (7.031)	–4074.7	3.245
QGARCH	0.632 (4.141)	0.0011 (2.481)	–0.0041 (–9.319)	1.070 (74.281)	0.769 (26.003)	0.016 (1.799)	0.343 (7.521)	–4075.1	3.245
GJR-GARCH	0.948 (5.974)	0.00007 (0.145)	–0.0005 (–10.887)	0.869 (2.332)	0.140 (7.016)	0.431 (0.646)	1.410 (13.187)	–4054.14	3.228
GARCH	0.357 (2.938)	0.0019 (5.289)	–0.0034 (–9.460)	1.039 (73.490)	0.809 (28.274)	0.011 (1.251)	--	–4080.33	3.248

Table 6 Continued

(b) Alternative Volatility Models

Model	α_0	α_1^+	α_1^-	β_0	β_1^+	β_1^-	β_1	β_2	Log-L	Akaike info criterion
TGARCH	0.808 (7.990)	0.00068 (2.468)	–0.0044 (–15.327)	0.904 (59.365)	0.752 (28.274)	0.276 (21.877)	--	0.039 (1.513)	–4041.03	3.218
TS-GARCH	0.367 (4.686)	0.0019 (8.316)	–0.0033 (–14.281)	0.745 (23.558)	--	--	0.527 (43.719)	0.173 (4.796)	–4067.98	3.238
	α_0	α_1^+	α_1^-	β_0	β_1	β_2	θ_1	θ_2	Log-L	
EGARCH	–0.095 (–0.635)	0.0026 (3.791)	–0.0013 (–2.160)	–0.122 (–4.095)	0.358 (1.619)	0.644 (2.881)	0.196 (4.660)	0.108 (3.396)	–3542.5	2.822
	α_0	α_1^+	α_1^-	β_0	β_1	β_2	β_3	θ	Log-L	
ESTGARCH	0.245 (3.425)	0.0021 (10.528)	–0.0029 (–14.028)	0.569 (16.148)	0.359 (5.537)	1.909 (21.619)	0.204 (9.415)	0.414 (6.419)	–4063.94	3.238
	α_0	α_1^+	α_1^-	β_1	β_1	η	ρ	ϕ	Log-L	
Component GARCH	–0.205 (–0.976)	0.0028 (4.133)	–0.0011 (–1.644)	0.258 (2.565)	0.009 (0.124)	8.225 (0.094)	0.999 (135.74))	0.049 (1.955)	–3513.2	2.799

Notes: Except for the EGARCH and GARCH-component models, which were estimated with E-Views 4.0, all functional forms were fitted to the data by the maximum-likelihood procedure of TSP 4.5. Asymptotic t-statistics are between parentheses.

Kalman-Filter Models	β	μ	γ	ξ	Log-L	Akaike info criterion
(1) $\ln(\hat{\upsilon}) = x_t + \ln(z_{1t}^2)$ $x_t = \beta x_{t-1} + \xi z_{2t}$	0.389 (23.638)	--	--	2.432 (143.616)	–5810.9	4.617
(2) $\ln(\hat{\upsilon}) = x_t + \ln(z_{1t}^2)$ $x_t - \mu = \beta(x_{t-1} - \mu) + \xi z_{2t}$	0.102 (5.593)	–1.494 (–26.642)	--	2.166 (97.588)	–5518.7	4.386
(3) $\ln(\hat{\upsilon}) = x_t + 2\gamma\ln(S_{t-1}) + \ln(z_{1t}^2)$ $x_t = \beta x_{t-1} + \xi z_{2t}$	0.103 (5.668)	--	–0.128 (–26.629)	2.167 (97.510)	–5520.3	4.387
(4) $\ln(\hat{\upsilon}) = x_t + 2\gamma\ln(S_{t-1}) + \ln(z_{1t}^2)$ $x_t - \mu = \beta(x_{t-1} - \mu) + \xi z_{2t}$	0.103 (6.199)	–6.822 (–12.109)	0.463 (9.485)	2.102 (88.656)	–5516.8	4.394

Note: asymptotic t-statistics are between parentheses. Estimation was carried out with E-Views 4.0. The variable $\hat{\upsilon}_t$ is estimated from a least-square regression of ΔS_t on a constant term, S_{t-1}^+, and S_{t-1}^-. Model 1 states that there is no mean reversion of $\ln(h_t)$, and no dependence of the volatility of ΔS_t on S_{t-1}; model 2 states that there is mean reversion of $\ln(h_t)$, but there is no dependence of the volatility of ΔS_t on S_{t-1}; model (3) states that there is no mean reversion of $\ln(h_t)$, but there is dependence of volatility of ΔS_t on S_{t-1}; finally, model (4) states that there are both mean reversion of $\ln(h_t)$ and dependence of volatility of ΔS_t on S_{t-1}.

Table 7 Descriptive Statistics of In-sample Volatility Forecasts

(a) GARCH and Asymmetric GARCH Models

	GARCH	NGARCH	VGARCH	AGARCH	QGARCH	GJRGARCH
Mean	1.235	1.238	1.194	1.257	1.234	1.370
Median	1.126	1.129	1.107	1.153	1.131	1.231
Maximum	9.200	9.201	9.376	9.126	9.159	12.840
Minimum	1.024	1.027	1.008	1.036	1.024	1.173
Std. Dev.	0.508	0.498	0.424	0.498	0.501	0.619
Skewness	8.666	8.559	9.676	8.611	8.663	10.952
Kurtosis	105.633	103.970	136.154	105.065	106.040	162.965
Observations	2214	2214	2214	2214	2214	2214

(b) Alternative Volatility Models

	TGARCH	TSGARCH	EGARCH	ESTGARCH	Component GARCH	Kalman Filter(*)
Mean	1.246	1.294	1.128	1.218	0.904	1.398
Median	1.164	1.219	0.673	1.142	0.766	1.239
Maximum	8.620	6.415	17.195	6.176	5.936	21.038
Minimum	0.944	0.917	0.163	0.857	0.433	0.000
Std. Dev.	0.453	0.397	1.471	0.382	0.476	1.454
Skewness	8.121	5.499	4.321	4.991	3.381	6.042
Kurtosis	102.085	51.355	28.643	48.738	24.197	62.714
Observations	2214	2214	2214	2214	2214	2214

Note (*): specification 3 in Table 6(b)

Table 8 Comparing Forecasting Performance of Stochastic Volatility Models

Model	$R^2_{volatility}$ (1)	$R^2_{volatility}$ (2)	$R^2_{volatility}$ (3)
GARCH	0.165	0.045	0.155
QGARCH	0.171	0.048	0.163
NGARCH	0.189	0.065	0.183
VGARCH	0.128	0.028	0.134
TSGARCH	0.208	0.107	0.198
TGARCH	0.173	0.043	0.160
GJRGARCH	0.175	0.056	0.166
AGARCH	0.183	0.063	0.175
ESTGARCH	0.220	0.141	0.222
GARCH Component	0.337	0.146	0.329
EGARCH	0.331	0.132	0.283
Kalman Filter(*)	0.142	0.026	0.046

Notes: (1) The $R^2_{volatility}$ (1) is measured as the R^2 of a regression of the EWMA model volatility estimate on the volatility estimate of each corresponding model. Similarly, $R^2_{volatility}$ (2) is measured as the R^2 of a regression of the naïve volatility estimate on the volatility estimate of each corresponding model. For both R^2 the sample period is January 1993-September 2001, and the data are daily. The $R^2_{volatility}$ (3) is measured as the R^2 of a regression of the price range volatility estimate on the volatility estimate of each corresponding model. The sample period is November 1996-September 2001, and the data are daily. (*): specification 3 in Table 6(b).

Table 9 Average volatility computed between shifts dates

	Time period	Average volatility per day
1	4-Jan-93/3-Feb-93	0.74
2	4-Feb-93/9-Mar-93	1.56
3	10-Mar-93/2-Jun-93	0.62
4	3-Jun-93/24-Jun-93	0.91
5	25-Jun-93/11-Nov-93	0.46
6	12-Nov-93/13-Dec-93	1.55
7	14-Dec-93/29-Aug-94	0.79
8	29-Aug-94/27-Nov-94	1.15
9	28-Nov-94/5-Dec-94	3.96
10	6-Dec-94/22-Nov-95	1.50
11	23-Nov-95/5-Dec-95	1.37
12	6-Dec-95/14-Jan-97	0.59
13	15-Jan-9718-Feb-97	1.02
14	19-Feb-97/10-Apr-97	0.60
15	11-Apr-97/30-Jul-97	0.35
16	31-Jul-97/21-Oct-97	0.42
17	22-Oct-97/2-Jan-98	1.12
18	3-Jan-98/11-Jan-98	3.97
19	12-Jan-98/25-Jan-98	2.17
20	26-Jan-98/25-Feb-98	1.99
21	26-Feb-98/2-Mar-98	1.55
22	3-Mar-98/29-Mar-98	0.63
23	30-Mar-98/23-Jun-98	0.42
24	24-Jun-98/13-Jun-99	1.25
25	14-Jun-99/23-Jun-99	3.17
26	24-Jun-99/28-Jun-00	1.05
27	29-Jun-00/10-Jul-00	1.27
28	11-Jul-00/19-Jul-00	1.06
29	20-Jul-00/2-Jul-01	1.52
30	3-Jul-01/28-Sep-01	3.30

Source: Own elaboration based on sudden breaks in volatility detected by the ICSS algorithm.

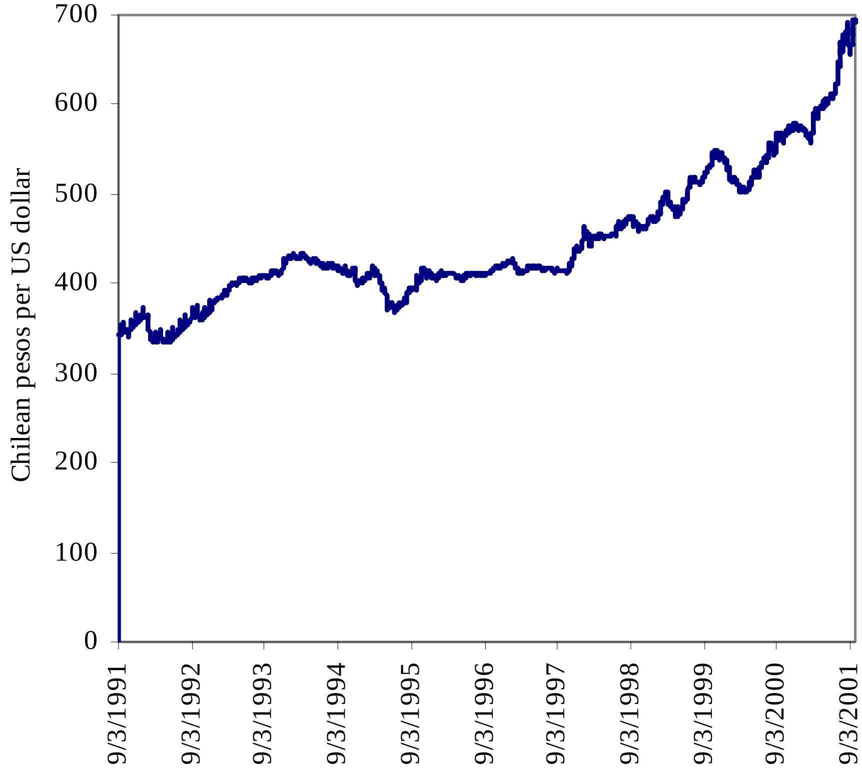
Table 10 Daily Variations of Different Currencies under Free/Dirty Float

	Australia	**Brazil**	**Canada**	**Chile**	**Indonesia**	**Japan**	**South Korea**	**Mexico**	**New Zealand**	**Peru**	**Turkey**	**Thailand**
1998-August 1999												
Mean (%)	0.004	0.128	0.011	0.038	–0.069	–0.047	–0.087	0.036	0.029	0.051	0.218	–0.055
Maximum (%)	2.625	12.913	1.434	3.922	19.019	3.788	4.960	3.980	2.953	1.700	29.314	4.669
Minimum (%)	–4.864	–9.033	–1.635	–1.834	–21.078	–5.855	–9.857	–2.646	–4.155	–1.873	–22.916	–6.000
Standard dev.(%)	0.804	1.507	0.390	0.530	3.476	1.058	1.261	0.732	0.845	0.423	3.506	1.165
IQ range[1]	0.995	0.493	0.428	0.537	2.540	1.138	0.833	0.712	0.964	0.442	0.447	0.823
Asymmetry	-0.650	1.893	-0.239	0.968	0.113	–0.564	–1.513	0.966	-0.510	0.155	2.370	-0.997
Kurtosis	6.670	26.053	4.777	10.653	12.656	6.591	16.036	7.668	6.132	5.207	43.824	10.210
September 1999-2001												
Mean (%)	0.038	0.032	0.011	0.040	0.054	0.031	0.018	-0.004	0.035	0.003	0.189	0.025
Maximum (%)	3.964	3.594	0.851	3.644	5.592	2.268	1.897	1.707	3.852	0.942	22.879	1.762
Minimum (%)	–2.231	–4.013	–1.054	–2.116	–8.831	–3.054	–1.890	–3.577	–3.300	–1.841	–16.002	–3.316
Standard dev.(%)	0.741	0.868	0.330	0.558	1.385	0.689	0.505	0.516	0.812	0.319	2.081	0.484
IQ range	0.890	0.934	0.436	0.604	1.278	0.833	0.550	0.624	0.953	0.370	0.947	0.543
Asymmetry	0.263	–0.363	–0.002	0.721	–0.676	–0.447	0.349	–0.425	0.104	–0.241	3.059	–0.363
Kurtosis	4.382	5.762	2.837	8.579	9.166	4.885	4.565	7.207	4.799	5.302	48.839	7.694

Source: Author's elaboration based upon data from the Bank of Canada. The data analyzed are daily returns of the different currencies against the US dollar. [1] IQ range stands for interquartile range, and it is computed as $Q_{3t}–Q_{1t}$, where Q_{3t} and Q_{1t} are the third and first quartile of the sample period, respectively.

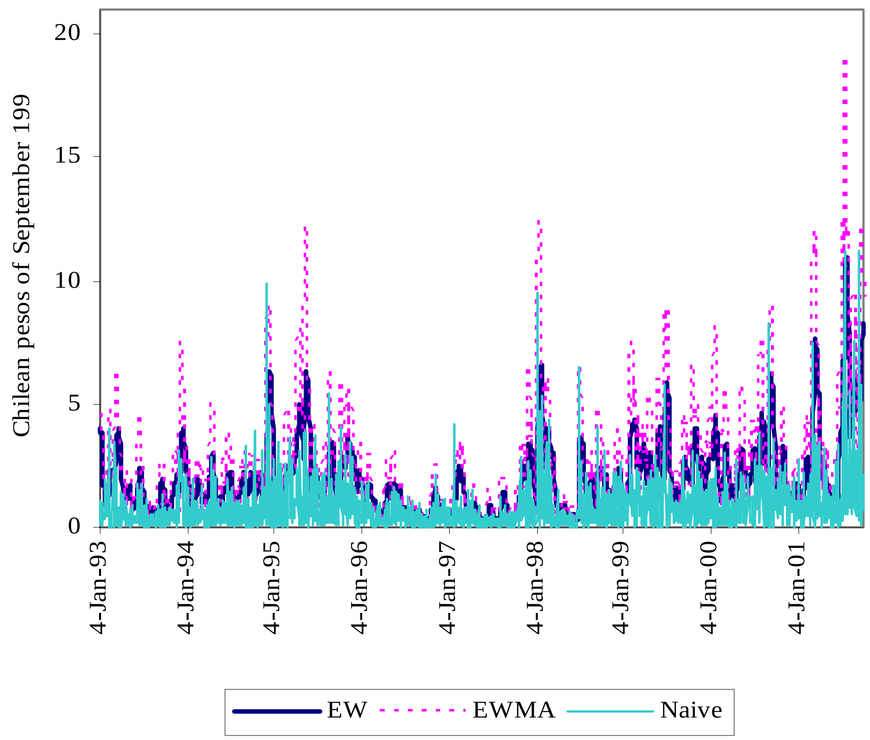
FIGURES

Figure 1 Evolution of the Nominal Exchange Rate: September 1991-September 2001



Data source: Central Bank of Chile. The figures are daily, and correspond with the observed market exchange rate in nominal terms.

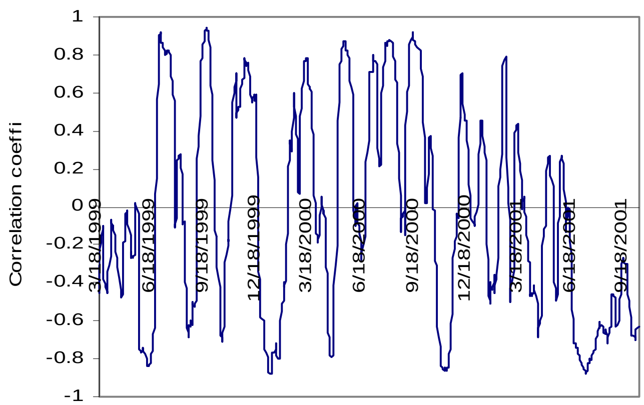
Figure 2 Estimates of Volatility of the Nominal Exchange Rate: January 1993-September 2001



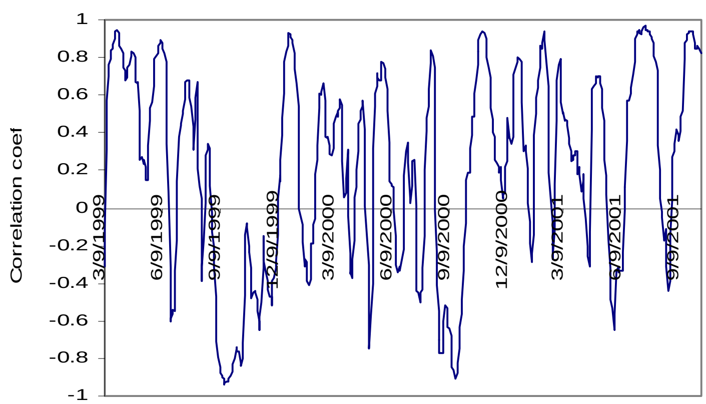
Source: Based upon on daily data of the observed market exchange rate, provided by the Central Bank of Chile. The observed exchange rate series was deflated by the daily percent variation of the *Unidad de Fomento* (base=1, September 1, 1991).

Figure 3 Moving average estimates of the correlation coefficient between the Ch$/US$ rate and other Series (January 1999-September 2001)

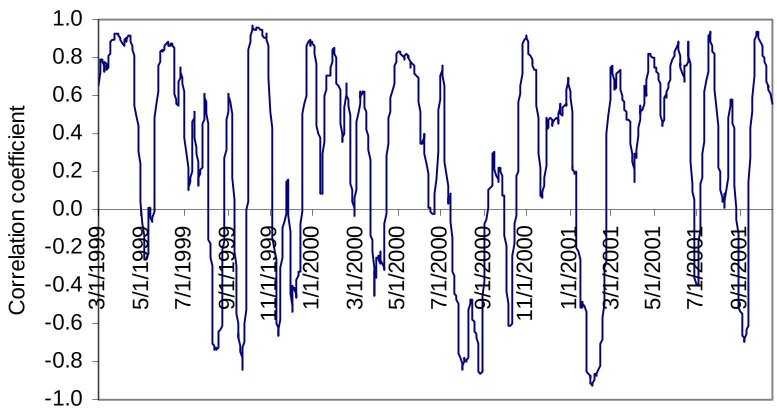
(a) Spot price of copper and Ch$/US$ exchange rate



(b) Argentina's EMBI and Ch$/US$ exchange rate



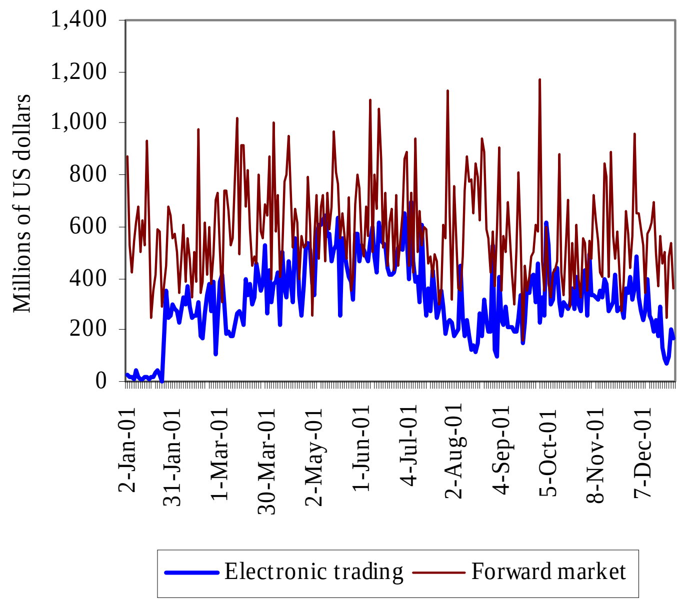
(c) Brazil's real and Ch$/US$ exchange rate



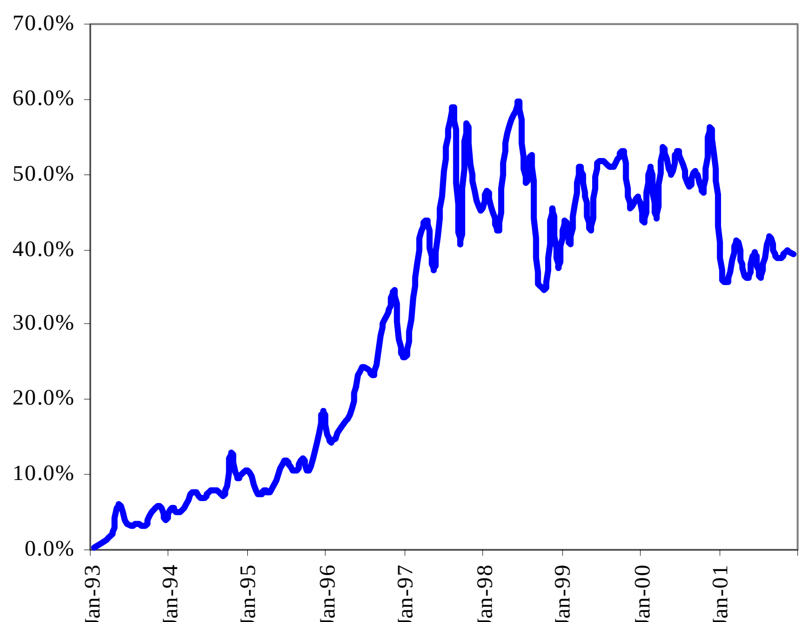
Data source: Bloomberg.

Figure 4 Spot and Forward Markets

(a) Electronic trading and domestic forwards turnover: January-December 2001 (daily figures)

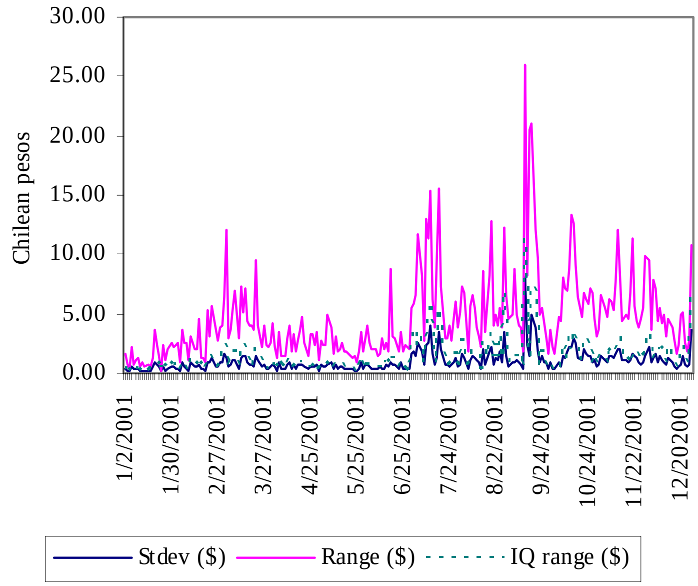


(b) Domestic Forwards Market as a share of the Spot Transactions: January 1993-December 2001



Source: OTC trade and Central Bank of Chile

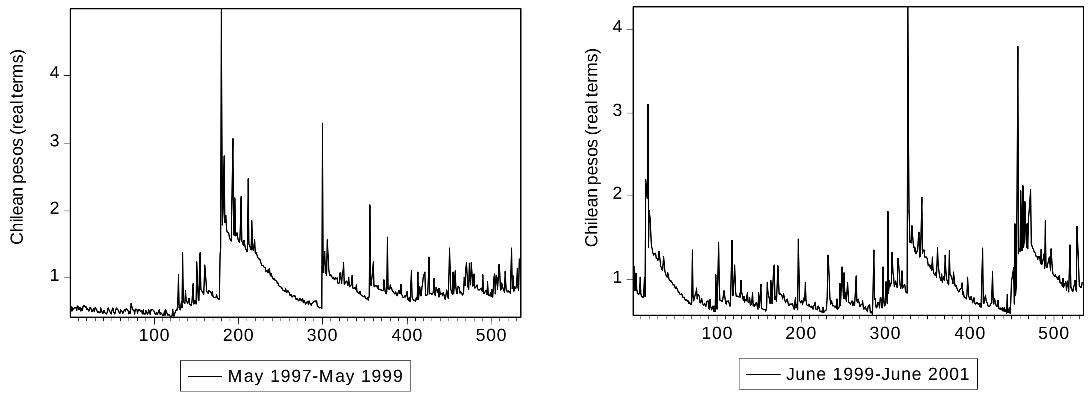
Figure 5 Three Volatility Measures for Intraday Data: January-December 2001



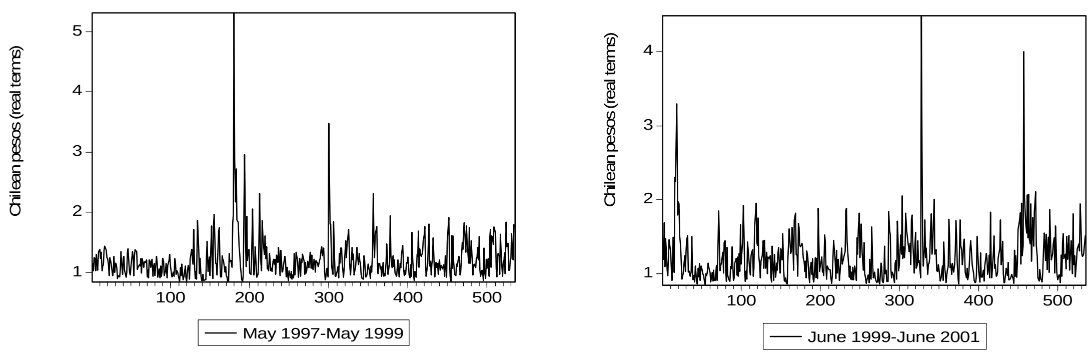
Source: Author's elaboration based on data from OTC trade.

Figure 6 Conditional volatility in-sample Estimates

GARCH Component Model



EST GARCH model



EST GARCH model

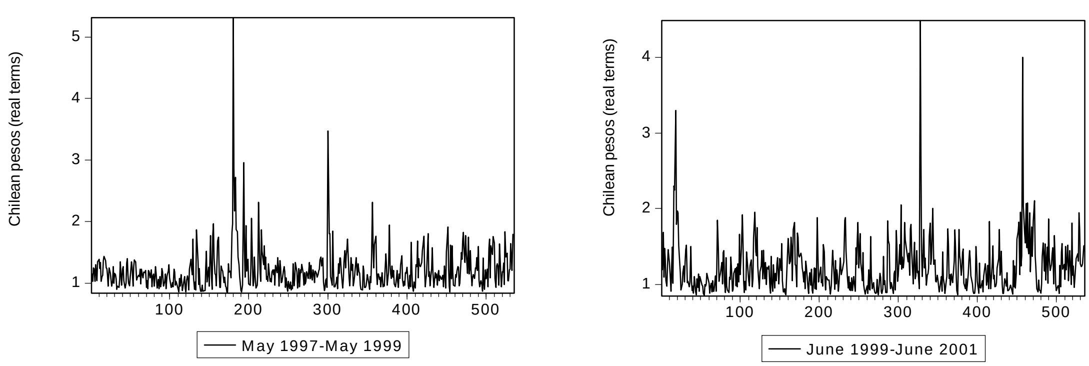
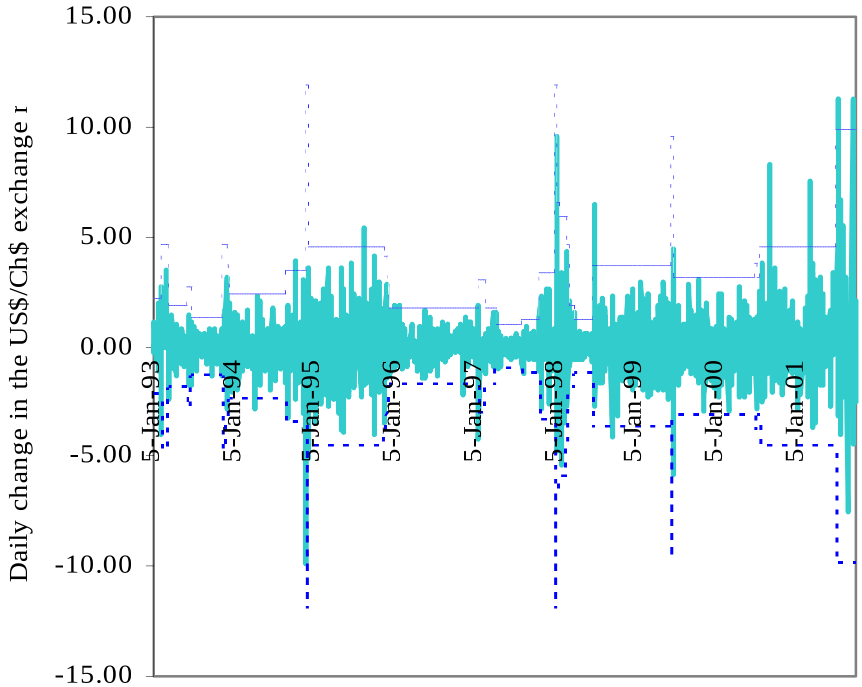
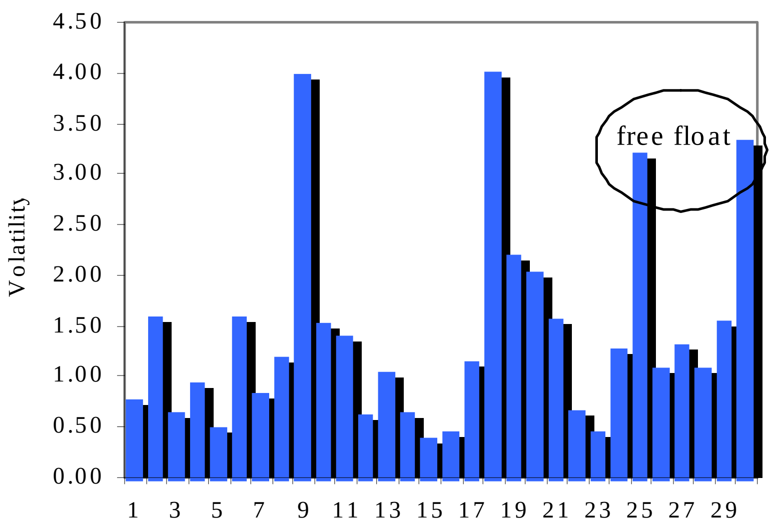


Figure 7 Daily change of the US$/Ch$ exchange rate: January 1993-September 2001



Notes: The US$/Ch$ rate was previously deflated by the UF. Breakpoints were detected by the ICSS algorithm; the dotted lines represent ±3 standard deviations.

Figure 8 Shifts in unconditional variance: January 1993-September 2001



Source: own elaboration based on results in Table 9.