INTEREST RATE VOLATILITY AND NOMINALIZATION

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Abstract

Most Latin American economies in the 1980's and early 1990's were burdened with extremely high inflation rates. Chile's strategy to strengthen its financial market was to rely on inflation-linked securities. Indeed, indexation pervaded the whole economy for almost thirty years. However, the sharp decrease in the annual inflation rate over the last decade—from 26 percent in 1990 to 4 percent in 2001—led the Central Bank of Chile to set its monetary policy interest rate in nominal terms from August 2001 onwards. This paper analyzes the effect of nominalization on the behavior of nominal and inflation-linked interest rates. We find that nominalization has made nominal interest rates less volatile, while the opposite holds for inflation-linked interest rates. We use different volatility measures, and test the presence of structural breaks in unconditional variance by the Iterative Cumulative Sums of Squares (ICSS) algorithm. In addition, we model the co-movements of short and long maturity interest rates in the presence of volatility breakpoints. We also show that deposits in Chilean pesos have now a higher share of total deposits, and that trading of derivatives to hedge inflation risk has become much more active since nominalization took place. At the same time, the market of derivatives on interest rates also seems to have taken off.

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I Introduction

Indexation has been a characteristic of Chile's economy since August 1977. *Unidad de Fomento* (U.F.) is an accounting measure, whose daily variation depends on the previous month inflation rate.[2] Long-term deposits and loans, and almost any contract between two parties are denominated in U.F. Until July 2001, monetary policy consisted of setting a target premium over the variation of the UF. That is to say, every month the Central Bank of Chile modified the level of the nominal overnight rate at which provided commercial banks with liquid loans, in order to meet the already known variation of the UF.

Currently, the target is a nominal interest rate, which has as a counterpart an overnight interbank market in Chilean pesos. As a consequence of nominalization, the Central Bank started issuing short and medium-term bonds in nominal rates (33, 90, 360, and 733 days (PDBC); 2 and 5 years (BCP)), and long term bonds in interest rates adjusted by the variation of the UF (5, 10 and 20 years, known as BCU).[3] Until July 2001, the Central Bank of Chile also issued inflation-linked bonds with maturities of 90 days, 12 and 14 years.

In the past, academic circles and practitioners took a dim view on a monetary policy interest rate indexed to past inflation. Indeed, in their opinion, it validated indexation in the financial system, which in turn gave feedback to price stickiness in other markets that relied on indexation as well (e.g., labor market). However, such policy was adopted in the mid-1980's, when inflation in Chile was both high and unstable, and, consequently, fixed-income security markets linked to past inflation were the most liquid and developed ones. For instance, the annual inflation rate averaged 18.2 percent per year between 1983 and 1990, while the difference between the maximum and the minimum monthly inflation rate within a year averaged 3.4 percent points in the same time period.

From the 1990's onwards, inflation showed a downward trend and became more stable, making room for the possibility of reducing the degree of indexation of the economy. Indeed, for the period 1991-2001 the annual inflation rate averaged 9 percent, whereas the difference between the maximum and the minimum monthly inflation rate within a year averaged 1.5 percent points. However, the decision of nominalization was not an easy one. One argument against it was that real interest rates would become more volatile, as the Central Bank would be unwilling to frequently offset changes in expected inflation. The second argument against it was that the main transmission channel of monetary policy to aggregate demand (i.e., consumption and investment) is the real interest rate. Therefore, an inflation-linked monetary policy interest rate was a more efficient instrument.

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[2]That is to say, $UF_t = UF_{t-1}\sqrt[30]{1+\pi_{-1}}$, where UF_t and UF_{t-1} are the values of the UF on day t and t–1, respectively, and π_{-1} is the inflation rate in the previous month. The value of the UF is set on the ninth day of each month, according to this formula, for the following thirty days.

[3] PDBC stands for Discount Bond of the Central Bank of Chile, BCP for Central Bank bonds in pesos, and BCU for Central Bank bonds in UF.

Counterarguments to the above statements were that inflation-linked interest rates are imperfect proxies for real interest rates, and that a nominal interest rate might be a more efficient way to target real interest rates, especially under a low inflation rate scenario, and to exploit nominal channels, such as the exchange rate and money. For further insights on this subject, see Morande (2002).

The aim of this paper is to study the behavior of interest rates before and after nominalization, and to look at the impact of nominalization on the Chilean financial market. The paper is organized as follows. Section II analyzes the behavior of interest rates and excess returns before and after nominalization, particularly in what refers to volatility and Markov-regime switching (e.g, Harvey, 1989; Franses and van Dijk, 2000). Section III formally tests the presence of structural breaks in volatility by the ICSS algorithm (e.g., Inclan and Tiao, 1994; Aggarwal, Inclan, and Leal, 1999), and presents a multivariate GARCH model (e.g., Zivot and Wang, 2003) for interest rates that accommodates for such breaks. Section IV focuses on the effects of nominalization on the Chilean financial market, particularly on the credit and derivative markets. Finally, Section V presents the conclusions.

The contributions of this paper are the following. First, it analyzes a significant institutional change in one of Latin America's most successful economy, and looks into its impact on Chile's financial market. Second, it takes account of institutional changes when modeling the behavior of interest rates in a multivariate setting. As far as the author of this paper knows, nobody has yet tackled this issue in a highly quantitative manner.

II Behavior of Interest Rates before and after Nominalization

2.1 Different measures of volatility

Chile has gone through a process of declining inflation over the past 10 years. Table 1(a) shows some figures of annual inflation rates for Chile and other Latin American economies for the last decade. Both Argentina and Brazil started up with hyperinflations at the beginning of the 1990's. While Brazil has reduced annual inflation to one digit, Argentina has gone from very low inflation rates to deflation in the past three years. Both Mexico and Chile show a most stable pattern, in which at the beginning of the 1990's both countries had inflation rates of about 26 percent per year, and ended up with one-digit rates, below 6 percent, in 2001.

Table 1(b) shows in further detail the evolution of annual inflation in Chile from 1983 to 2001, and computes two measures of volatility of monthly inflation for each year. As mentioned in the Introduction, both the level and the volatility of inflation has considerably dropped in the past few years.

[Table 1 about here]

In this section, we focus on the behavior of interest rates and excess returns. Figure 1 shows daily data on nominal and inflation-linked interest rates for the period December 1992-April 2002. Descriptive statistics are given in Table 2. The data correspond with interest rates earned on domestic deposits. The Central Bank of Chile does not issue inflation-linked zero-coupon bonds, and zero-coupon bonds denominated in Chilean pesos have been regularly issued only since nominalization took place. Data on inflation-linked zero-coupon bonds, which are stripped from coupon bonds issued by the Central Bank, are available only since December 2001. Therefore, given that domestic banks were unlikely to default over the sample period, we considered interest rates on deposits as approximately riskless.

[Figure 1 and Table 2 about here]

We next compute three different volatility estimates. The exponentially weighted moving average (EWMA) estimator is defined as:

$$\sigma_{ewma} = \sqrt{\sum_{t=1}^{T} \frac{\lambda^{t-1}}{\sum_{j=1}^{T} \lambda^{j-1}} (r_t - \bar{r})^2} \qquad (1)$$

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

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

(see, for example, Harvey, 1989).

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

$$\hat{r}_{t+1|t} = \lambda \hat{r}_{t|t-1} + (1-\lambda) r_t \qquad (2)$$

with the initial condition $\hat{r}_{2|1} = r_1$.

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.

The naïve estimate is the simplest measure of volatility. It is calculated as the absolute value of the (daily) change in the interest rate:

$$\sigma_{naïve} = |r_t - r_{t-1}| \qquad (3)$$

Finally, our Kalman filter approach combines both Bali (2000)'s and Ball and Torous (1999)'s models. Bali's two-factor discrete time stochastic volatility model is given by:

$$r_t - r_{t-1} = \alpha_0 + \alpha_1^+ r_{t-1}^+ + \alpha_1^- r_{t-1}^- + r_{t-1}^{\gamma}\sqrt{h_t}\, z_{1t},\ \varepsilon_t = \sqrt{h_t}\, z_t, \text{ and } z_{1t} \overset{iid}{\sim} N(0,1) \qquad (4)$$

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

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

From equation (4), the conditional distribution of the change in the interest rate Δr_t is normal, and given by $\Delta r_t | r_{t-1} \sim N(\alpha_0 + \alpha_1^+ r_{t-1}^+ + \alpha_1^- r_{t-1}^-,\ r_{t-1}^{2\gamma} h_t)$. In addition, the drift of the diffusion function of the interest rate is asymmetric, given that the conditional mean of Δr_t depends on the sign of Δr_t when $\alpha_1^+ \neq \alpha_1^-$. When $\alpha_1^+ = \alpha_1^-$, the interest rate follows a linear mean-reverting drift. Different functional forms for h_t can be considered. In this case, we follow Ball and Torus:

$$\ln(h_t) - \mu = \beta(\ln(h_{t-1}) - \mu) + \xi z_{2t} \qquad (5)$$

where z_{1t} and z_{2t} are i.i.d standard normal. The parameter γ allows volatility of Δr to depend on the lagged level of the interest rate. Equation (5) states that $\ln(h_t)$ follows an AR(1) process, which reverts to its unconditional mean μ at rate β, and that $\text{Var}(\ln(h_t)|\ln(h_{t-1}))=\xi^2$.

Following Ball and Torous, we estimate equations (4) and (5) by a two-step procedure. In the first step, we run a regression of $\Delta r_t \equiv r_t - r_{t-1}$ on a constant, r_{t-1}^+, and r_{t-1}^-. The error term $\upsilon_t \equiv r_{t-1}^{\gamma}\sqrt{h_t}\, z_{1,t}$ 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 $\hat{\upsilon}_t = \Delta r_t - \hat{\alpha}_0 - \hat{\alpha}_1^+ r_{t-1}^+ - \hat{\alpha}_1^- r_{t-1}^-$. Consequently, equation (4) can be written as:

$$\hat{\upsilon} = r_{t-1}^{\gamma}\sqrt{h_t}\, z_{1t} \qquad (4')$$

If we square both sides of (4') and take logs, we get:

$$\ln(\hat{\upsilon}) = x_t + 2\gamma \ln(r_{t-1}) + \ln(z_{1t}^2) \qquad (5a)$$

In turn equation (5) becomes:

$$x_t - \mu = \beta(x_{t-1} - \mu) + \xi z_{2t} \qquad (5b)$$

The error term of equation (5a) is not normally distributed, but chi-square with one degree of freedom. Still, equations (5a) and (5b) can be estimated by the Kalman filter approach, using quasi-maximum likelihood, as suggested by Harvey, Ruiz, and Shepard (1994).

Figure 2 depicts the three different volatility estimates described above for nominal and inflation-linked interest rates at a daily frequency for the sample period January 1999-April 2002. We can easily see that from August 2001 onwards volatility of inflation indexed-rates has become noticeably higher than before, while the opposite holds for nominal rates. A formal test for detecting breakpoints in volatility is discussed in Section III.

[Figure 2 about here]

We also investigated what happened to excess returns. In particular, we focused on inflation-linked rates because in such case we do not have to deal with expectations of future inflation for different time horizons. Figure 3 shows series of 180-day and 360-day excess returns for December 1992-December 2001 (daily frequency). The 180-day excess return is computed as the difference between the return on a 180-day deposit and the return obtained by rolling over a 90-day deposit. Similarly, the 360-day excess return is computed as the difference between the return on a 360-day deposit and the return obtained by rolling over a 180-day deposit.

[Figure 3 about here]

As we can see, the 180-day excess return and the spread between 180-day and 90-day interest rates are negative for most of the sample period. Indeed, only 24 and 20 percent of the observations of the excess return and the spread are positive, respectively. This pattern is far less pronounced for the 360-day excess return and the spread between 360-day and 180-day interest rates: 75 percent of the observations are positive for the former and 78 percent for the latter. Table 3 gives additional descriptive statistics of the excess returns and the spreads.

[Table 3 about here]

From the table, we see that mean excess returns for the whole sample period are relatively small: 1.2 and 1.6 percent a year for 180-day and 360-day time horizons, respectively. In turn mean spreads over the sample period are not large either: −0.8 percent points (annual terms) for the difference between 180-day and 90-day interest rates, and 0.21 percent points (annual terms) for the difference between 360-day and 180-day interest rates. This phenomenon of having either a relatively flat or a downward-sloping term structure of interest rates is further discussed in Fernandez, 2001 and 2002.

2.2 Markov-Switching Model and the behavior of excess returns

We also looked into what happened to excess returns when nominalization took place. In doing so, we resorted to a 2-regime Markov-Switching Model (MSW) with an AR(2) specification:

$$y_t = \begin{cases} \phi_{0,1} + \phi_{1,1} y_{t-1} + \phi_{2,1} y_{t-2} + \varepsilon_t & \text{if } s_t = 1 \\ \phi_{0,2} + \phi_{1,2} y_{t-1} + \phi_{2,2} y_{t-2} + \varepsilon_t & \text{if } s_t = 2 \end{cases} \tag{6}$$

or in shorthand notation:

$$y_t = \phi_{0,s_t} + \phi_{1,s_t} y_{t-1} + \phi_{2,s_t} y_{t-2} + \varepsilon_t$$

Under the assumption that ε_t is normally distributed (conditional upon the history Π_{t-1}), y_t is normally distributed with mean $\phi_{0,s_t} + \phi_{1,s_t} y_{t-1} + \phi_{2,s_t} y_{t-2}$ and variance σ^2:

$$f(y_t | s_t = j, \Pi_{t-1}; \boldsymbol{\theta}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y_t - \boldsymbol{\phi}_j{}' \mathbf{x}_t)^2}{2\sigma^2} \right) \tag{7}$$

where $\mathbf{x}_t=(1, y_{t-1}, y_{t-2})'$, $\boldsymbol{\phi}_j=(\phi_{0,j}, \phi_{1,j}, \phi_{2,j})'$ for j=1,2, and $\boldsymbol{\theta}=(\phi_1', \phi_2', p_{11}, p_{22}, \sigma^2)'$. The parameters p_{11} and p_{22} are the transitions probabilities of moving from one state to the other:

$P(s_t=1| s_{t-1}=1)=p_{11}$
$P(s_t=2| s_{t-1}=1)=p_{12}=1-p_{11}$
$P(s_t=1| s_{t-1}=2)=p_{21}=1-p_{22}$
$P(s_t=2| s_{t-1}=2)=p_{22}$

In turn the unconditional probabilities that the process is in each regime, $P(s_t=j)$, j=1, 2, are given by:

$$P(s_t = 1) = \frac{1 - p_{22}}{2 - p_{11} - p_{22}} \qquad P(s_t = 2) = \frac{1 - p_{11}}{2 - p_{11} - p_{22}} \tag{8}$$

See, for example, Franses and van Dijk (2000), chapter 3, and Hamilton (1994), chapter 22.

The estimation results of equation (6) for 180-day and 360-day excess returns are reported in Table 4 and shown in Figure 4. Computations were carried out in GAUSS 4.0 based on a computer code developed by Franses and Dijk. Smoothed and filtered probabilities are depicted. The former quantifies the probability of being in either regime at time t given all observations up to time t–1, that is, $P(s_t=j| \Pi_{t-1}, \boldsymbol{\theta})$, whereas the latter estimates the probability that regime j occurs at time t given all available observations, that is, $P(s_t=j| \Pi_n, \boldsymbol{\theta})$.

[Table 4 and Figure 4 about here]

Panel (a) of Figure 4 depicts smoothed and filtered probabilities of state 2 for the 180-day excess return, conditional on being in state 2 at time t–1. The unconditional probability of being in state 2 is 0.964, which indicates the most likely event of a negative or close-to-zero excess return. Similarly, Panel (b) shows the smoothed and filtered probability of state 1, conditional on being in state 1 at time t–1, for the 360-day excess return. The unconditional probability of being in state 1 is 0.257, which corresponds with the less likely event of a highly positive excess return.

Both graphs suggest that nominalization had an impact on conditional probabilities around the time it was announced. For example, the conditional probability of a very low 180-day excess return went to zero in mid-July 2001, whereas the conditional probability of an unusually high 360-day excess return went up by the end of August 2001. This behavior of the excess returns is explained by the fact that nominalization temporarily led to higher inflation-linked interest rates for short maturities. Indeed, the Central Bank of Chile switched from an inflation-linked interest rate of 3.5 percent per year to a nominal interest rate of 6.5 percent per year in August 2001. This in turn signaled an expected inflation of 3 percent per year. However, monthly inflation turned out to be negative in July 2001 (–0.2 percent), which in practice led to higher real interest rates than previously expected.[4]

III Term Structure of Interest Rates and Breakpoints in Volatility

Sudden changes in volatility can be detected by Inclan and Tiao (1994)'s Iterative Cumulative Sums of Squares (ICSS) algorithm, which is described in the Appendix. 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:

$$\sigma_t^2 = \begin{cases} \tau_0^2 & 1 < t < \iota_1 \\ \tau_1^2 & \iota_1 < t < \iota_2 \\ & .... \\ \tau_M^2 & \iota_M < t < T \end{cases} \tag{9}$$

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 (9). Inclan and Tiao define the statistic:

$$D_k = \frac{C_k}{C_T} - \frac{k}{T} \qquad k=1, 2,.., T, \quad D_0=D_T=0, \tag{10}$$

as the centered and normalized cumulative sum of squares. If there are no changes in variance over the whole sample period, D_k oscillates around zero. In contrast, if there are one or more shifts in variance, D_k will departure from zero. Inclan and Tiao computed critical values based on the distribution of D_k under the null hypothesis of homogeneous variance, which provide upper and lower boundaries to detect a statistically significant

[4] This caused fixed-income mutual funds a capital loss of about 0.2 to 0.3 percent.

change in volatility.[5] The ICSS algorithm systematically looks for breaks in variance at different points in the series, as explained in the Appendix. For an application to emerging stock markets, see Aggarwal et al. (1999).

Figure 5 shows estimates of volatility breakpoints of daily frequency interest rates data for January 2000-April 2002. Estimation was carried out with the routine implemented in the TSM GAUSS module. Figure 5 (a) through (f) depict breakpoints for nominal interest rates (7-day, 30-day, and 60-day maturities) and inflation-linked rates (90-day, 180-day, 360-day maturities). It is clear that volatility breakpoints occur less often, and that volatility itself has gone down for nominal interest rates since nominalization took place in August 2001. By contrast, the opposite holds for inflation-linked rates. In particular, 90-day and 180-day interest rates seem considerably more volatile after nominalization.

[Figure 5 about here]

In what follows, we will model the interrelation between short and long-maturity interest rates by taking into account the volatility breakpoints detected with the ICSS algorithm. Prior to that, we present in Figure 6 univariate GARCH estimates of (average) daily volatility for 90-day, 8-year and 20-year interest rates, for the time period February 1993-April 2002 (monthly data). As we see, the 90-day interest rate is noticeably more volatile than the long-maturity interest rates. The peak of volatility for 90-day interest rates was reached in November 1998, with an average of 1.7 percent points per day, when the Central Bank of Chile adopted a very tight monetary policy. Similarly, 8-year and 20-year interest rates reached volatility peaks of 0.5 and 0.4 percent points per day, respectively, in the same time period. Thereafter, interest rates have shown increasing trends in volatility after nominalization in August 2001.

[Figure 6 about here]

Given that interest rates are usually correlated, more efficient estimates of volatility can be obtained from a multivariate GARCH model. Therefore, let us consider the following general form:

$$\mathbf{y}_t = \mathbf{c} + \sum_{l=0}^{L} \boldsymbol{\beta}_l \mathbf{x}_{t-l} + \boldsymbol{\varepsilon}_t \qquad t=1, 2, \ldots, T \tag{11}$$

where $\mathbf{y}_t$ is a vector k x 1, $\mathbf{c}$ is a k x 1 vector of constant terms, $\mathbf{x}_t$ is a m x 1 vector of regressors, $\boldsymbol{\beta}$ is a k x m matrix containing the coefficients on $\mathbf{x}_{t-l}$, and $\boldsymbol{\varepsilon}_t$ is a k x 1 vector of white noise with zero mean. The matrix variance-covariance of $\boldsymbol{\varepsilon}_t$ in a multivariate GARCH (p, q) model is given by:

[5] Under the null hypothesis of variance homogeneity, $\sqrt{T/2}\, D_k$ behaves like a Brownian bridge. (A process $Z(t)=W(t)-tW(1)$, $0\le t\le 1$, where W is a standard Wiener process, is called a Brownian bridge).

$$\mathbf{\Sigma}_t = \mathbf{A}_0{}'\mathbf{A}_0 + \sum_{i=1}^{p}(\mathbf{A}_i{}'\mathbf{A}_i) \otimes (\boldsymbol{\varepsilon}_{t-i}\boldsymbol{\varepsilon}_{t-i}{}') + \sum_{j=1}^{q}(\mathbf{B}_j\mathbf{B}_j{}') \otimes \mathbf{\Sigma}_{t-j} \tag{12}$$

where $\mathbf{A}_0$, $\mathbf{A}_i$ (i=1, 2, …, p) and $\mathbf{B}_j$ (j=1, 2,.., q) are lower triangular matrices, $\mathbf{\Sigma}_t$ and $\boldsymbol{\varepsilon}_{t-j}\boldsymbol{\varepsilon}_{t-j}'$ are symmetric matrices, and $\otimes$ denotes the Kronecker product. This functional form is called *matrix-diagonal model* (see, for example, Bollerslev, Engle, and Nelson, 1994; and, Zivot and Wang, 2003, chapter 13).

In particular, we focus on the following special case, which is a good approximation of the data generating process:

$$\mathbf{\Sigma}_t = \mathbf{A}_0{}'\mathbf{A}_0 + \mathbf{A}_1{}'\mathbf{A}_1 \otimes (\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}{}') + \mathrm{b}_1 \otimes \mathbf{\Sigma}_{t-1} \tag{13}$$

For the trivariate model (k=3) we fit to the data, equation (13) becomes:

$$\begin{pmatrix} \mathbf{\Sigma}_t^{(11)} & & \\ \mathbf{\Sigma}_t^{(21)} & \mathbf{\Sigma}_t^{(22)} & \\ \mathbf{\Sigma}_t^{(31)} & \mathbf{\Sigma}_t^{(32)} & \mathbf{\Sigma}_t^{(33)} \end{pmatrix} = \begin{pmatrix} \mathbf{A}_0^{(11)} & 0 & 0 \\ \mathbf{A}_0^{(21)} & \mathbf{A}_0^{(22)} & 0 \\ \mathbf{A}_0^{(31)} & \mathbf{A}_0^{(32)} & \mathbf{A}_0^{(33)} \end{pmatrix} \begin{pmatrix} \mathbf{A}_0^{(11)} & \mathbf{A}_0^{(21)} & \mathbf{A}_0^{(31)} \\ 0 & \mathbf{A}_0^{(22)} & \mathbf{A}_0^{(32)} \\ 0 & 0 & \mathbf{A}_0^{(33)} \end{pmatrix}$$

$$+ \begin{pmatrix} \mathbf{A}_1^{(11)} & 0 & 0 \\ \mathbf{A}_1^{(21)} & \mathbf{A}_1^{(22)} & 0 \\ \mathbf{A}_1^{(31)} & \mathbf{A}_1^{(32)} & \mathbf{A}_1^{(33)} \end{pmatrix} \begin{pmatrix} \mathbf{A}_1^{(11)} & \mathbf{A}_1^{(21)} & \mathbf{A}_1^{(31)} \\ 0 & \mathbf{A}_1^{(22)} & \mathbf{A}_1^{(32)} \\ 0 & 0 & \mathbf{A}_1^{(33)} \end{pmatrix} \begin{pmatrix} \boldsymbol{\varepsilon}_{t-1}^{(1)}\boldsymbol{\varepsilon}_{t-1}^{(1)} & & \\ \boldsymbol{\varepsilon}_{t-1}^{(2)}\boldsymbol{\varepsilon}_{t-1}^{(1)} & \boldsymbol{\varepsilon}_{t-1}^{(2)}\boldsymbol{\varepsilon}_{t-1}^{(2)} & \\ \boldsymbol{\varepsilon}_{t-1}^{(3)}\boldsymbol{\varepsilon}_{t-1}^{(1)} & \boldsymbol{\varepsilon}_{t-1}^{(3)}\boldsymbol{\varepsilon}_{t-1}^{(2)} & \boldsymbol{\varepsilon}_{t-1}^{(3)}\boldsymbol{\varepsilon}_{t-1}^{(3)} \end{pmatrix}$$

$$+ \mathrm{b}_1 \begin{pmatrix} \mathbf{\Sigma}_{t-1}^{(11)} & & \\ \mathbf{\Sigma}_{t-1}^{(21)} & \mathbf{\Sigma}_{t-1}^{(22)} & \\ \mathbf{\Sigma}_{t-1}^{(31)} & \mathbf{\Sigma}_{t-1}^{(32)} & \mathbf{\Sigma}_{t-1}^{(33)} \end{pmatrix}$$

where $\mathbf{A}^{(ij)}$ denotes the (i, j)-th element of the matrix $\mathbf{A}$, and $\boldsymbol{\varepsilon}^{(i)}$ is the i-th element of the vector $\boldsymbol{\varepsilon}$.

The above expression boils down to:

$$\mathbf{\Sigma}_t^{(11)} = \mathbf{A}_0^{(11)\,2} + \mathbf{A}_1^{(11)\,2}\,\boldsymbol{\varepsilon}_{t-1}^{(1)\,2} + \mathbf{A}_1^{(11)}\mathbf{A}_1^{(21)}\boldsymbol{\varepsilon}_{t-1}^{(1)}\boldsymbol{\varepsilon}_{t-1}^{(2)} + \mathbf{A}_1^{(11)}\mathbf{A}_1^{(31)}\boldsymbol{\varepsilon}_{t-1}^{(1)}\boldsymbol{\varepsilon}_{t-1}^{(3)} + \mathrm{b}_1\mathbf{\Sigma}_{t-1}^{(11)} \tag{14a}$$

$$\mathbf{\Sigma}_t^{(21)} = \mathbf{A}_0^{(21)}\mathbf{A}_0^{(11)} + \mathbf{A}_1^{(21)}\mathbf{A}_1^{(11)}\,\boldsymbol{\varepsilon}_{t-1}^{(1)\,2} + (\mathbf{A}_1^{(21)\,2} + \mathbf{A}_1^{(22)\,2})\boldsymbol{\varepsilon}_{t-1}^{(2)}\boldsymbol{\varepsilon}_{t-1}^{(1)}$$

$$+ (\mathbf{A}_1^{(21)}\mathbf{A}_1^{(31)} + \mathbf{A}_1^{(22)}\mathbf{A}_1^{(32)})\,\boldsymbol{\varepsilon}_{t-1}^{(3)}\boldsymbol{\varepsilon}_{t-1}^{(1)} + \mathrm{b}_1\mathbf{\Sigma}_{t-1}^{(21)} \tag{14b}$$

$$\mathbf{\Sigma}_t^{(22)} = \mathbf{A}_0^{(21)^2} + \mathbf{A}_0^{(22)^2} + \mathbf{A}_1^{(21)}\mathbf{A}_1^{(11)}\boldsymbol{\varepsilon}_{t-1}^{(2)}\boldsymbol{\varepsilon}_{t-1}^{(1)} + (\mathbf{A}_1^{(21)^2} + \mathbf{A}_1^{(11)\ 2})\boldsymbol{\varepsilon}_{t-1}^{(2)^2}$$

$$+ (\mathbf{A}_1^{(21)}\mathbf{A}_1^{(31)} + \mathbf{A}_1^{(22)}\mathbf{A}_1^{(32)})\ \boldsymbol{\varepsilon}_{t-1}^{(2)}\boldsymbol{\varepsilon}_{t-1}^{(3)} + \mathrm{b}_1\mathbf{\Sigma}_{t-1}^{(22)} \qquad \text{(14c)}$$

$$\mathbf{\Sigma}_t^{(31)} = \mathbf{A}_0^{(31)}\mathbf{A}_0^{(11)} + \mathbf{A}_1^{(31)}\mathbf{A}_1^{(11)}\boldsymbol{\varepsilon}_{t-1}^{(1)^2} + (\mathbf{A}_1^{(31)}\mathbf{A}_1^{(21)} + \mathbf{A}_1^{(32)}\mathbf{A}_1^{(22)})\boldsymbol{\varepsilon}_{t-1}^{(1)}\boldsymbol{\varepsilon}_{t-1}^{(2)}$$

$$+ (\mathbf{A}_1^{(31)^2} + \mathbf{A}_1^{(32)^2} + \mathbf{A}_1^{(33)^2})\boldsymbol{\varepsilon}_{t-1}^{(1)}\boldsymbol{\varepsilon}_{t-1}^{(3)} + \mathrm{b}_1\mathbf{\Sigma}_{t-1}^{(31)} \qquad \text{(14e)}$$

$$\mathbf{\Sigma}_t^{(32)} = \mathbf{A}_0^{(31)}\mathbf{A}_0^{(21)} + \mathbf{A}_0^{(32)}\mathbf{A}_0^{(22)} + \mathbf{A}_1^{(31)}\mathbf{A}_1^{(11)}\boldsymbol{\varepsilon}_{t-1}^{(1)}\boldsymbol{\varepsilon}_{t-1}^{(2)} + (\mathbf{A}_1^{(31)}\mathbf{A}_1^{(21)} + \mathbf{A}_1^{(32)}\mathbf{A}_1^{(22)})\boldsymbol{\varepsilon}_{t-1}^{(2)^2}$$

$$+ (\mathbf{A}_1^{(31)^2} + \mathbf{A}_1^{(32)^2} + \mathbf{A}_1^{(33)^2})\boldsymbol{\varepsilon}_{t-1}^{(2)}\boldsymbol{\varepsilon}_{t-1}^{(3)} + \mathrm{b}_1\mathbf{\Sigma}_{t-1}^{(32)} \qquad \text{(14f)}$$

$$\mathbf{\Sigma}_t^{(33)} = \mathbf{A}_0^{(31)^2} + \mathbf{A}_0^{(32)^2} + \mathbf{A}_0^{(33)^2} + \mathbf{A}_1^{(31)}\mathbf{A}_1^{(11)}\boldsymbol{\varepsilon}_{t-1}^{(1)}\boldsymbol{\varepsilon}_{t-1}^{(3)} + (\mathbf{A}_1^{(31)}\mathbf{A}_1^{(21)} + \mathbf{A}_1^{(32)}\mathbf{A}_1^{(22)})\boldsymbol{\varepsilon}_{t-1}^{(2)}\boldsymbol{\varepsilon}_{t-1}^{(3)}$$

$$+ (\mathbf{A}_1^{(31)^2} + \mathbf{A}_1^{(32)^2} + \mathbf{A}_1^{(33)^2})\boldsymbol{\varepsilon}_{t-1}^{(3)\ 2} + \mathrm{b}_1\mathbf{\Sigma}_{t-1}^{(33)} \qquad \text{(14g)}$$

Notice, for example, that both $\boldsymbol{\varepsilon}_{t-1}^{(2)}$ and $\boldsymbol{\varepsilon}_{t-1}^{(3)}$, the unexpected shocks in t–1 of the equations of the second and third series, also enter the equation of $\mathbf{\Sigma}_t^{(11)}$, the volatility of the first series in time t.

For our specification, we consider data for 90-day, 8-year and 20-year interest rates, and allow for a more general form for $\mathbf{\Sigma}_t$. In particular, equation (13) becomes:

$$\mathbf{\Sigma}_t = \mathbf{A}_0{}'\mathbf{A}_0 + \mathbf{A}_1{}'\mathbf{A}_1 \otimes \boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}{}' + \mathrm{b}_1 \otimes \mathbf{\Sigma}_{t-1} + \mathbf{D}\mathbf{Z}_t\mathbf{D}' \qquad (15)$$

where $\mathbf{Z}_t$ is a diagonal matrix with m x 1 exogenous variables ($Z_{t1},\ldots, Z_{tm}$), and $\mathbf{D}$ is a k x m coefficient matrix. As Zivot and Wang (2003) point out, as long as the elements of $\mathbf{Z}_t$ are non-negative, $\mathbf{D}\mathbf{Z}_t\mathbf{D}'$ is a positive semi-definite matrix. For the case we analyze, this last condition is satisfied because $\mathbf{Z}_t$ contains dummy variables that control for volatility breakpoints.

Our regressors in the mean equation, besides a vector of constants, are the contemporaneous 12-month growth rate of the Monthly Indicator of Economic Activity (IMACEC), and the first three lags of this variable.[6] Prior to estimation, we tested whether it was adequate to treat IMACEC as weakly exogenous. In doing so, we used a test of exogeneity devised by Engle (1984). As the computations in the Appendix show, we cannot reject the null hypothesis of weak exogeneity of IMACEC.

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[6] We also tried specifications that included the spreads and lagged values of the interest rates. However, none of them was satisfactory.

In the variance equation, we included dummy variables that control for volatility breakpoints. Figure 7 shows the breakpoints detected by the ICSS algorithm for 90-day, 8-year, and 20-year interest rates at a monthly frequency. The 90-day series is the one that exhibits the most breaks: November 1997 (outbreak of the Asian crisis), October 1998 (Central Bank of Chile's tight monetary policy), May 1999 (monetary policy interest rate is reduced in 50 percent basis points with respect to April 1999; high volatility in the Ch$/US exchange rate market), June 2001 (two months prior to nominalization). In turn the 8-year and 20-year interest rates exhibit fewer breaks in volatility and, when they are present, they take place around the same dates as those of the 90-day interest rate. For instance, the only breakpoint for the 8-year interest rate took place in October 1998.

[Figure 7 about here]

Therefore, in our model, we included as an explanatory variable in the variance equation only a dummy variable that takes account of the volatility shifts in the 90-day interest rate data (Z_{t1}). In this case, $\mathbf{DZ}_t\mathbf{D}'$ takes the form:

$$\mathbf{DZ}_t\mathbf{D}' = \begin{pmatrix} \mathbf{D}^{(11)} \\ \mathbf{D}^{(21)} \\ \mathbf{D}^{(31)} \end{pmatrix} Z_{t1} \left(\mathbf{D}^{(11)} \quad \mathbf{D}^{(21)} \quad \mathbf{D}^{(31)}\right) = Z_{t1} \begin{pmatrix} \mathbf{D}^{(11)\,2} & & \\ \mathbf{D}^{(21)}\mathbf{D}^{(11)} & \mathbf{D}^{(21)\,2} & \\ \mathbf{D}^{(31)}\mathbf{D}^{(11)} & \mathbf{D}^{(31)}\mathbf{D}^{(21)} & \mathbf{D}^{(31)\,2} \end{pmatrix} \quad (16)$$

And, therefore, the elements of $\boldsymbol{\Sigma}_t$ now become:

$$\boldsymbol{\Sigma}_t^{(11)} = \mathbf{A}_0^{(11)\,2} + \mathbf{A}_1^{(11)\,2}\,\boldsymbol{\varepsilon}_{t-1}^{(1)\,2} + \mathbf{A}_1^{(11)}\mathbf{A}_1^{(21)}\boldsymbol{\varepsilon}_{t-1}^{(1)}\boldsymbol{\varepsilon}_{t-1}^{(2)} + \mathbf{A}_1^{(11)}\mathbf{A}_1^{(31)}\boldsymbol{\varepsilon}_{t-1}^{(1)}\boldsymbol{\varepsilon}_{t-1}^{(3)} + b_1\boldsymbol{\Sigma}_{t-1}^{(11)} + Z_{t1}\mathbf{D}^{(11)\,2} \quad (14a')$$

$$\boldsymbol{\Sigma}_t^{(21)} = \mathbf{A}_0^{(21)}\mathbf{A}_0^{(11)} + \mathbf{A}_1^{(21)}\mathbf{A}_1^{(11)}\boldsymbol{\varepsilon}_{t-1}^{(1)\,2} + (\mathbf{A}_1^{(21)\,2} + \mathbf{A}_1^{(22)\,2})\boldsymbol{\varepsilon}_{t-1}^{(2)}\boldsymbol{\varepsilon}_{t-1}^{(1)}$$

$$+ (\mathbf{A}_1^{(21)}\mathbf{A}_1^{(31)} + \mathbf{A}_1^{(22)}\mathbf{A}_1^{(32)})\,\boldsymbol{\varepsilon}_{t-1}^{(3)}\boldsymbol{\varepsilon}_{t-1}^{(1)} + b_1\boldsymbol{\Sigma}_{t-1}^{(21)} + Z_{t1}\mathbf{D}^{(21)}\mathbf{D}^{(11)} \quad (14b')$$

and, so on.

In this case, $\mathbf{x}_t$=12-month growth rate of IMACEC in t. We included three lags of $\mathbf{x}_t$, so L=3 in equation (11). Therefore, $\boldsymbol{\beta}_0 = \begin{pmatrix} \boldsymbol{\beta}_0^{(11)} \\ \boldsymbol{\beta}_0^{(21)} \\ \boldsymbol{\beta}_0^{(31)} \end{pmatrix}$ contains the coefficients on $\mathbf{x}_t$ for the equations of the 90-day interest rate (first equation), 8-year interest rate (second equation), and 20-year interest rate (third equation), respectively. Similarly, $\boldsymbol{\beta}_1 = \begin{pmatrix} \boldsymbol{\beta}_1^{(11)} \\ \boldsymbol{\beta}_1^{(21)} \\ \boldsymbol{\beta}_1^{(31)} \end{pmatrix}$, $\boldsymbol{\beta}_2 = \begin{pmatrix} \boldsymbol{\beta}_2^{(11)} \\ \boldsymbol{\beta}_2^{(21)} \\ \boldsymbol{\beta}_2^{(31)} \end{pmatrix}$

and $\boldsymbol{\beta}_3 = \begin{pmatrix} \boldsymbol{\beta}_3^{(11)} \\ \boldsymbol{\beta}_3^{(21)} \\ \boldsymbol{\beta}_3^{(31)} \end{pmatrix}$ contain, respectively, the coefficients on the first, second and the third lag of $\mathbf{x}_t$ for the equations of the 90-day, 8-year, and 20-year interest rates.

Table 5 shows our estimation results obtained with the *FinMetrics S-Plus 6.1* module. The contemporaneous value of the 12-month growth rate of IMACEC (IMAC) is statistically significant only in the 8-year and 20-year interest rates equations, whereas the first three lags of IMAC are only significant in the 90-day interest equation. The latter implies that past information contained in IMAC helps to predict the behavior of short rates but not that of long rates. This finding probably comes from the fact that short rates are more correlated with the monetary policy interest rate than long rates are. And, the monetary policy interest rate is set by the Central Bank according to what the pace of economic activity has been in the past few months.

[Table 5 about here]

From the table, we also see that all ARCH coefficients and the GARCH coefficient are statistically significant. Moreover, the dummy variable that controls for volatility breakpoints in the 90-day interest rate is only statistically significant (at the 2 percent level) in the 90-day interest rate equation.

Figure 8(a) shows estimates of volatility for each interest rate series. If we compare Figure 6 with Figure 8(a), we see that the univariate GARCH models tend to underestimate volatility. However, both graphs show similar patterns. Figure 8(b) in turn shows estimates of the correlation coefficients between the 90-day and 20-year rates, and between the 8-year and 20-year rates. As we see, the former randomly fluctuates between -1 and 1, while the latter is between 0.8 and 1 for the whole sample period. This implies that long rates paths move closely, whereas short rates seem to move rather independently from long rates.

[Figure 8 about here]

IV Changes in Chile's Financial Market after Nominalization

The most noticeable effects of the new monetary policy rule on the domestic financial markets are the nominalization of deposits and loans, and the boost of derivatives markets to hedge inflation and interest rate risk.

Figure 9 shows the composition of deposits and loans denominated in Chilean pesos and UF. Panel (a) clearly shows an increasing share of 90-365 day deposits in Chilean pesos, as opposed to 90-365 day deposits in UF, since July 2001. Short-term deposits (30-89 days) also present an increasing trend after nominalization. Meanwhile, inflation-linked loans have lost a little ground with respect to loans in pesos (Panels b and c).

[Figure 9 about here]

The domestic market for derivatives is relatively undeveloped. At present, all trading is OTC, and takes place between banks and between banks and large firms. The most actively traded contracts are US$/Chilean peso and US$/*Unidad de Fomento* (UF) forwards. These financial instruments, which were designed to hedge currency risk, were introduced in the domestic market in the early 1990's. In addition, around the same time period, trading of UF/Chilean peso forwards, instruments designed to hedge inflation, began.

There have been additional attempts to expand the type of contracts available domestically. In particular, interest rates derivatives and fixed-income assets derivatives were introduced in 1999 and 2000, respectively. To date, these instruments have been traded in OTC markets (typically, between commercial banks), and have taken the form of Forward Rate Agreements (FRAs) and swaps on interest rates denominated in local currency.

Figure 10 shows figures of short and long positions in UF/Ch$ forwards held by commercial banks for the time period January 1999-May 2002. Maturities of these contracts usually are over 40 days. The minimum amount to be traded is UF 50,000 and contracts are settled in Chilean pesos, according to the actual variation of inflation. The graph shows a clear upward trend in total positions since May 2001, approximately, suggesting that nominalization has led to a more active hedging of inflation. However, banks positions in UF/Ch$ forwards are still negligible as a percentage of all derivatives positions. For instance, in August 2001, total long positions in derivatives held by commercial banks reached US$32,373 million.

[Figure 10 about here]

Nominalization appears also to have triggered changes in the value of positions in interest rates derivatives held by banks. Figure 11 gives account of this. Although the increase in the positions in derivatives on interest rates is still small when compared with all trading, nominalization seems to have had a non-negligible effect on inflation-linked interest rate derivatives. This might be explained by the fact that nominalization has made UF-denominated interest rates more volatile. Therefore, agents might have engaged in more active hedging of inflation-linked interest rates positions.

[Figure 11 about here]

Finally, a potential benefit of nominalization for the Central Bank is to have more control over the more liquid components of money supply. Table 6 shows that volatility of currency and M1A has slightly dropped since nominalization took place, suggesting that the latter has contributed to the stability of most liquid money.

[Table 6 about here]

V Conclusions

For almost thirty years, indexation characterized Chile's financial market. Long-term deposits and loans, and almost any contract between two parties are denominated in the Uni*dad de Fomento* (UF). Until July 2001, monetary policy consisted of setting a target premium over the variation of the UF. However, the sharp decrease in the annual inflation rate over the last decade led the Central Bank of Chile to set its monetary policy rate in nominal terms from August 2001 onwards.

We find that nominalization has made nominal interest rates less volatile, while the opposite holds for inflation-linked interest rates. We used different volatility measures, and tested the presence of structural breaks in unconditional variance by the ICSS algorithm. In addition, we modeled the co-movements of short and long maturity interest rates by taking volatility breakpoints into account. We also showed that deposits in Chilean pesos have now a higher share of total deposits, and that trading of derivatives to hedge inflation has become much more active since nominalization took place. The market of derivatives on interest rates also seems to have taken off.

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APPENDIX

1) 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 $\varepsilon[t_1:t_2]$. When several breakpoints are suspected, the procedure is iterated, as described by Inclan and Tiao :

Step 1: Let $t_1=1$

Step 2: 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.

Step 3a: 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 $k_{first}=t_2$.

Step 3b: 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.

Step 3c: 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.

Step 4: 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.

2) Testing for weak exogeneity

Consider the following system of equations:

$$\begin{aligned} \mathbf{y}_{t1} &= y_{t2}\boldsymbol{\beta} + \mathbf{x}_1\boldsymbol{\gamma}_1 + \boldsymbol{\varepsilon}_{t1} \\ y_{t2} &= \mathbf{y}_{t1}\boldsymbol{\alpha} + \mathbf{x}_2\boldsymbol{\gamma}_2 + \varepsilon_{t2} \end{aligned} \tag{1}$$

where $\mathbf{y}_{t1}$ is a 3 x 1 vector containing the contemporaneous observations of the 90-day, 8-year, and 20-year interest rates, and $\mathbf{x}_1$ contains lags of the interest rates. In turn, y_{t2} is the contemporaneous value of the 12-month growth rate of IMACEC, and $\mathbf{x}_2$ contains lags of this variable. Under the null hypothesis of weak exogeneity of IMACEC, $\boldsymbol{\alpha}=\mathbf{0}$ and the elements of $\boldsymbol{\varepsilon}_{t1}$ are uncorrelated with ε_{t2}. Therefore, in this case, there are six constraints. Engle (1984) shows that the test boils down to a test for the omitted variables $\bar{\mathbf{y}}_1'$ and $\hat{\mathbf{u}}_1'$ from the equation of y_2, where $\bar{\mathbf{y}}_1'$ is the reduced form prediction of $\mathbf{y}_1'$, and $\hat{\mathbf{u}}_1 = \mathbf{y}_{t1} - y_{t2}\hat{\boldsymbol{\beta}} - \mathbf{x}_1\hat{\boldsymbol{\gamma}}_1$. Under the null hypothesis, the above two equations can be estimated consistently by ordinary least squares.

The regressors of the ancillary regression are defined as: $\hat{u}_2 = y_2 - \hat{\boldsymbol{\gamma}}_2\mathbf{x}_2$, $\hat{\mathbf{u}}_1^{(11)} = \mathbf{y}_1^{(11)} - \hat{\boldsymbol{\beta}}^{(11)}y_2 - \mathbf{x}_1\hat{\boldsymbol{\gamma}}_{11}$, $\hat{\mathbf{u}}_1^{(21)} = \mathbf{y}_1^{(21)} - \hat{\boldsymbol{\beta}}^{(21)}y_2 - \mathbf{x}_1\hat{\boldsymbol{\gamma}}_{21}$, $\hat{\mathbf{u}}_1^{(31)} = \mathbf{y}_1^{(31)} - \hat{\boldsymbol{\beta}}^{(31)}y_2 - \mathbf{x}_1\hat{\boldsymbol{\gamma}}_{31}$, 90-day_res= $\mathbf{y}_1^{(11)} - \hat{\boldsymbol{\beta}}^{(11)}\hat{u}_2$, 8-year_ res= $\mathbf{y}_1^{(21)} - \hat{\boldsymbol{\beta}}^{(21)}\hat{u}_2$, 20-year_res= $\mathbf{y}_1^{(31)} - \hat{\boldsymbol{\beta}}^{(31)}\hat{u}_2$, IMAC is the 12-month growth rate of IMACEC, $\mathbf{x}_1$ contains the first two lags of the 90-day, 8-year, and 20-year interest rates, and $\mathbf{x}_2$ contains the first two lags of IMAC. The Lagrange multiplier test is TR^2, where T is the sample size and R^2 comes from the above ancillary regression. In this case, the test takes on the value of 9.790, with 6 degrees of freedom. Given that the p-value of the test is 0.134, we cannot reject the null hypothesis

		Dependent Variable: $\hat{u}_2$		
Variable	Coefficient	Std. Error	t-Statistic	p-value
Constant	0.028	0.031	0.902	0.369
IMAC(–1)	–0.026	0.096	–0.267	0.790
IMAC(–2)	0.037	0.096	0.387	0.699
$\hat{\mathbf{u}}_1^{(11)}$	0.414	0.417	0.993	0.323
$\hat{\mathbf{u}}_1^{(21)}$	–2.091	4.408	–0.474	0.636
$\hat{\mathbf{u}}_1^{(31)}$	1.108	4.580	0.242	0.809
90-day_res	–0.637	0.267	–2.383	0.019
8-year_res	2.938	1.880	1.563	0.121
20-year_res	–2.752	2.003	–1.374	0.173
R^2	0.090	Number of observations		109

TABLES

Table 1 Evolution of the Inflation Rate in Chile

(a) Chile compared with other Latin American economies[1]

Year	Argentina	Brazil	Chile	Mexico
1990	2,314.0	2,947.7	26.0	26.7
1997	0.3	4.8	6.5	15.7
1998	0.7	–1.2	4.8	18.8
1999	–1.8	8.6	2.4	12.7
2000	–0.7	6.0	4.9	8.4
2001	–1.5	7.5	4.1	5.5

(b) Descriptive Statistics of Inflation in Chile: 1983-2001 [2]

Year	Annual inflation (%)	Monthly std. dev (% points)	Max-Min (% points)
1983	19.0	0.83	2.89
1984	19.1	2.12	8.06
1985	21.7	0.85	2.76
1986	14.3	0.53	2.08
1987	17.6	0.61	2.10
1988	10.5	0.63	1.81
1989	17.6	0.72	2.80
1990	25.9	1.29	4.52
1991	22.0	0.79	2.78
1992	15.5	0.73	2.91
1993	12.8	0.80	2.49
1994	11.5	0.35	1.10
1995	8.1	0.36	1.50
1996	7.3	0.22	0.71
1997	6.0	0.35	1.10
1998	5.0	0.25	0.90
1999	3.3	0.23	0.96
2000	3.8	0.20	0.63
2001	3.5	0.38	1.10
Average 83-90	**18.2**	**0.9**	**3.4**
Average 91-01	**9.0**	**0.4**	**1.5**

Source: [1]The World Bank; "Latin American Economic and Financial Outlook 2002", BCP Securities, LCC. Figures are the annual variation of the Consumer Price Index (%, year-end) for each corresponding year; [2] the Central Bank of Chile.

Table 2 Descriptive Statistics of Interest Rates in Chile: December 1992-April 2002

(a) Nominal interest rates

	7-day rate	**Δ 7-day rate**	**30-day rate**	**Δ 30-day rate**	**60-day rate**	**Δ 60-day rate**
# observations	2299	2298	2299	2298	2299	2298
Maximum	0.421	0.132	0.370	0.078	0.316	0.121
Minimum	0.002	–0.235	0.005	–0.194	0.030	–0.138
Mean	0.118	–6.03E-05	0.117	–7.28E-05	0.107	–1.17E-04
Std. Dev.	0.057	0.015	0.051	0.009	0.043	0.010
Skewness	1.369	–3.022	1.131	–5.277	1.210	–0.596
Kurtosis	6.335	58.838	5.139	110.225	5.388	33.296
ρ_1	0.965	–0.073	0.983	–0.137	0.968	–0.326
ρ_2	0.934	0.004	0.969	0.016	0.953	–0.015
ρ_3	0.904	0.013	0.956	–0.026	0.939	0.055
ρ_4	0.872	0.016	0.943	0.142	0.922	–0.001
ρ_{13}	0.617	0.033	0.732	–0.101	0.75	–0.023
ρ_{26}	0.435	0.005	0.517	–0.093	0.565	–0.008
ρ_{60}	0.334	–0.004	0.382	–0.038	0.388	0.01
ADF stat	–7.821 (0.000)	–51.601 (0.000)	–7.362 (0.000)	–12.996 (0.000)	–5.067 (0.000)	–15.379 (0.000)
Corr(Δr_t, r_{t-1})	0.132 (0.000)		0.0885 (0.000)		0.097 (0.000)	

(b) Inflation-indexed rates

	90-day rate	**Δ 90-day rate**	**180-day rate**	**Δ 180-day rate**	**360-day rate**	**Δ 360-day rate**
# observations	2299	2298	2299	2298	2299	2298
Maximum	0.219	0.023	0.150	0.019	0.135	0.010
Minimum	0.001	–0.074	0.002	–0.026	0.020	–0.019
Mean	0.066	–2.69E-05	0.061	–2.17E-05	0.062	–1.98E-05
Std. Dev.	0.021	0.003	0.016	0.002	0.013	0.002
Skewness	1.206	–11.290	0.460	–0.881	0.419	–1.887
Kurtosis	11.400	325.308	8.334	27.982	7.161	32.327
ρ_1	0.99	–0.003	0.989	–0.269	0.991	–0.236
ρ_2	0.981	–0.056	0.983	–0.055	0.986	–0.015
ρ_3	0.972	–0.042	0.978	0.061	0.981	–0.033
ρ_4	0.964	0.017	0.972	0.106	0.976	–0.019
ρ_{13}	0.87	0.047	0.893	–0.02	0.918	–0.03
ρ_{26}	0.727	–0.144	0.794	–0.021	0.843	–0.04
ρ_{60}	0.612	–0.054	0.672	0.054	0.714	–0.009
ADF stat	–2.733 (0.223)	–10.638 (0.000)	–2.276 (0.447)	–19.651 (0.000)	–2.526 (0.316)	–18.933 (0.000)
Corr(Δr_t, r_{t-1})	0.078 (0.000)		0.043 (0.019)		0.074 (0.000)	

Notes: The data are daily and were obtained from Bloomberg. Interest rates are in annual terms. The lag length in the Augmented Dickey-Fuller (ADF) test statistic is determined by the Schwartz information criterion. P-values are between parentheses.

Table 3 **Descriptive Statistics of Excess Return Series in Chile: December 1992-December 2001**

	180 and 90-day rates spread	**360 and 180-day rates spread**	**180-day excess return**	**Δ 180-excess return**	**360-excess return**	**Δ 360-excess return**
# observations	2210	2210	2210	2209	2210	2209
Maximum	0.006	0.009	0.016	0.023	0.038	0.018
Minimum	–0.027	–0.009	–0.047	–0.014	–0.038	–0.016
Mean	–0.002	5.43E-04	0.003	6.7E-06	0.004	7.2E-06
Std. Dev.	0.002	0.001	0.005	0.002	0.009	0.002
Skewness	–3.605	–0.639	–1.640	2.175	1.210	0.046
Kurtosis	33.198	13.759	12.994	52.658	5.388	19.182
ρ_1	0.924	0.867	0.960	–0.231	0.979	–0.259
ρ_2	0.879	0.813	0.937	–0.049	0.969	–0.125
ρ_3	0.84	0.806	0.919	–0.070	0.963	0.023
ρ_4	0.824	0.788	0.906	0.053	0.957	0.006
ρ_{13}	0.679	0.63	0.754	–0.042	0.884	0.018
ρ_{26}	0.533	0.438	0.541	–0.117	0.758	–0.026
ρ_{60}	0.441	0.41	0.403	0.555	0.042	0.010
ADF stat	–4.666 (0.000)	–6.221 (0.000)	–3.918 (0.002)	–34.667 (0.000)	–2.334 (0.161)	–35.470 (0.000)
Corr(Δr_t, r_{t-1})			0.144 (0.000)		0.104 (0.000)	

Notes: Excess returns and spreads are measured in quarterly terms, and were constructed from the data in Table 2(b). The lag length in the augmented Dickey-Fuller test statistic is determined by the Schwartz information criterion. P-values are between parentheses.

Table 4 Markov Switching Regime Model Estimation

(a) 180-day excess return

Estimation results

Parameters	Value	Std. error	t-stat	p-value
$\phi_{0,1}$	−1.004E-03	2.165E-04	−4.636	0.000
$\phi_{0,2}$	−3.390E-05	2.644E-05	−1.282	0.100
p_{11}	0.319	0.102	3.128	0.001
p_{22}	0.975	0.008	122.155	0.000
$\phi_{1,1}$	−0.078	0.043	−1.812	0.035
$\phi_{2,1}$	0.486	0.035	13.733	0.000
$\phi_{1,2}$	−0.001	0.007	−0.193	0.423
$\phi_{2,2}$	0.991	0.006	159.618	0.000
Unconditional probabilities				
	p(1)	p(2)		
	0.036	0.964		

(b) 360-day excess return

Estimation results

Parameters	Value	Std. error	t-stat	p-value
$\phi_{0,1}$	−2.528E-04	8.964E-05	−2.820	0.002
$\phi_{0,2}$	1.776E-04	4.704E-05	3.775	0.000
p_{11}	0.188	0.071	2.662	0.004
p_{22}	0.719	0.083	8.629	0.000
$\phi_{1,1}$	0.532	0.061	8.707	0.000
$\phi_{2,1}$	0.598	0.063	9.433	0.000
$\phi_{1,2}$	0.790	0.029	26.788	0.000
$\phi_{2,2}$	0.145	0.033	4.455	0.000
Unconditional probabilities				
	p(1)	p(2)		
	0.257	0.743		

Table 5 Multivariate GARCH estimation

(a) Parameter estimates

Parameter	Value	Std. error	t-stat	p-value
$c^{(11)}$	0.065	0.001	63.690	0.000
$c^{(21)}$	0.064	0.001	93.710	0.000
$c^{(31)}$	0.063	0.001	98.610	0.000
$\beta_0^{(11)}$	–0.001	–0.011	0.093	0.463
$\beta_0^{(21)}$	0.016	0.008	1.872	0.032
$\beta_0^{(31)}$	0.017	0.010	1.735	0.043
$\beta_1^{(11)}$	0.031	0.013	2.356	0.010
$\beta_1^{(21)}$	0.006	0.007	0.868	0.194
$\beta_1^{(31)}$	0.005	0.007	0.702	0.242
$\beta_2^{(11)}$	0.032	0.010	3.158	0.001
$\beta_2^{(21)}$	–0.002	0.007	–0.260	0.398
$\beta_2^{(31)}$	–0.004	0.008	–0.533	0.298
$\beta_3^{(11)}$	0.023	0.016	1.473	0.072
$\beta_3^{(21)}$	–0.003	0.009	–0.316	0.376
$\beta_3^{(31)}$	–0.007	0.010	–0.696	0.244
$A_0^{(11)}$	8.695E-04	2.279E-04	3.815	0.000
$A_0^{(21)}$	–7.412E-04	2.693E-04	-2.752	0.004
$A_0^{(31)}$	–9.646E-04	2.514E-04	-3.837	0.000
$A_0^{(22)}$	6.126E-04	2.947E-04	2.079	0.020
$A_0^{(32)}$	4.210E-04	4.089E-04	1.030	0.153
$A_0^{(33)}$	3.867E-05	9.744E-04	0.040	0.484
$A_1^{(11)}$	0.976	0.170	5.749	0.000
$A_1^{(21)}$	0.843	0.175	4.823	0.000
$A_1^{(31)}$	0.831	0.179	4.638	0.000
$A_1^{(22)}$	0.271	0.047	5.771	0.000
$A_1^{(32)}$	0.292	0.052	5.666	0.000
$A_1^{(33)}$	–0.052	0.020	–2.631	0.005
b_1	0.213	0.058	3.699	0.000
$D^{(11)}$	0.026	0.013	2.045	0.022
$D^{(21)}$	0.005	0.004	1.178	0.121
$D^{(31)}$	0.005	0.005	0.963	0.169

(b) Specification Tests

Equation	Jarque Bera[(1)] p-value	Ljung-Box test[(2)] for squared standardized residuals (12 d.f) p-value	Lagrange multiplier test[(3)] (12 d.f.) p-value
90-day interest rate	0.092	0.412	0.423
8-year interest rate	0.620	0.570	0.469
20-year interest rate	0.664	0.913	0.931

Notes: [(1)] It detects whether the error terms are normally distributed. [(2)] It detects whether there are additional ARCH terms. [(3)] It detects the presence of serial autocorrelation.

Table 6 Volatility of Currency and M1A

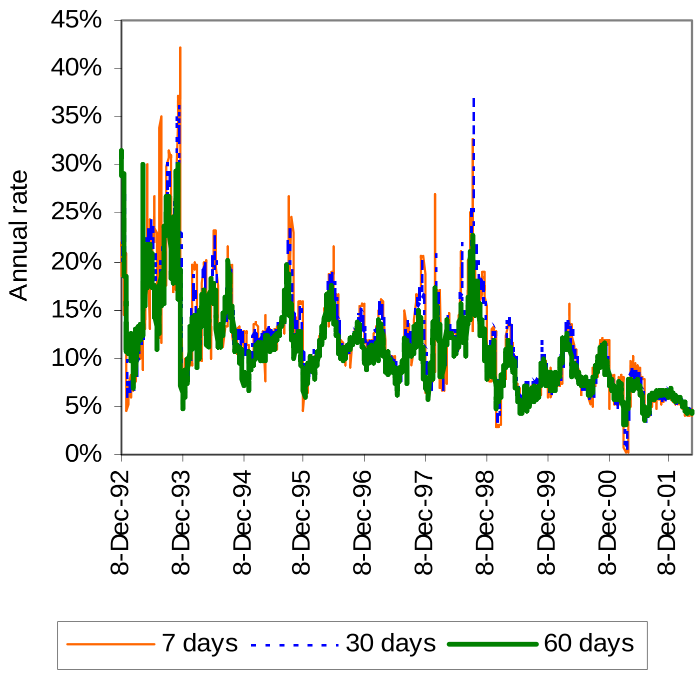
Period	Money classification	
	Currency	M1A
2000	0.041	0.039
2001-November 2002	0.029	0.030

Notes: the data are monthly, and volatility represents the standard deviation of percent changes per month. The data source is the Central Bank of Chile.

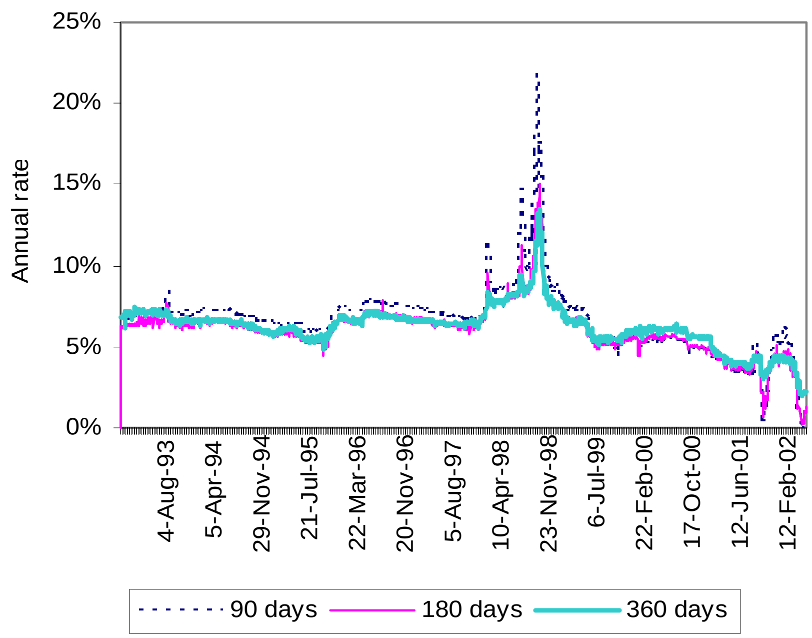
FIGURES

Figure 1 Interest Rates of the Chilean Financial System: December 1992-April 2002

(a) Nominal interest rates



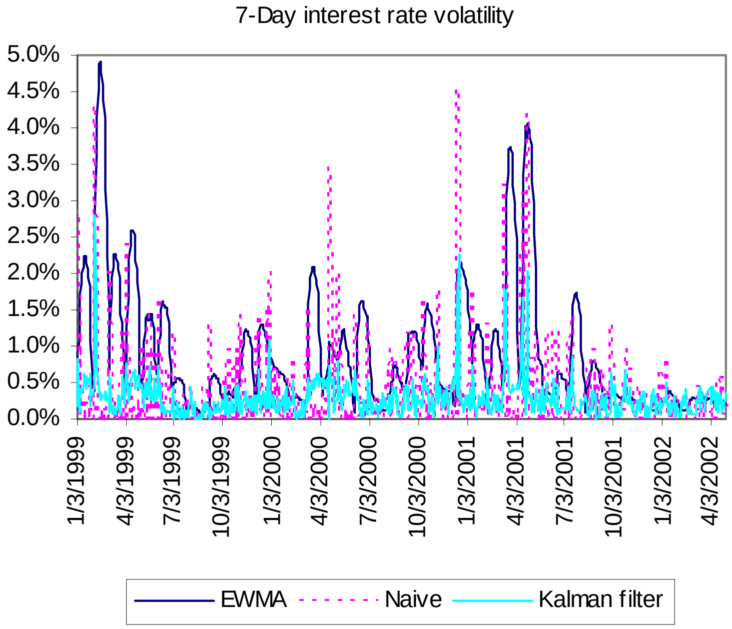
(b) Inflation-linked interest rates

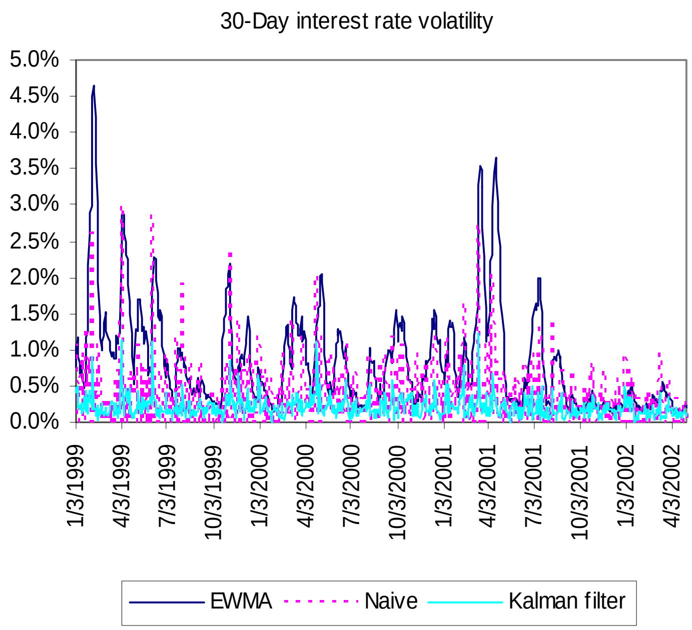


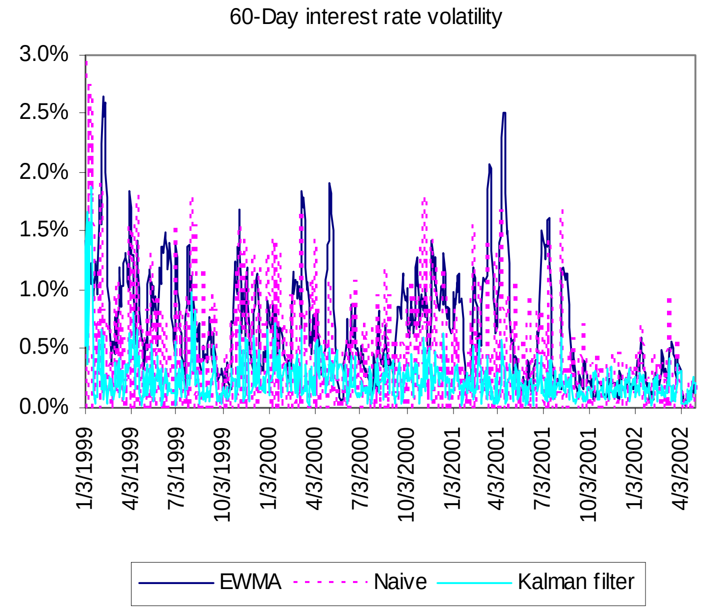
Data source: Bloomberg. The data are daily.

Figure 2 Volatility Estimates of Interest Rates: January 1999-April 2002

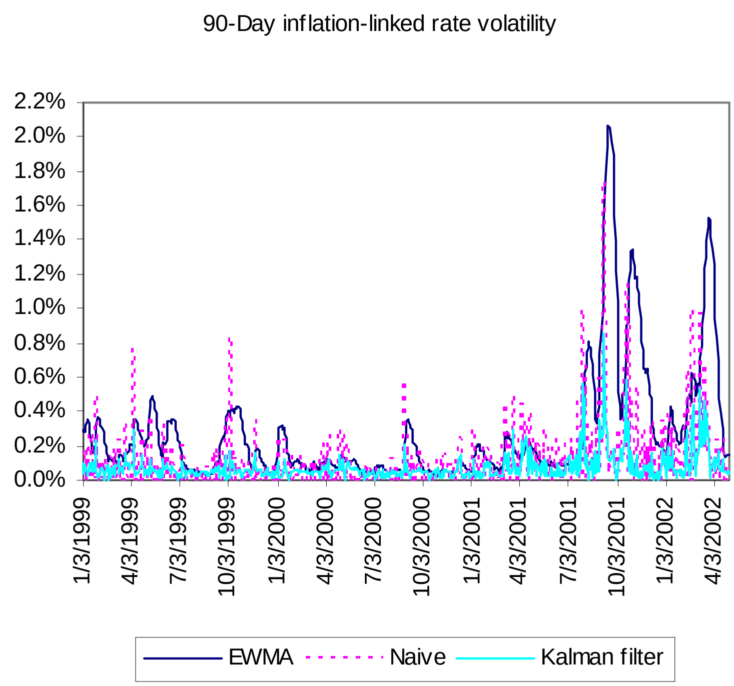
(a) Nominal interest rates

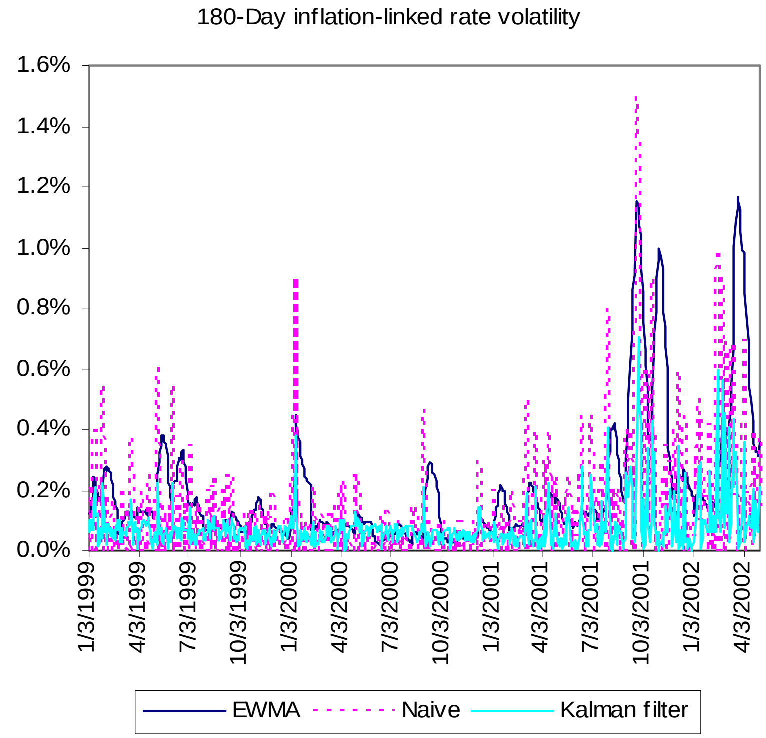


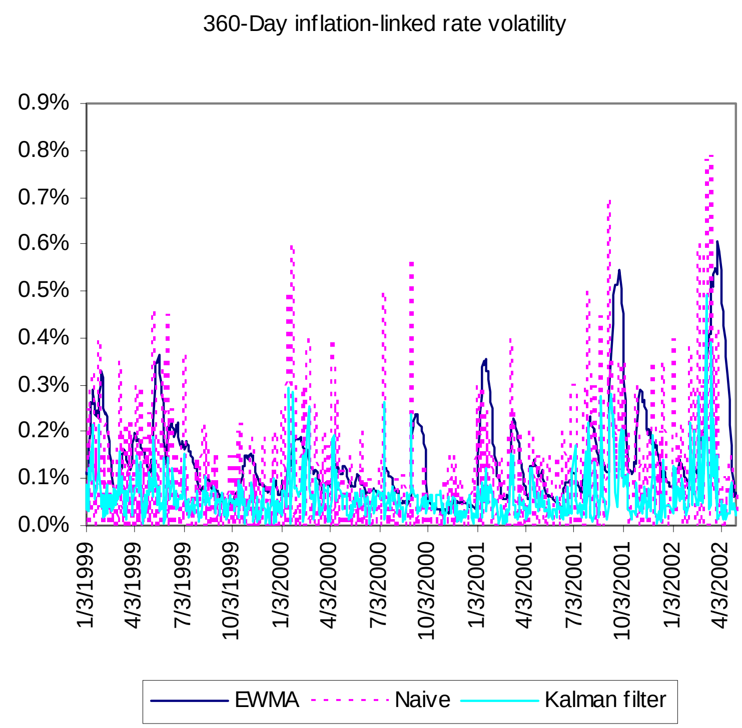




(b) Inflation-linked interest rates

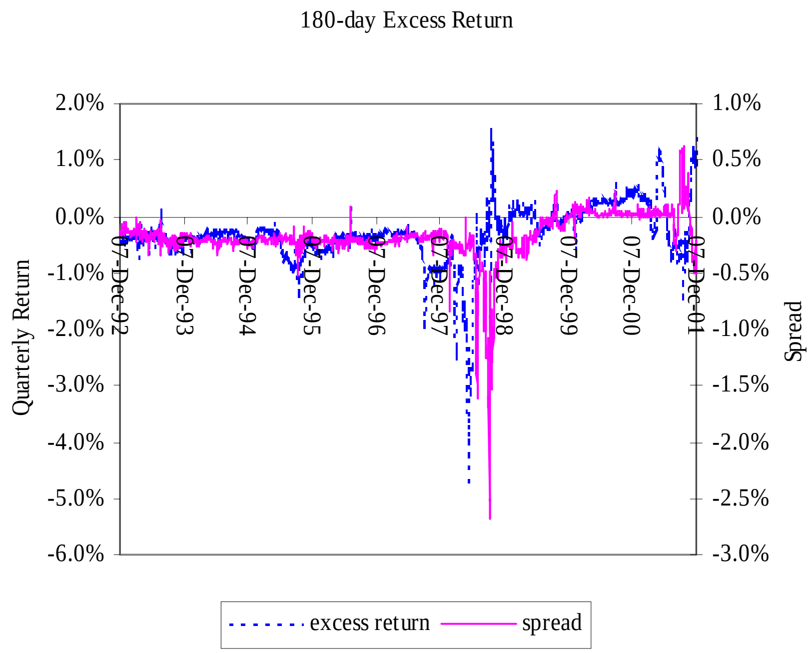


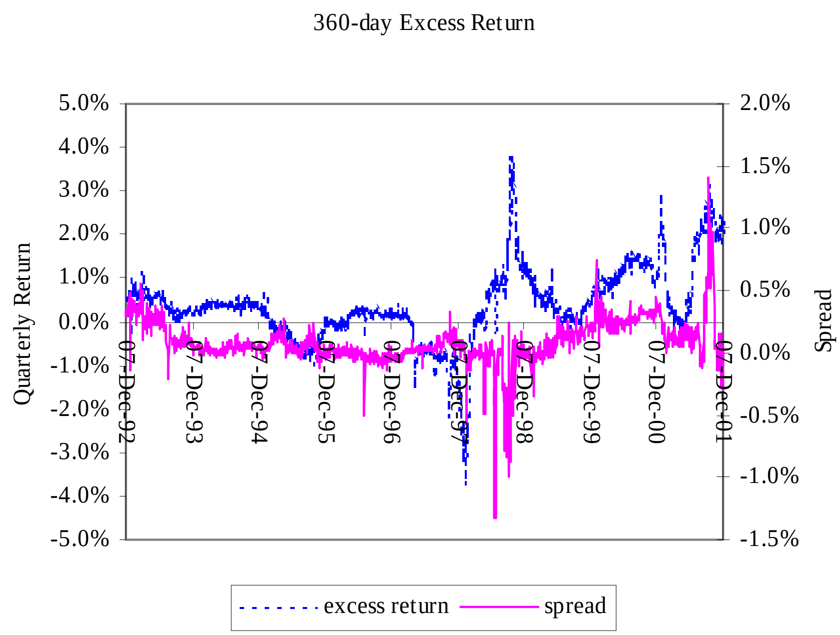




Notes: The Exponentially Weighted Moving Average (EWMA) estimate is computed by using a λ parameter of 0.94, 0.73, and 0.62 for the 7-day, 30-day, and 60-day interest rates, respectively; for the 90-day, 180-day, and 360-day interest rates λ takes on the value of 0.87, 0.93, and 0.88, respectively. The data are daily and were obtained from Bloomberg.

Figure 3 Excess Returns of Inflation linked-interest rates: December 1992-December 2001

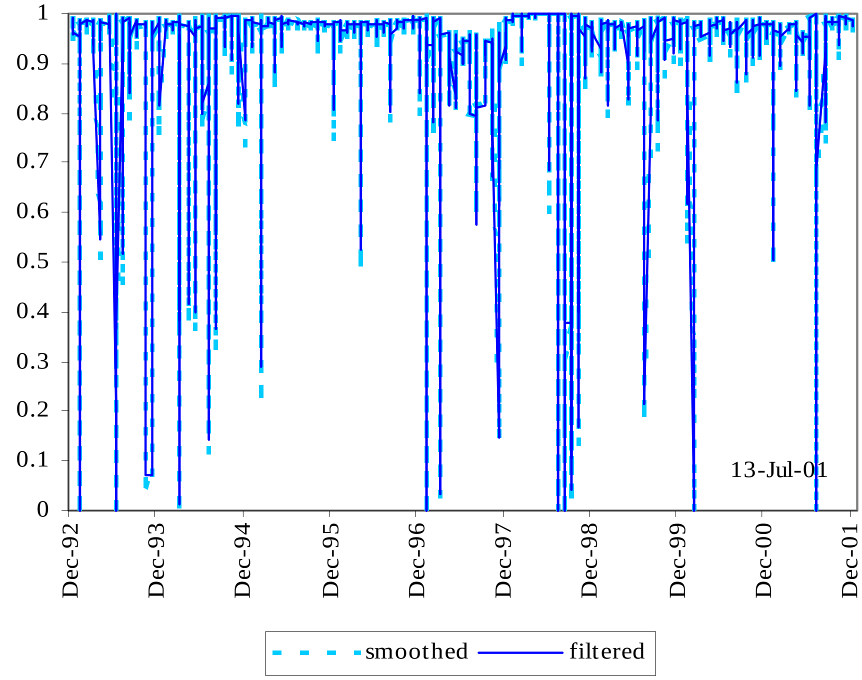




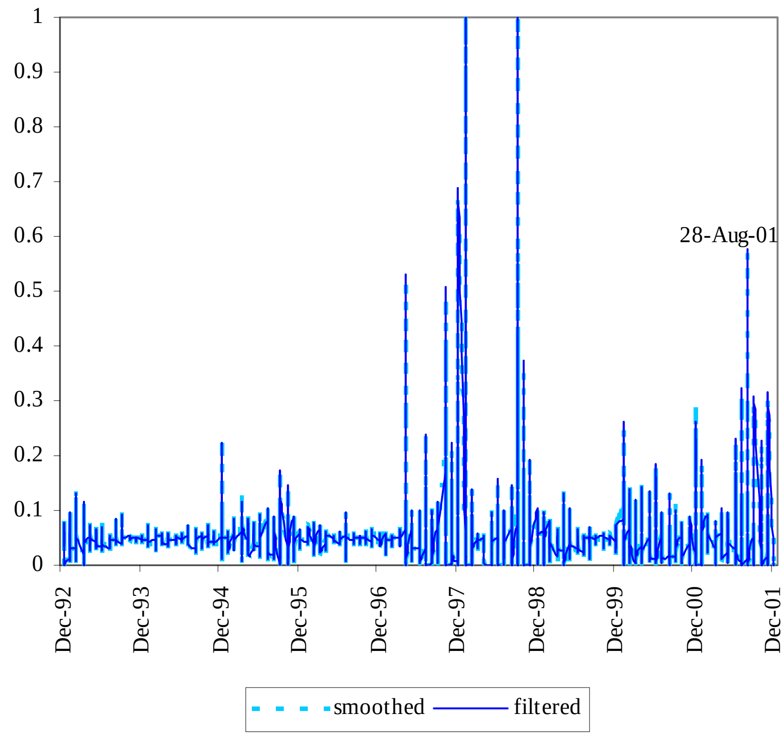
<u>Notes</u>: The 180-day excess return is computed as the difference between the return on a 180-day deposit and the return obtained by rolling over a 90-day deposit. Similarly, the 360-day excess return is computed as the difference between the return on a 360-day deposit and the return obtained by rolling over a 180-day deposit. The data are daily and were obtained from Bloomberg.

Figure 4 Excess Return Series and Nominalization: Regime Switching (December 1992-December 2001)

(a) 180-day excess return



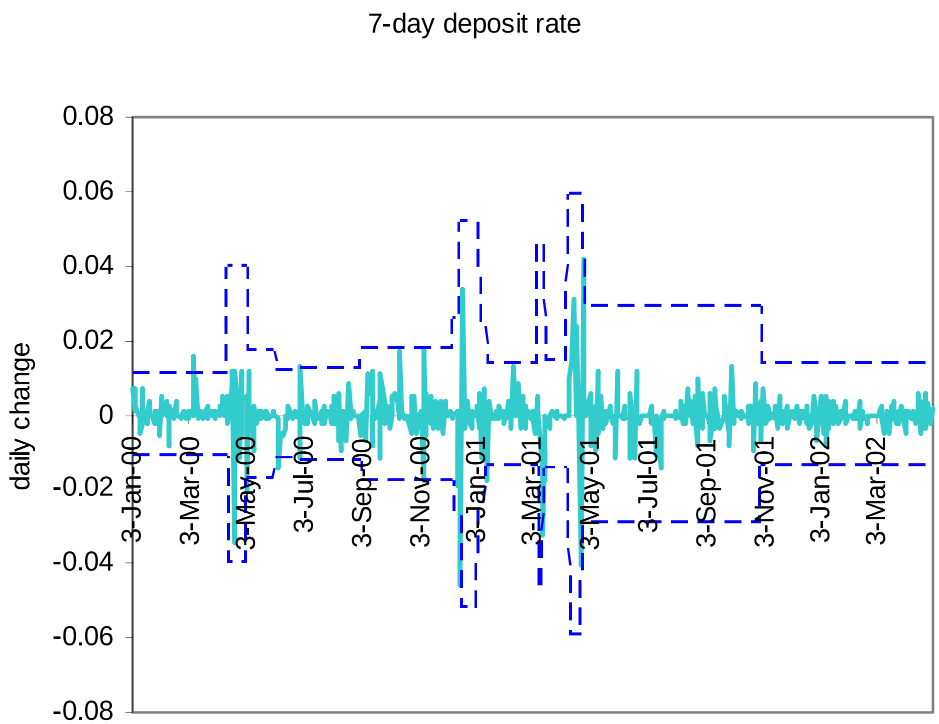
(b) 360- day excess return



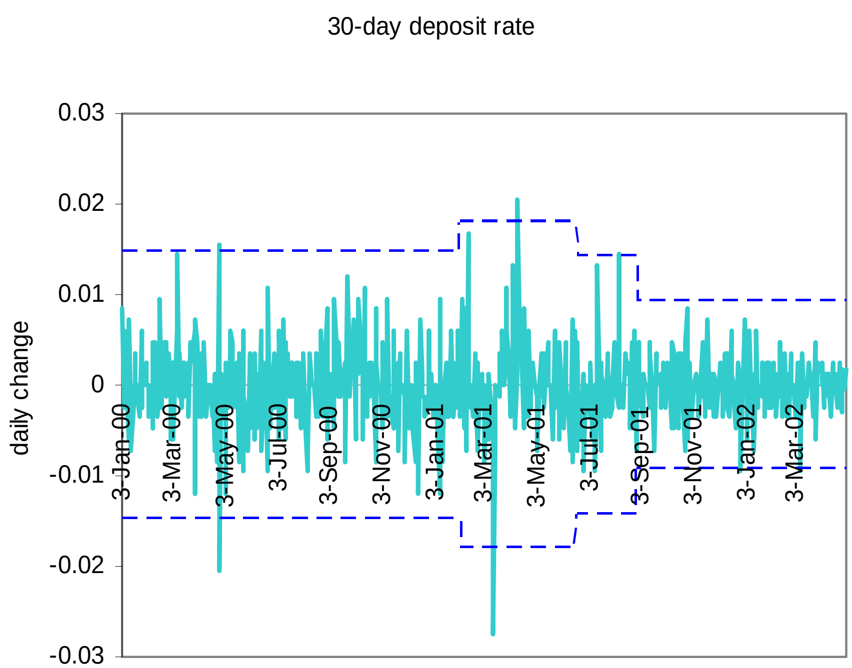
<u>Notes:</u> The 180-day excess return is computed as difference of the return on a 180-day deposit and the return obtained by rolling over a 90-day deposit. Similarly, the 360-day excess return is computed as the difference of the return on a 360-day deposit and the return obtained by rolling over a 180-day deposit. The data are daily and were obtained from Bloomberg.

Figure 5 ICSS Algorithm and Structural Breaks in Volatility of Interest Rates: January 2000-April 2002

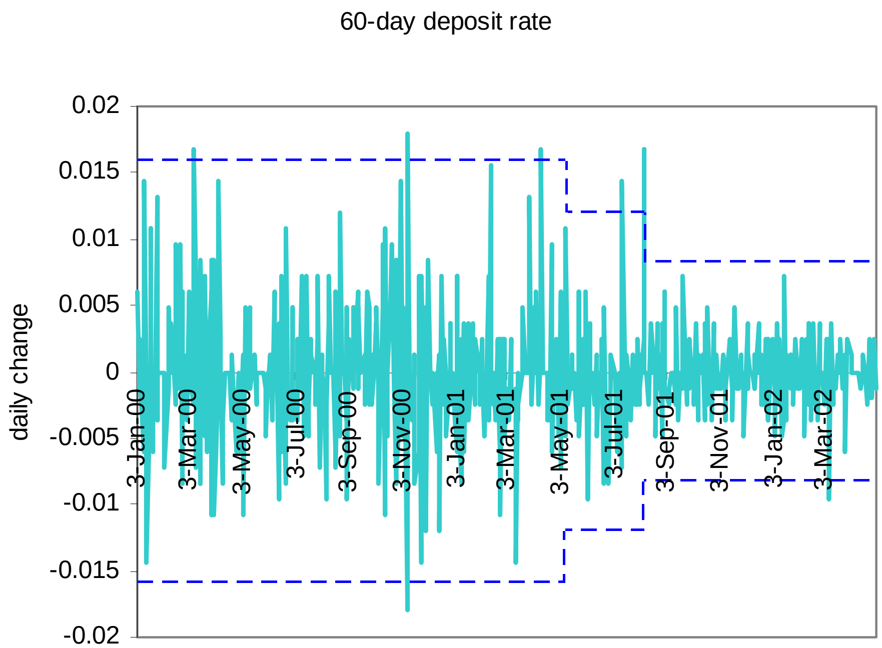
(a)



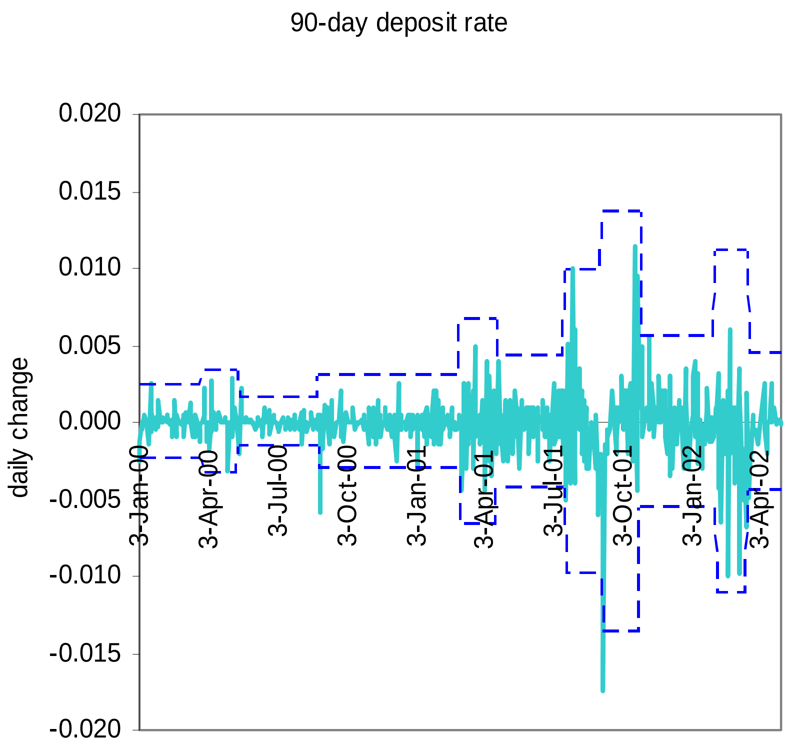
(b)



(c)

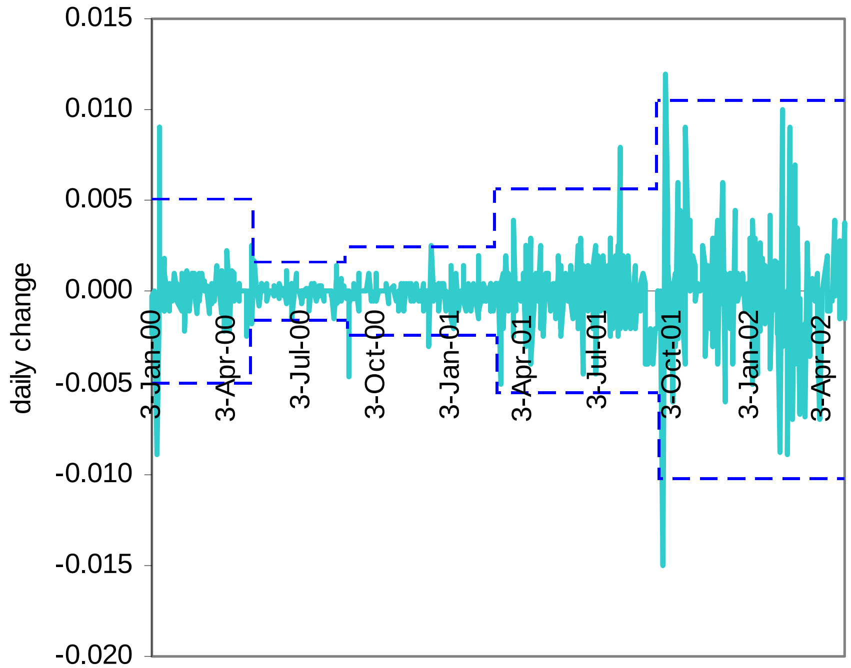

60-day deposit rate
daily change
0.02
0.015
0.01
0.005
0
-0.005
-0.01
-0.015
-0.02
3-Jan-00
3-Mar-00
3-May-00
3-Jul-00
3-Sep-00
3-Nov-00
3-Jan-01
3-Mar-01
3-May-01
3-Jul-01
3-Sep-01
3-Nov-01
3-Jan-02
3-Mar-02

(d)


90-day deposit rate
daily change
0.020
0.015
0.010
0.005
0.000
-0.005
-0.010
-0.015
-0.020
3-Jan-00
3-Apr-00
3-Jul-00
3-Oct-00
3-Jan-01
3-Apr-01
3-Jul-01
3-Oct-01
3-Jan-02
3-Apr-02

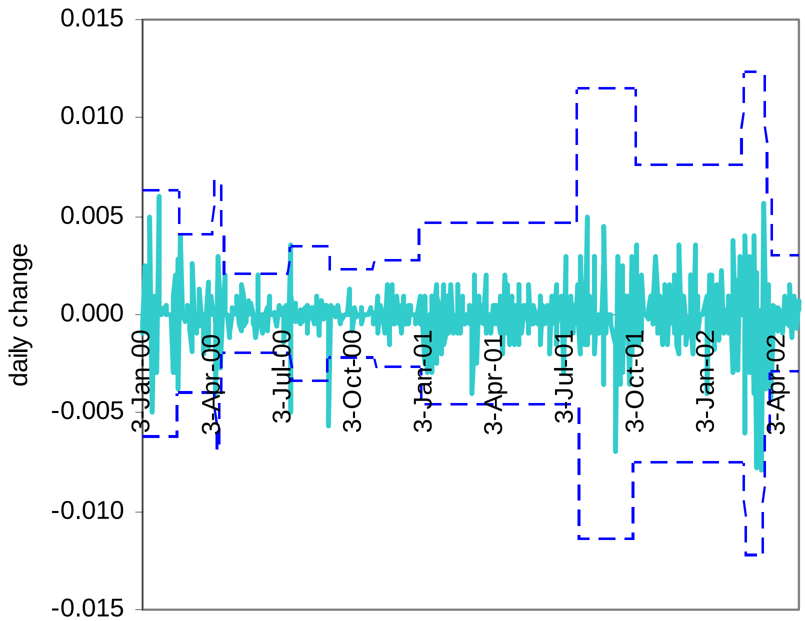
(e)

180-day deposit rate



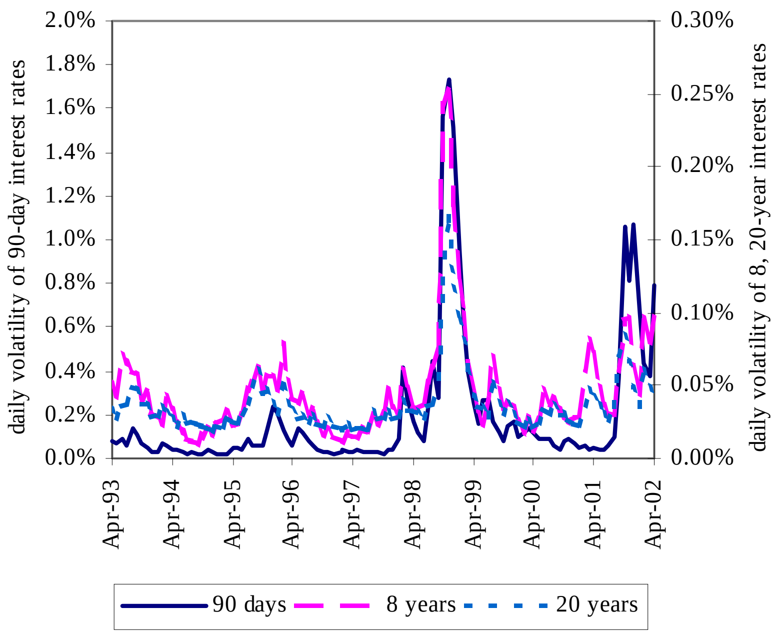
(f)

360-day deposit rate



Note: The data are daily and were obtained from Bloomberg.

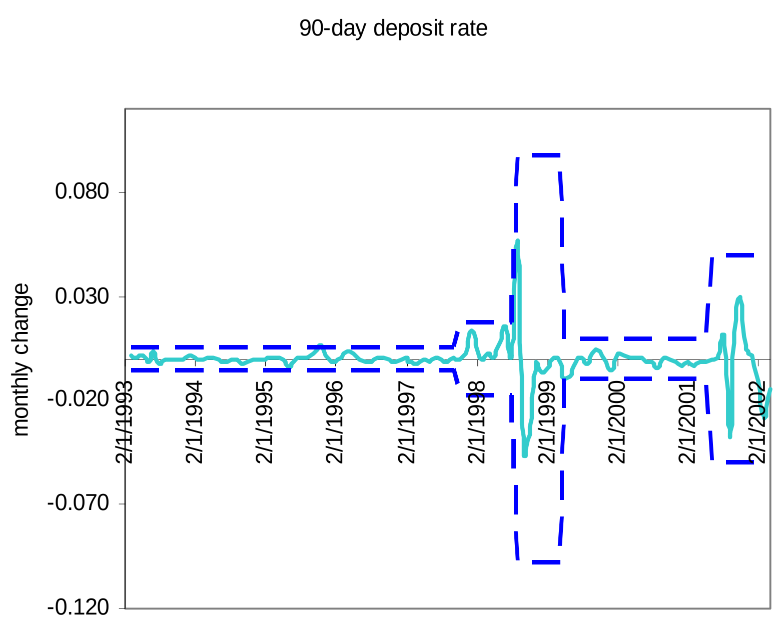
Figure 6 Univariate GARCH estimates of Volatility of Short and Long maturity Interest Rates: February 1993-April 2002



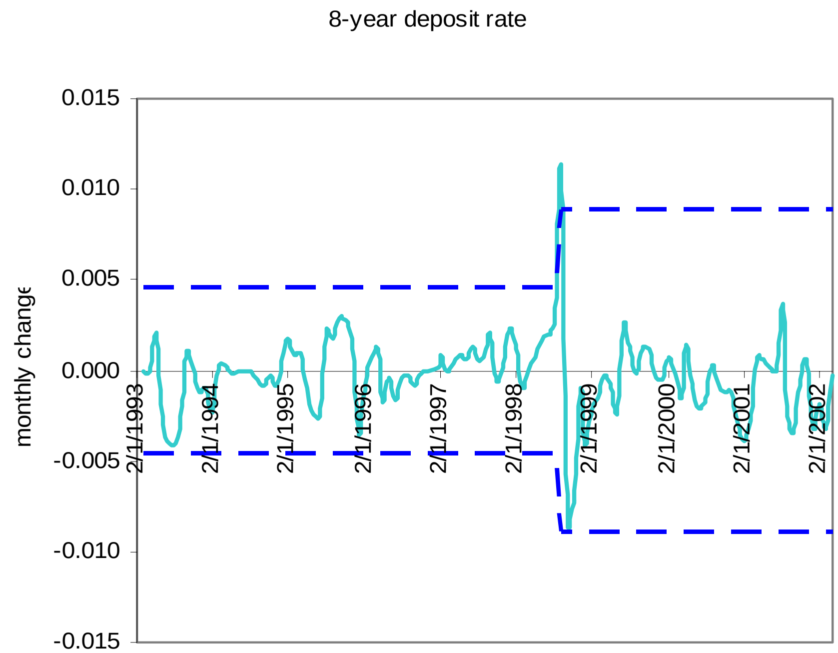
Note: The data are monthly and were obtained from the Central Bank of Chile

Figure 7 Volatility Breakpoints of Interest Rate Data: 90 days, 8 and 20 years: February 1993-April 2002

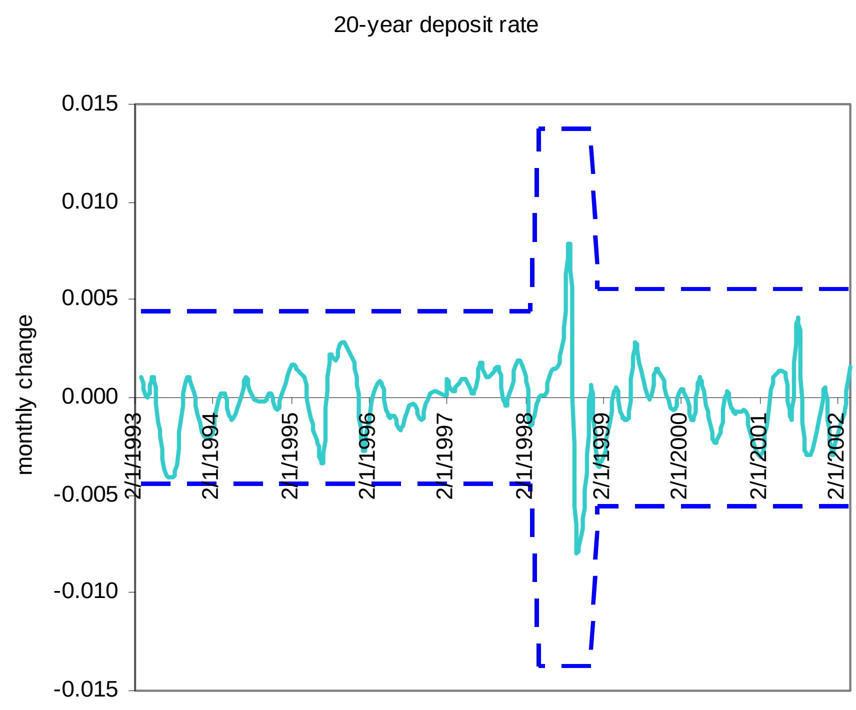
(a)



(b)



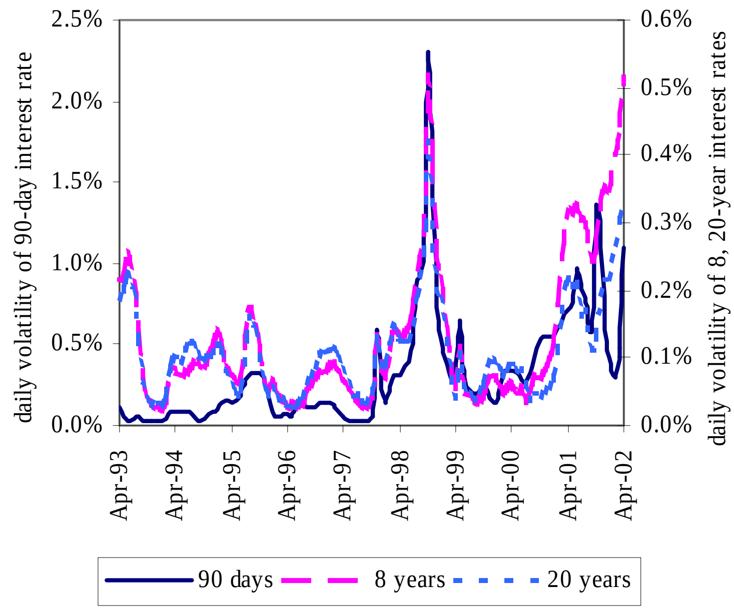
(c)



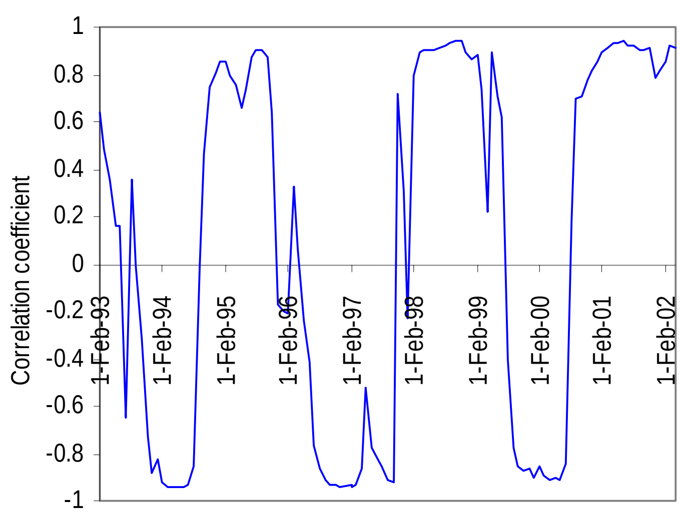
Note: The data are monthly and were obtained from the Central Bank of Chile

Figure 8 Multivariate GARCH estimates: February 1993-April 2002

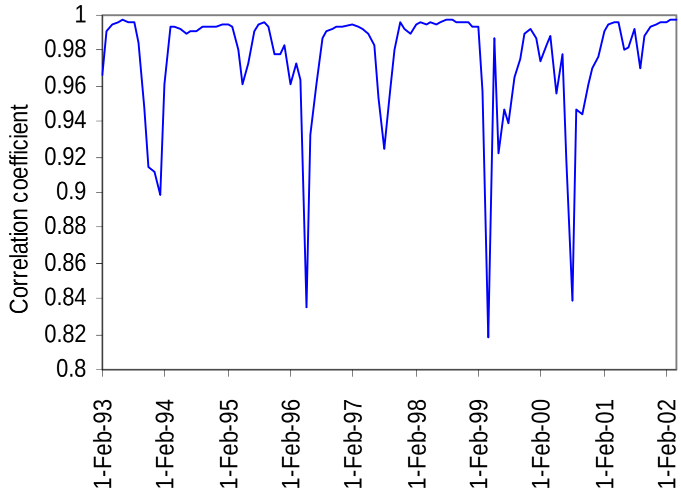
(a) Volatility estimates



(b) Correlation between 90-day and 20-year interest rates



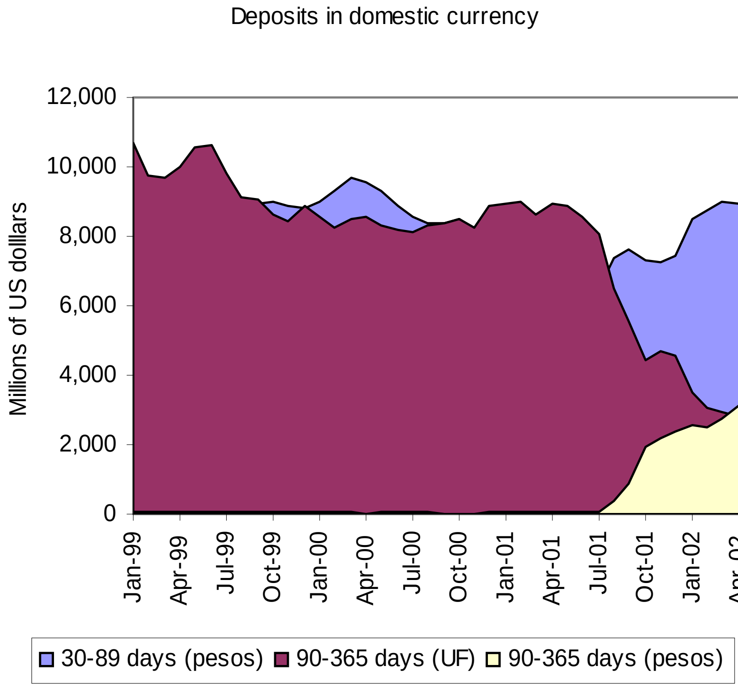
(c) Correlation between 8-year and 20-year interest rates



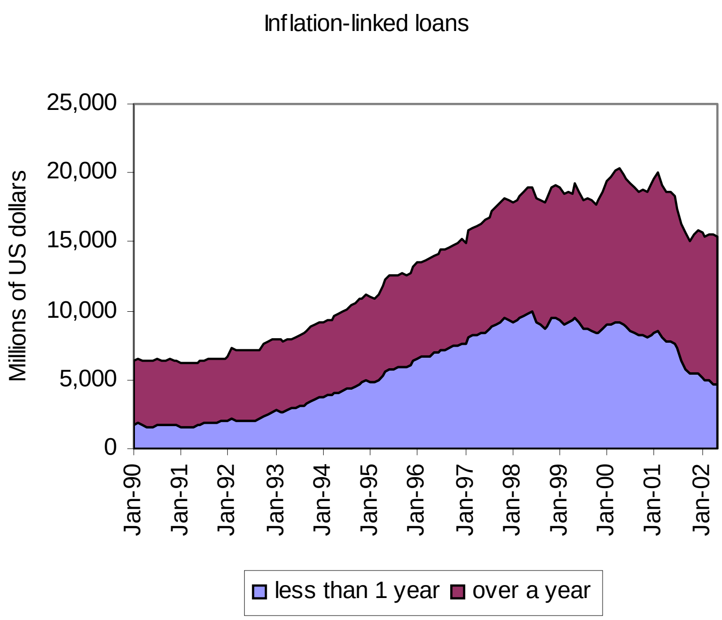
Note: The data are monthly and were obtained from the Central Bank of Chile

Figure 9 Composition of Domestic Deposits and Loans: January 1999-April 2002

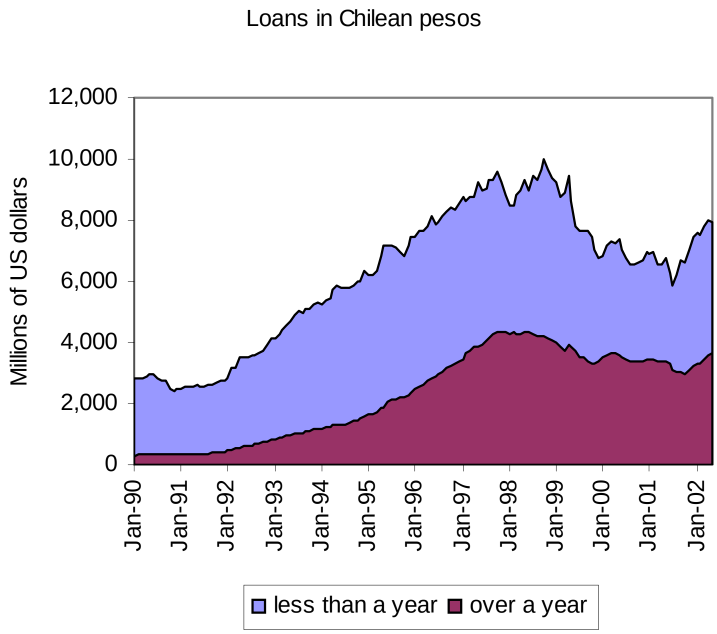
(a)



(b)

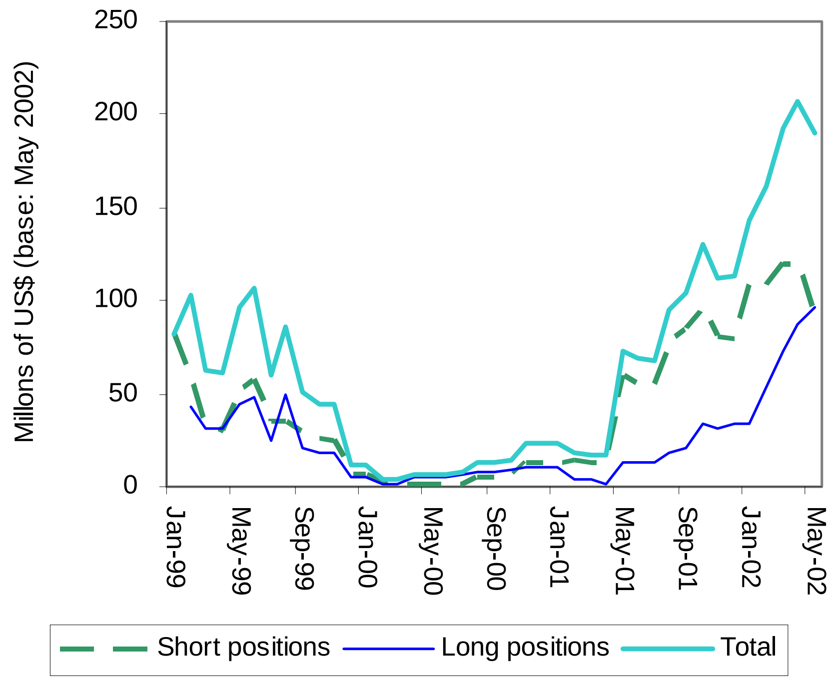


(c)



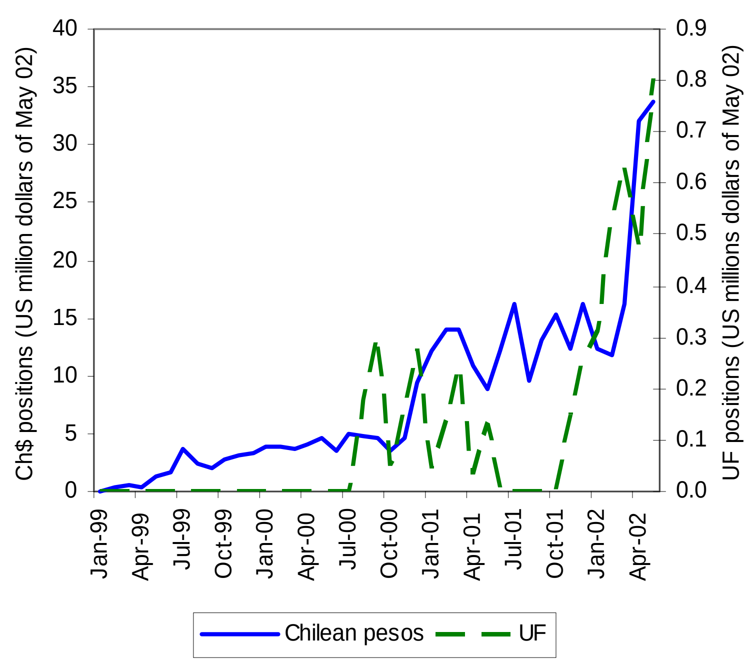
Source: Author' elaboration based upon data from the Superintendence of Banks and Financial Institutions. The data are monthly.

Figure 10 UF/Ch$ Forwards Positions held by Domestic Banks: January 1999-May 2002



Source: Author's elaboration based on data from the Superintendence of the Banks and Financial Institutions. Long positions are purchases of UF made by banks at a future date, whereas short positions are sales of UF to third parties at a future date. All positions are closed out in Chilean pesos. The data are monthly.

Figure 11 Value Change in Banks Positions on Interest Rates Derivatives: January 1999-May 2002



Source: Author's elaboration based on data from the Superintendence of the Banks and Financial Institutions. The data are monthly.