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SEASONAL COINTEGRATION AND THE STABILITY OF THE DEMAND FOR MONEY

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Resumen

La búsqueda de una función de demanda de dinero estable ha sido una larga y generalmente infructuosa tarea para la econometría aplicada. Las estimaciones tradicionales han resultado inestables, poco satisfactorias en términos teóricos y con una pobre capacidad predictiva. El presente trabajo centra su atención en un área cuya omisión puede explicar los decepcionantes resultados encontrados en estudios previos. Al considerar de manera explícita la posible existencia de raíces unitarias en los componentes estacionales de las variables, se desarrolla un modelo de cointegración estacional capaz de capturar relaciones de largo plazo no incorporadas en los trabajos anteriores. De esta forma, se obtiene una demanda de dinero que, sin incluir ninguna variable dummy ad hoc, es estable por casi 25 años y tiene mejor capacidad predictiva que los modelos utilizados tradicionalmente.

Abstract

Studies on money demand in both developed and developing countries coincide in reporting systematic over predictions of monetary aggregates, non-robust estimated parameters and out-of-sample forecast variances that are too large to guide monetary policy. Several explanations have been given for these failures, including dynamic misspecification, omitted variables such as financial innovations, and non observed components. This paper explores an alternative, simpler way to approach the instability of money demand using seasonal-cointegration techniques. Using Chilean data we find that seasonal cointegrating vectors exist and, when omitted from the estimation, account for a substantial fraction of the observed instability in money demand functions. Because seasonal cointegrating vectors act as additional long-run restrictions, they can substantially reduce the variance of forecast errors. The estimated demand for money in Chile is remarkably stable in spite of the profound structural and financial reforms carried out throughout the 1977-2000 period, parameters are robust and similar to those suggested by economic theories.

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1. Introduction

A stable money demand function is of paramount importance not only to monetary policy, but also for economic theory. The empirical estimation of money demand functions has been, consequently, a popular topic in applied econometrics. Yet, satisfactory results in terms of the consistency of estimated parameters with theoretical specifications and their stability remain elusive. Likewise, it is not unusual to observe out-of-sample forecasts that do not meet the accuracy standards required to make useful recommendations for monetary policy.

During the late 1970s, studies on money demand in both developed and developing countries coincided in reporting a systematic over prediction of monetary aggregates and the tendency of estimated parameters to be non-robust. These "missing money" episodes have been extensively documented for the US by Goldfeld (1973 and 1976) and for most other developed countries by Fair (1987). Likewise, episodes of systematic under prediction are not unusual (Goldfeld and Sichel, 1990).

In the Chilean case, a number of papers have tested different specifications of the demand for money using increasingly sophisticated econometric techniques (see Mies and Soto, 2000 for a survey). In general, the stability, robustness and out-of-sample forecast variance of estimated models are disappointing. Traditional specifications a-la-Cambridge yield non-robust parameters and high residual autocorrelation, an indication of misspecified dynamics (e.g., Matte and Rojas, 1989 and Rosende and Herrera, 1991).

Cointegration is not usually achieved and level-shift dummies are typically introduced in an ad-hoc manner (e.g., Herrera and Vergara, 1992). Instability led several authors to exclude the pre-1983 period from their samples, as in Apt and Quiroz (1992) or Adam (2000), but robustness remained elusive. Neural network models have also been estimated by Soto (1996) obtaining stable and robust estimates with very low out-of-sample forecast errors but at the cost of substantial econometric complexity. All of these estimations produce out-of-sample forecasts with variances that are too large for conducting monetary policy.

This paper explores an alternative, simpler way to approach the instability of money demand using seasonal-cointegration techniques. An overlooked issue in all previous papers is that of seasonality. In general, it is removed either using dummy variables or prefiltering the series using period-to-period differences or the X-11 methodology. These methodologies have important drawbacks: the use dummies assumes that seasonality is a deterministic phenomenon, while filters either impose a particular stochastic structure (a unit root in the monthly or quarterly frequency) or induce excess persistence (X-11). As discussed in Soto (2000) most macroeconomic variables in Chile are seasonally integrated and, consequently, standard deseasonalizing methods are inappropriate. More worrisome, failing to account for seasonal unit roots in previous estimation of money demands may lead to spurious correlations and unstable parameterizations.

The existence of seasonal unit roots suggests the need to test for seasonal cointegration. The main hypothesis of this paper is that, if such cointegrating vectors exist and were omitted from previous empirical models, they could account for a substantial fraction of the instability observed in estimated money-demand functions. Seasonal cointegrating vectors could act, in this sense, as an additional long-run restriction and reduce the variance of forecast errors.

Section 2 of the paper briefly describes the analytical framework we use to derive an empirical specification from the demand for money and presents a summary of the estimated money demand functions for the Chilean case and their main characteristics in terms of the consistency of estimated parameters with economic theory, robustness, stability, and forecasting abilities. Section 3 presents the main features of the econometric of seasonal unit roots are then presented, as well as the testing procedures involved. Seasonal cointegration in the context of error correction models is then discussed. A direct result of this analysis is to highlight the role that seasonal cointegration can play in providing better estimations in terms of forecasting power and parameter stability. The omission of common trends in seasonal frequencies can lead to unstable estimated models with omitted variables problems.

Section 4 presents the main econometric results, which are divided in three areas. We first show that money and its fundamental determinants are most likely characterized by long-run and seasonal non-stationary components. This suggests that most previous studies are subject to econometric estimation problems and suspect of spurious correlations. We then proceed to estimate long-run and seasonal cointegrating vectors and their corresponding error-correction representations. We obtain three different cointegrating vectors corresponding to the long run, semiannual, and quarterly frequencies. This suggests that previous estimates may suffer from severe omitted-variable problems, since common trends in seasonal components had not been included in the estimation. Parameters of the long run cointegrating vector are similar to those obtained by previous estimates but the short-run dynamics are markedly different. In particular, we show that the adjustments to the long-run equilibrium are much faster than those found in models that use seasonally adjusted data. This suggest that deseasonalizing methods may induce excess persistence in the data as documented by Soto (2000) for the Chilean data. Seasonal shocks dissipate also quite fast. Moreover, the estimated models do not include dummies. In the third part of the empirical analysis we compare the forecasting abilities of our model with other studies. We found that the seasonal cointegration-error correction model is superior in its forecasting abilities as it displays lower mean-square forecast errors and mean absolute errors. Section 5 collects the conclusions and suggests areas for further research.

2. Analytical Framework and Estimated Money Functions for Chile

Since the main purpose of this paper is to explore the econometric dimensions of seasonality, this study does not develop a micro funded model of the demand of money but it uses the following standard expression:

$$\frac{M_t^{\,d}}{P_t} = L(y_t, r_t, z_t) \tag{1}$$

where M^d are money balances kept by agents, P is the price level, y is a scale variable that reflects the number of transactions or the income level, r is the alternative cost of money, and z represents variables which can affect the level of money demand, such as financial innovation or technical change.

This specification of the demand for money is consistent with the money in the utility function developed by Sidrauski (1967), transaction costs models in the spirit of Wilson (1989) and cash in advance models (Clower, 1967; Lucas, 1980). It is also a standard specification of most empirical studies (Goldfeld and Sichel, 1990).

A particular case of the general function for money demand presented in (1) is used in this paper:

$$m_t^{\,d} = \alpha + \beta y_t - \gamma \frac{i_t}{1+i_t} - \phi \frac{i_t^{\,e}}{1+i_t^{\,e}} + \theta z_t \tag{2}$$

where m^d are real money balances, all variables are in logs and the alternative cost of holding money has been split into its domestic (i) and international (i^e) components. The latter, which includes the foreign interest rate and the expected nominal exchange rate devaluation for the current period, arises from considering that agents hold both domestic and foreign assets (e.g., bonds). In partial equilibrium setups *y* is usually limited to private consumption. However, when money demand is derived from a general equilibrium framework with households, firms and the government, it is more appropriate to include GDP as the scale variable.[1]

Equation (2) is a long-run equilibrium relationship between the demand for money and its determinants. No reference is made to stochastic seasonal components, which are at the heart of this paper. This reflects the relative ignorance of economic theory regarding the elements that, besides weather, determine seasonal behavior. This study assumes that the particular short-run dynamics of money demand –including seasonal components– as well as its adjustment to the long-run equilibrium is purely an empirical issue.

3. Unit Roots and Cointegration in Seasonal Components

Seasonality in money demand estimations has been only superficially studied. The use of simple, standard procedures makes strong assumptions regarding the underlying process that determines seasonal components. Seasonal dummies, one of the most widely used methods, implicitly assumes that seasonality is a deterministic phenomenon. Alternative procedures, such as differencing or filtering with an ARIMA X-11 procedure, account for stochastic seasonality but assume stationarity. Furthermore, in their attempt of removing seasonality, these methods generally alter the stochastic structure of series (Franses, 1997). Whenever macroeconomic series are seasonally integrated (this is, if seasonal shocks have permanent components), seasonal adjustments using the former methods is inadequate. Furthermore, not accounting for the existence of seasonal unit roots could cause spurious correlations and unstable parameters in empirical studies.

Moreover, seasonal adjustments can affect the power of unit root and cointegration tests. If seasonality is deterministic, removing it with the aid of dummy variables has no effect whatsoever on unit root tests (Dickey et al., 1984). However, when seasonal effects are stochastic, standard filters can greatly affect the power of unit root tests. Ghysels (1990) shows that removing seasonality using the X-11 method or the “variation in x periods” induces excess persistence in the series and consequently reduces the power of unit root tests to reject non stationarity. Olekalns (1994) extends this result to the cases in which dummies or *band-pass* filters are used to remove seasonality. Abeysinghe (1994) shows that removing stochastic seasonality with dummy variables leads to the spurious regression problem.

Soto (2000) shows that this is also the case in the Chilean data: the removal of seasonal components using dummy variables, X-11 filters, or x-period differences leads to severe statistical problems and distorts the evaluation of the presence of unit roots in 8 of the 15 main macroeconomic series. For our purposes, it is important to note that GDP, real money, consumption, the price level, nominal interest rates, and exchange rates are all affected by standard seasonal adjustment methods.

If seasonal components are stochastic, the variable can have a unit root not only in its long-run behavior, but also at its seasonal frequencies. To assess the presence of stochastic, possibly non-stationary, seasonal effects we use a seasonal unit-root test developed by Hylleberg et al (1993). Although there are other testing procedures (e.g., Canova and Hansen, 1995), we rely on this test –dubbed as HEGY– on the grounds that it proceeds from general to specific, tends to be more robust when there are additional non-seasonal unit roots in the variables, and is in general of higher power than alternative tests (see Hylleberg, 1995).

The HEGY test is based on the fact that the annual growth rate of any series in quarterly frequency can be expressed as the following polynomial:

$$(1 - L^4) \;=\; (1 - L)(1 + L)(1 - iL)(1 + iL) \qquad \textbf{(3)}$$

where L is the lag operator and i=%-1. The left-hand side term correspond to the annual growth rate or the 4-period log difference. The right hand side terms correspond to the long-run, semiannual, and quarterly components.

Decomposition (3) is very useful, as it allows to develop a general test, nesting several hypotheses regarding the behavior of the series. The generalized expression of equation (3) is:

$$(1 - l^4) \;=\; (1 - \alpha_1 L)(1 + \alpha_2 L)(1 - \alpha_3 iL)(1 + \alpha_4 iL) \qquad \textbf{(4)}$$

where $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ are parameters. Their value determines the existence of unit roots in the different frequencies:

- if $\alpha_1 = 1$ the variable has one non-seasonal (long run) unit-root.
- if $\alpha_2 = 1$ the variable has a unit root in its semi-annual frequency.
- if $\alpha_3 = 1$ or $\alpha_4 = 1$ the variable has a unit root in its quarterly frequency

In the vicinity of $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 1$ equation (4) can be expressed as:

$$\begin{aligned}(1-L^4) \;=\; &(\alpha_1-1)L(1+L+L^2+L^3)+(\alpha_2-1)L(1-L+L^2-L^3)+\\ &(\alpha_3-1)(1-L^2)(1+iL)L+(\alpha_4-1)iL(1-L^2)(1-iL)\end{aligned} \quad \textbf{(5)}$$

Defining $\gamma_i = \alpha_i - 1$ and applying (5) to y_t, the following expression can be obtained to test for the presence of stochastic seasonal components (i.e., the HEGY test):

$$(1-L^4)y_t \;=\; \gamma_1(1+L+L^2+L^3)y_{t-1}+\gamma_2(1-L+L^2-L^3)y_{t-1}+(1-L^2)(\gamma_3-\gamma_4 L)y_{t-1}+\epsilon_t \quad \textbf{(6)}$$

To implement the HEGY test, define the auxiliary variables:

$$\begin{aligned} y_{1t} &= (1+L+L^2+L^3)y_{t-1} = y_{t-1}+y_{t-2}+y_{t-3}+y_{t-4}\\ y_{2t} &= (1-L+L^2-L^3)y_{t-1} = y_{t-1}-y_{t-2}+y_{t-3}-y_{t-4}\\ y_{3t} &= y_{t-1}-y_{t-3}\end{aligned} \quad \textbf{(7)}$$

These variables are used to estimate the following equation by OLS:

$$(1-L^4)y_t \;=\; \pi_1 y_{1t-1}+\pi_2 y_{2t-1}+\pi_3 y_{3t-1}+\pi_4 y_{3t-2}+\epsilon_t \quad \textbf{(8)}$$

Some interesting questions can now be directly tested: (a) if the null hypothesis $\pi_1 = 0$ cannot be rejected, then there is a non-seasonal (long-run) unit root in y_t; (b) if the null hypothesis $\pi_2 = 0$ cannot be rejected, then there is a unit root in y_t's semiannual frequency; (c) if it is not possible to reject the null hypothesis $\pi_3 = \pi_4 = 0$, then there is a seasonal unit root in the quarterly frequency of y_t. Note that, in addition to t-tests, the latter would require joint testing of the parameters with an F-test. Note also that the test is constructed around non stationarity null hypotheses and is subject to power limitations. Nevertheless, the test can be augmented with lags of y_1 to control for potential residual correlation and increase power. Likewise, a richer alternative hypothesis can be accommodated by including an intercept, trends, and deterministic seasonality.

Under the null hypothesis of non-stationarity, the tests for the estimated parameters do not have the standard distribution, so that the results must be compared to the critical values tabulated by Hellyberg et al. (1990). As customary, these critical values depend on the presence of nuisance parameters.

Seasonal Cointegration

The existence of seasonal unit roots naturally suggests to test for the presence of seasonal cointegrating vectors when testing for long-run common trends. It is only natural to think that if money is demanded for transaction purposes, then seasonality in GDP –which is marked in the Chilean case as shown below– should be accompanied by seasonal shifts in money demand. Seasonal cointegration can be viewed as a parallel shift in these variables in the same sense that is implied by long-run cointegration, i.e., as the result of equivalent common trends. Engle et al. (1993) extend the popular error correction-cointegration framework of Engle and Granger (1987) to accommodate cointegration at different frequencies.

Using the above decomposition of the series, our interest is to test the existence of cointegrating vectors at different frequencies. When cointegration is achieved only at the long-run components, then the setup reproduces the classic Engle-Granger (1987) error-correction model:

$$\Delta y_t = \alpha\beta y_{t-1} + \epsilon_t \tag{9}$$

where β is the cointegrating vector and α is the loading factor, i.e., the fraction of last-period's disequilibrium that is adjusted at time "t". When cointegration is achieved at the semiannual components, then the model corresponds to:

$$y_t - y_{t-2} = ½\alpha_1\beta_1(y_{t-1} + y_{t-2}) + ½\alpha_2\beta_2(y_{t-1} - y_{t-2}) + \epsilon_t \tag{10}$$

where α_1 and α_2 are adjustment factors. The first term in equation (10) is just the annual average and, consequently, β_1 is a standard long-run cointegrating vector. The second term measures the within-year variation and β_2 gives the vector of parameters that makes the annual variation of the variables cointegrate. When cointegration is also achieved at the quarterly frequency, then the model corresponds to:

$$y_t - y_{t-4} = \tfrac{1}{4}\alpha_1\beta_1(y_{t-1}+y_{t-2}+y_{t-3}+y_{t-4}) + \tfrac{1}{4}\alpha_2\beta_2(y_{t-1}-y_{t-2}+y_{t-3}-y_{t-4}) + \tfrac{1}{4}(\alpha_R\beta_R+\alpha_I\beta_I)(y_{t-2}-y_{t-4}) + \tfrac{1}{4}(\alpha_I\beta_R-\alpha_R\beta_I)(y_{t-1}-y_{t-3}) + \epsilon_t \tag{11}$$

The first two terms provide exactly the same information as before. The second pair of terms, however, are more difficult to elucidate as it conforms a case of polynomial cointegration (sub indexes *I* and *R* refer to the solution's imaginary and real components). The problem with equation (11) is that these polynomials need not have reduced rank and parameters may not be identified. To achieve identification, Lee (1992) proposes to eliminate the second term by assuming $\alpha_R\beta_I - \alpha_I\beta_R = 0$. Alternatively, one could impose a less demanding restriction, $\beta_I = 0$ (as in Johansen and Schaumburg, 1999), in which case equation (11) becomes:

$$y_t - y_{t-4} = \tfrac{1}{4}\alpha_1\beta_1(y_{t-1}+y_{t-2}+y_{t-3}+y_{t-4}) + \tfrac{1}{4}\alpha_2\beta_2(y_{t-1}-y_{t-2}+y_{t-3}-y_{t-4}) + \tfrac{1}{4}(\alpha_R L - \alpha_I)\beta_R'(y_{t-1}-y_{t-3}) + \epsilon_t \tag{12}$$

The interpretation of the last term is now somewhat easier: either $\beta_R'(y_{t-1}-y_{t-3})$ is stationary or it cointegrates with its own lag.

The specification of seasonal cointegration evidences the role it could play in providing a better understanding of the determinants of money demand and obtaining more robust estimations. If there is no cointegration in the semiannual or quarterly frequencies, equation (12) becomes the standard error correction model that has been widely used in previous estimations for money demand in Chile. However, if there is cointegration at any of the seasonal frequencies, equation (12) indicates that previous models have been misspecified, at they have omitted relationships which provide valuable information about the money balances demanded by agents.

4. Empirical Analysis of the Chilean data

Based on the model developed in the previous section, we estimate the demand for money using GDP as the scale variable (y) and the definition of money (m) which is the closest to the money-for-transactions concept underlying the analytical framework (3-month average of real M1 balances). Based on the evidence gathered in previous papers, we deflate money balances by the CPI. With regards to the alternative cost of money, we use the domestic nominal deposit rate (i) and the foreign nominal interest rate (i^*) which corresponds to the LIBO rate plus the effective nominal quarterly devaluation of the Chilean peso. The latter assumes that agents have perfectly myopic rational expectations, in the sense of Turrnovsky (2000). All series are seasonally *unadjusted,* quarterly and cover the 1977:1-2000:4 period (the longest available). Figure 1 presents the data, where seasonal patterns and common trends are notorious in money and GDP.

Figure 1a
Real Money Balances and GDP in Chile

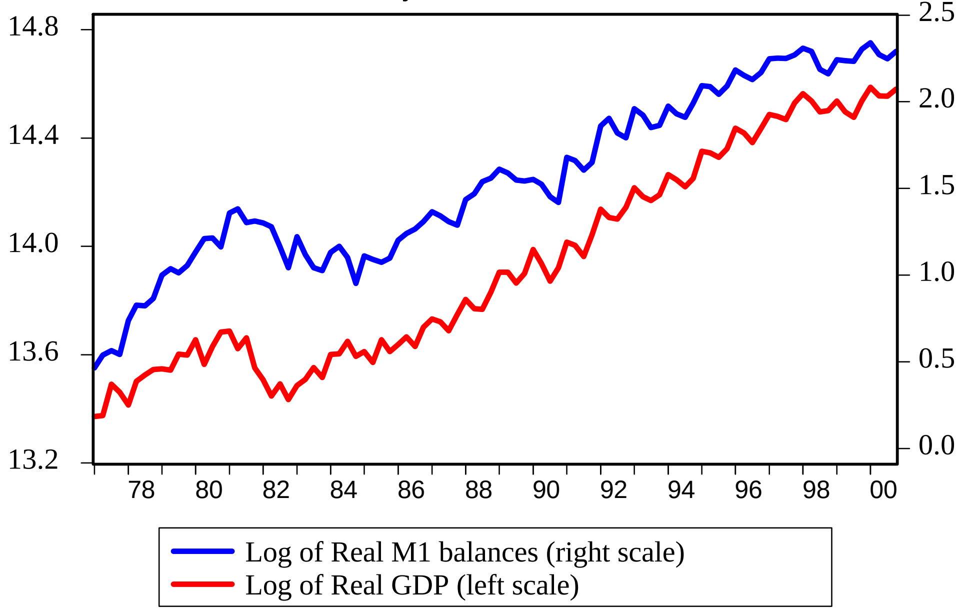
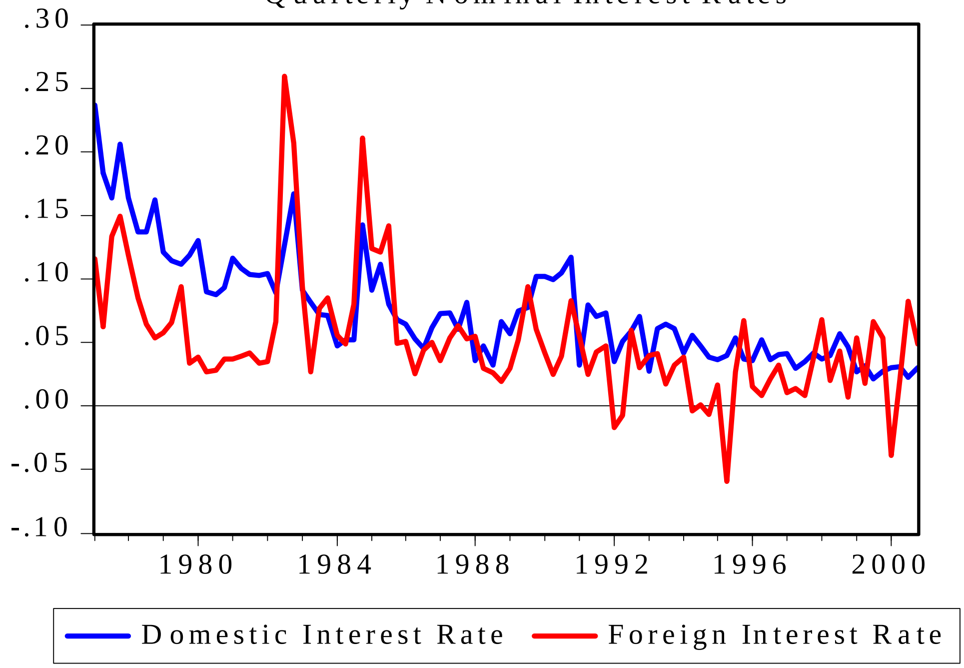


Figure 1b
Quarterly Nominal Interest Rates



The econometric strategy is straightforward. First, the order of integration of the variables is assessed for their annual, semiannual, and quarterly frequencies, using HEGY tests. Then, a seasonal cointegration model, with its corresponding error-correction structure, is estimated using two alternative procedures. The estimated models are then evaluated in terms of their stability and their forecasting power in and out of sample. Finally, these models are compared to standard cointegration and error correction models which do not account for seasonal cointegration. We restrict our estimation to the 1977:1-1999:2 period and leave the remaining six observations for out-of-sample evaluations.

Assessing the order of integration of the variables

Unit root tests are provided in Table 1. It can be seen that most variables display rather high first-order autocorrelation levels. It would not be surprising, then, to find unit-roots in the data. In general, Dickey-Fuller tests suggest all variables are integrated of order one. On the other hand, Phillips-Perron tests do not reject non-stationarity in the cases of money balances and GDP. Finally, KPSS tests reject the null of stationarity in all cases.

The contradictory picture emerging from unit-root tests on interest rates could be the result of the well-known low power of these tests when the true process is close to, but different than, a unit root (see Cochrane, 1988). But, as discussed by Ghysels (1990), Lee and Siklos (1991), and Abeysinghe (1994) among others, it could also be that seasonal factors distort unit-root tests.

Table 1
Unit Root Tests
1977.1-2000.4

	Autocorrelations		Unit Root Tests			HEGY Seasonal Unit Root Tests				
	1st order	Sum of first four	Dickey Fuller	Phillips Perron	KPSS	t π_1	t π_2	t π_3	t π_4	F $\pi_3 \cap \pi_4$
Money Balances (real $ 1986)	0.95	0.97	-2.83	-2.81	1.86	-2.88	-2.08	-2.17	-2.35	5.14
GDP (real $ 1986)	0.97	1.05	-1.84	-1.90	1.77	-1.89	-2.58	-2.08	-1.32	4.94
Foreign Interest Rate (nominal)	0.56	0.69	-2.48	-5.76	1.68	-2.03	-5.01	-4.07	-3.16	13.22
Domestic Interest Rate (nominal)	0.76	1.15	-2.83	-6.31	1.51	-3.37	-2.48	-3.51	-1.33	5.61
Critical values 95%	-	-	-3.48	-3.48	0.46	-3.71	-3.08	-2.26	-4.02	6.55

Note: unit root tests control for drift, deterministic trend, and seasonal dummies. Lags were optimized according to marginal significance.

Table 1 also presents the results of testing the money demand variables for seasonal unit-roots. The tests for non-seasonal unit roots (t_{π_1}) suggest that all variables can be adequately characterized as non-stationary in frequency zero (that is, long-run non-stationary). Moreover, HEGY tests found that most variables present unit roots at other frequencies. In particular, all variables present a unit-root at the semiannual (t_{π_2}) and quarterly frequencies (t_{π_1}, t_{π_4}), with the only exception of the foreign interest rate. While in most variables we are unable to reject the null hypothesis of non-stationarity according to π_4, the evidence is mixed when considering tests on $\pi_{3.}$ F tests of the joint hypothesis presented in the last column allow us to determine that unit-roots at the seasonal frequency are present in all variables except the foreign interest rate.[2]

These results also help us understand the mixed evidence regarding unit roots found in previous studies. As discussed above, DF, PP, and KPSS tests are sensitive to the presence of non stationarity in the residuals or to the incorrect pre-filtering of the series to remove seasonality. Moreover, since unit-root tests are sensitive to these problems, it is likely that cointegration tests applied in several studies of the demand for money in Chile may also be distorted.

Cointegration and Seasonal Cointegration

We test for cointegration at the long run, semiannual, and quarterly frequencies using a two-stage strategy. In the first stage, we use Johansen's (1988) maximum-likelihood trace statistic to determine the number of cointegrating vectors in each frequency. An alternative procedure would be to follow the suggestion of Engle et al. (1993) of searching directly for unit roots in the residuals of the cointegrating vector. Nevertheless, Johansen´s procedure to determine the number of cointegrating vectors is usually considered superior when there is high residual autocorrelation, as is our case when testing the long-run and semiannual frequencies in which quarterly variation would possibly filter through the residuals (see Hargreaves, 1994). Table 2 presents the results of estimating the trace statistics in each frequency. We use the critical values tabulated by Johansen and Schaumburg (1999). It can be seen that the data is consistent with only one hypothesized cointegrating vector in each frequency. The presence of seasonal cointegrating vectors suggests that previously estimated models may be misspecified. In particular, there is no evidence of a second cointegrating vector at the zero frequency as claimed by Adam (2000), which suggests the presence of spurious correlation problems in his paper.

In the second stage, we estimate the cointegrating vectors at each frequency using Engle and Granger’s (1987) procedure and save the residuals to be used in the estimation of the seasonal error-correction models. An alternative strategy explored below is to estimate the non linear version single-step of the error correction-cointegration regression.

Table 2
Testing the Number of Long Run Cointegrating Vectors
1977.1-2000.4

Hypothesized number of vectors	Eigenvalues	Trace statistic	Johansen-Schaumburg 5% critical value
Frequency: long run			
None	0.320	61.74*	47.21
At most 1	0.188	30.47	29.68
At most 2	0.139	13.60	15.41
At most 3	0.018	1.50	3.76
Frequency: semiannual			
None	0.437	76.40*	62.9
At most 1	0.211	29.31	34.9
At most 2	0.113	9.84	14.9
Frequency: quarterly			
None	0.403	69.93*	62.9
At most 1	0.169	26.10	34.9
At most 2	0.115	10.40	14.9

Note: * denotes rejection of the hypothesis at 5% significance level. Tests at frequency zero and semiannual include 5 lags. Quarterly frequency includes 2 lags.

In the first row of table 3 we present the results for the long-run cointegration vector which, according to table 2, includes money balances, the scale variable (GDP), and domestic and foreign interest rates.[3] Cointegration is achieved according to Dickey Fuller tests applied to residuals (cointegration DF tests apply with critical value of -3.75 at 95%, as described in Engle et al., 1993). Note that the scale elasticity is almost unitary, as found in other studies of the Chilean case, and the fit is quite high. Semi-elasticities for the interest rates are, as expected, negative and comparable in size to those found in previous studies. The disparate size of these parameters are, nevertheless, difficult to reconcile with the notion of asset substitutability.

The second row in table 3 presents the result of testing for cointegration in the semiannual frequency. According to seasonal unit roots, only money, income, and domestic interest rates should be included. It can be seen that residuals are stationary (again cointegration DF tests apply as described in Engle et al, 1993). Seasonal dummies were included but they were found not significant at 95%. The inclusion of seasonal dummies is justified by the fact that, along with non-stationary seasonality, there can also be deterministic seasonal components. The fit of these models is low (especially when compared to the long-run cointegrating vector), thus suggesting that some of the determinants of intra-annual fluctuations have been omitted. Determining which are those variables is an open area for further research. At the present time, we know that this is not caused by the exclusion of the foreign interest rate, which, as seen before, does not have a unit root in this frequency.

Table 3
Seasonal Cointegration Tests
1977.1-1999.2

	Constant	GDP	Deposit Interest Rate	Foreign Interest Rate	Lagged GDP	Lagged Deposit Int Rate	Adjusted R^2	Unit Root Test of Residuals
Long run	-50.93	1.04	-2.69	-0.24	-	-	0.96	-4.00
	(2.55)	(0.04)	(0.42)	(0.38)				(ADF test)
Semi Annual	-0.02	0.42	-1.44	-	-	-	0.52	-4.10
	(0.01)	(0.11)	(0.19)					(ADF test)
Quarterly	0.03	0.22	-1.61	-	0.24	-0.12	0.65	17.09
	(0.01)	(0.12)	(0.30)		(0.13)	(0.29)		(HEGY test)

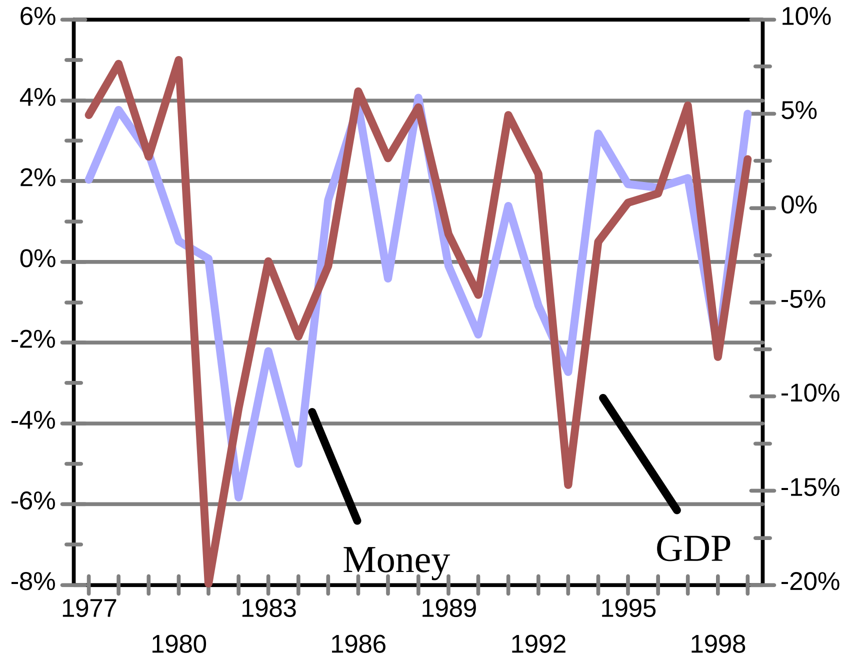
Note: standard errors in parenthesis.

Row 3 of table 3 presents the estimation of the cointegrating vector at quarterly frequency. The model cointegrates and there is no evidence of deterministic or stochastic seasonality in the residuals according to HEGY tests applied to the residuals. The cointegrating seasonal vector adequately describes the seasonal aspects of the demand for money: since some seasonal dummies are significant in this model, seasonality is caused by both stochastic and deterministic factors.

Since the intuition behind the meaning of a cointegrating vector at the quarterly frequency may be hard to grasp, we provide a graphical description of what are these common seasonal trends. In figure 2 we present the seasonal component for the fourth quarter of real money balances and GDP. These components are obtained for each year by computing the actual value of each variable in the fourth quarter less the annual average. It can be seen that these seasonal components fluctuate stochastically but tend to move together in the long run. Although in the short run they may deviate, it is likely that the seasonal components of series cointegrate. It is precisely this co-movement that is helpful when modeling the demand for money as it puts restrictions to seasonal fluctuations, allowing for more parsimonious and stable specifications.

Figure 2

Fourth Quarter Seasonal Components of GDP and Real Money Balances



Estimating Seasonal Error Correction Models

We estimate error-correction models using two methodologies to ensure the robustness of the results. The first alternative, suggested by Engle et al. (1993), is to compute the residuals from the estimated cointegration vectors in each frequency and include them in the dynamic error-correction model. In this case, one is implicitly disregarding the covariance between parameters in the cointegrating vector and those of the error-correction specification. The second alternative is to estimate all parameters in a nonlinear single-step error-correction model. The advantage of the former procedure is that it tends to be more robust to model mis-specification, while the latter provides consistent estimates. Both methods are less sensitive to model misspecification than Johansen's maximum likelihood technique and are thus preferred (Hargreaves, 1994).

The results of estimating both seasonal error correction models are presented in the first two columns of table 4. As a benchmark of comparison, we estimated an error correction model using seasonally adjusted data (with X-12 methodology) which we report in column three of the same table.

The results can be summarized as follows. First, when comparing the results of the two models of seasonal cointegration, it can be seen that the fit to the data, the size of the parameters of the short-term variables, and the residuals are quite similar in both cases. The only notable exemption are the parameters of the foreign interest rate which are much bigger in the non-linear model. In general, the similarity between the two models indicates that the nonlinear estimation does not yield a local maximum. The estimated loading factors (α), nevertheless, bigger in the non-linear case.

Both seasonal cointegration models produce stationary residuals at all frequencies. Moreover, cointegration is achieved *avoiding the use of dummy variables* and, as discussed below, our model is stable according to CUSUM tests (see Figure 3). The fit is very high (above 0.90), considering that the sample includes previously reported episodes of "missing money" as well as a severe depression between 1982 and 1984.[4]

Table 4
Standard and Seasonal Error Correction Models
1977:1-1999:2
Dependent Variable: $(1-L^4)$ log Real Money Balances

	Two-Step Seasonal Error Correction	Nonlinear Seasonal Error Correction	Deseasonalized data Error Correction
	Long run cointegrating vector		
Loading factor	0.10 (0.05)	0.36 (0.08)	0.14 (0.04)
Constant	-50.93 (2.55)	-44.14 (3.79)	-12.92 (0.59)
GDP	1.04 (0.04)	0.93 (0.07)	1.05 (0.04)
Domestic Interest Rate	-2.69 (0.42)	-2.44 (0.66)	-2.74 (0.37)
Foreign Interest Rate	-0.24 (0.38)	-2.15 (0.63)	0.001 (0.27)
	Semiannual cointegrating vector		
Loading factor	0.64 (0.12)	0.76 (0.10)	-
GDP	0.42 (0.11)	0.46 (0.12)	-
Domestic Interest Rate	-1.44 (0.30)	-1.25 (0.18)	-
	Quarterly cointegrating vector 1		
Loading factor	0.27 (0.10)	-0.15 (0.07)	-
GDP	0.22 (0.13)	-0.72 (0.78)	-
Domestic Interest Rate	-1.61 (0.19)	-5.29 (1.78)	-
	Quarterly cointegrating vector 2		
Loading factor	0.24 (0.11)	0.22 (0.07)	-
GDP	0.24 (0.13)	1.00 (0.43)	-
Domestic Interest Rate	-0.12 (0.29)	-2.10 (0.97)	-
	Short Run Dynamics		
ΔGDP	0.22 (0.11)	0.28 (0.11)	0.15 (0.12)
ΔGDP (t-1)	0.29 (0.14)	0.23 (0.15)	0.07 (0.14)
ΔGDP (t-2)	0.05 (0.13)	-0.27 (0.14)	0.26 (0.13)
Δ Domestic Interest Rate	-1.94 (0.18)	-1.96 (0.22)	-1.32 (0.17)
Δ Domestic Interest Rate (t-1)	-0.45 (0.20)	-0.39 (0.25)	-1.52 (0.19)
Δ Domestic Interest Rate (t-3)	-	0.30 (0.19)	-0.57 (0.20)
Δ Foreign Interest Rate (t-1)	0.25 (0.10)	0.17 (0.10)	0.26 (0.10)
Δ Foreign Interest Rate (t-2)	-	0.17 (0.11)	0.31 (0.11)
Dependent variable (t-2)	0.25 (0.06)	0.20 (0.06)	0.21 (0.09)
Adjusted R^2 Cointegration	0.96	-	0.96
Adjusted R^2 Error Correction	0.90	0.92	0.54

Notes: standard errors in parenthesis.

With regards to the estimated elasticities, the scale coefficient is slightly below 1 in the non-linear model, a similar result to those found in previous studies and to the one obtained when estimating the cointegrating vectors of the two-stage model. The parameter of the foeign interest rate elasticity in the non-linear model (-2.15), is substantially larger to that obtained in the two-stage procedure (-0.25), similar to coefficients found in previous studies (Soto, 1996; Adam, 2000). The semiannual cointegrating parameters are very similar in both the nonlinear and two-step error correction model, with a scale elasticity statistically equal to one half, while the parameter of the domestic interest rate being one half of the long-run parameter. When considering the quarterly frequency error-correction components, the results are mixed. For the second cointegrating vector, the estimated parameters differ significatively with to the two-step seasonal cointegration model. The scale variable in the first quarterly cointegrating vector is, surprisingly, not significant at conventional levels in the case of the non-linear model.[5]

The adjustment towards the long-run equilibrium is much faster in the seasonal non-linear cointegration model than in the standard error-correction model or the two-step model. In fact, this result suggests that the adjustment is much faster than what previously believed, yielding new evidence on the speed at which the market operates. The adjustment towards equilibrium at semiannual frequencies is very fast (0.75), which suggest that within-year variations are eliminated quickly in the short run. On the contrary, at the quarterly frequency shocks dissipate slower than the semiannual frequency.

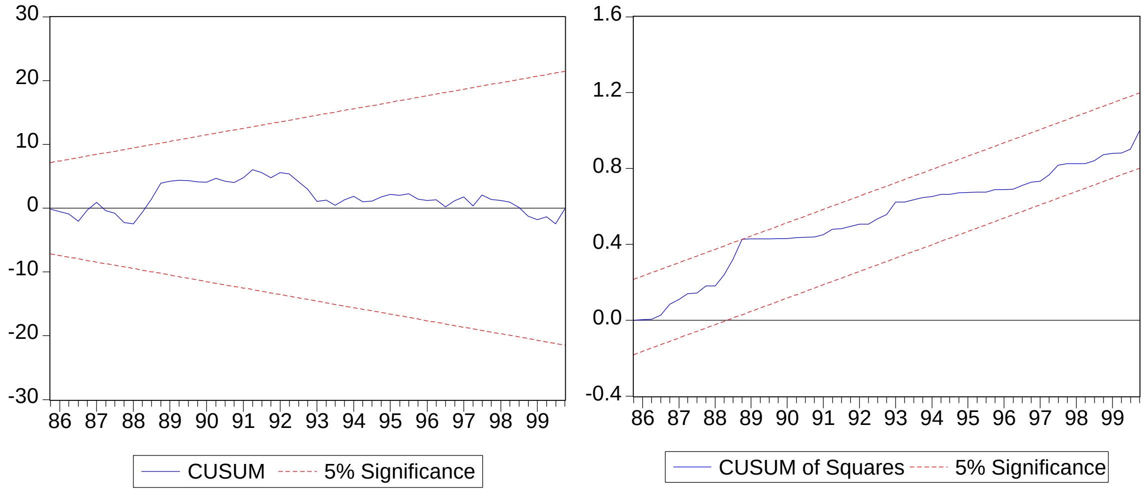
The standard error-correction model presents estimated coefficients which are of similar size to those found in previous studies and, consequently, provides an adequate counterpoint to seasonal error-correction models. Nevertheless, these estimated models have three important problems: (1) CUSUM and CUSUM of squares tests reveal models are unstable, (2) they present evidence of unit roots at the semiannual and quarterly frequency when the HEGY test is applied to the residuals of the cointegrating vector, (3) the fit of the error-correction model is markedly low.[6] These problems led other authors to include a substantial number of dummy variables to account for “structural breaks”, “special events”, “outliers”, etc. Seasonal models suggest that the need to include dummies reflects only misspecification problems.

The Stability of the Seasonal Error Correction Model

The stability of these models can be graphically assessed by examining recursive tests on the linear error-correction specification (non-linear models cannot be estimated recursively). The results of estimating recursively the coefficients are displayed in Appendix Figure 1, while CUSUM tests are presented in figure 3. It can be seen that there is little evidence of structural instability in the estimated model. Likewise, the cumulative sum of forecast errors does not cross the 95% confidence boundaries in the CUSUM and CUSUM of square tests and, consequently, the null hypothesis of model stability cannot be rejected.

Figure 3

Stability Tests: CUSUM and CUSUM of squares



Comparative Forecasting Performances

Table 5 presents a comparative analysis of the forecast capacities of each type model. We use two standard measures in the evaluation: the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). It can be seen the superiority of the nonlinear seasonal error-correction model with regards to standard dynamic models seasonally adjusted data, reflected in RMSE and MAE indicators that are significantly smaller than those of the linear models.

Table 5
Comparing the within-sample forecastability of alternative specifications

Error Correction Model	1977.1-1999.2		1977.1-1985.4		1986.1-1999.2	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
Seasonally Adjusted Data	3.6%	2.7%	4.4%	3.4%	3.0%	2.3%
Seasonal Two-Step Model	3.5%	2.7%	3.7%	3.5%	2.9%	2.3%
Seasonal Single-Step Model	2.8%	2.1%	3.4%	2.7%	2.6%	1.9%

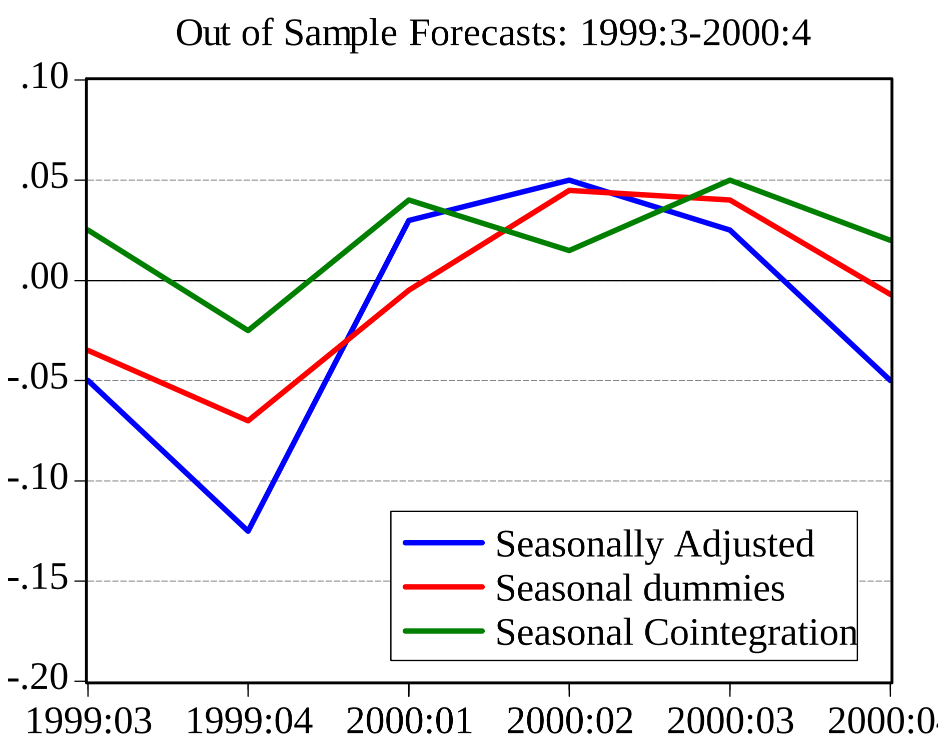
Note: RMSE is root mean square error and MAE is mean absolute error.

The results of the seasonal cointegrating models are similar to those obtained in previous studies with linear specifications, with the important difference that no dummies were included in the forecasting exercise. A more important advantage, though, is that the model does not show the deterioration of its forecasting abilities during turmoil that characterizes the performance of standard error-correction models. The MAE and RMSE deteriorates but only marginally when comparing the first with the second half of the sample.

Additional testing is provided by out-of-sample forecasts. We compare the non-linear version of the seasonal ECM with the two standard ECMs. The models were estimated in the 1977:1-1999:2 period and a dynamic, out of sample forecast errors we computed for the 1999:3-2000:4 period. This period comprises one of the most peculiar phenomenon in money markets. Agents began to increase their monetary holdings by the end of 1999 in precaution of potential computing problems in the financial sector derived from the change in the millenium (the so called Y2K effect). Monetary balances increased by 7.3% in the last quarter of 1999, on an annual basis, being the second largest increase in the 1977-1999 period. Since Y2K problems in Chile were non existent, money balances adjusted quickly downwards in the first quarter of 2000.

The results are presented in Figure 4. It can be seen that in all models Y2K is a completely unanticipated event. Consequently, there is a tendency to underestimate money balances in late 1999 that ranges from a high 13% (seasonally adjusted models) to 3% (seasonal ECM). The seasonal ECM is always closer to the real value of money balances than the traditional ECM models, although it overestimates money demand throughout 2000. In terms of their errors throughout the forecast, the seasonal ECM has a RMSE of only 3.1%, a small figure when compared to the 6.6% of the seasonally adjusted model.

Figure 4



5. Conclusions

A stable money demand function is of paramount importance not only to monetary policy, but also for economic theory. The empirical estimation of money demand functions in the Chilean case has been, as in many countries, a popular topic in applied econometrics. Yet, satisfactory results in terms of the consistency of estimated parameters with theoretical specifications and their stability remain elusive. Likewise, it is not unusual to observe out-of-sample forecasts that over predict actual levels and are not useful to make recommendations for monetary policy based on monetary aggregates, a fact that has led most central banks to adopt interest rates as their instruments.

This study finds an empirical specification for money demand in the case of Chile, which solves many of the unstability and lack of robustness found on previous estimations. The methodology relies in a largely ignored issue, the information contained in the seasonal components of the determinants of money demand. Evidence shows that money and its determinants have non-stationary seasonal processes. This made the use of seasonal dummies or filters inadequate. The use of incorrect seasonal adjustment leads to spurious correlations and unstable parameters in traditional estimations.

A two-stage procedure reveals the existence of cointegrating vectors in all seasonal frequencies. When these vectors are used to estimate money demand, the existence of common seasonal processes acts as an additional restriction that provides a better modeling of the behavior of money balances in the long run. As this allows to distinguish with more clarity temporary and permanent shocks, a stable empirical estimation of money demand is found for the period 1977-2000, without using ad-hoc dummies. The estimated function remains stable even through the 1982-83 crisis.

Finally, the forecasting abilities of the seasonal cointegration models are way beyond those of traditional ECMs. With data for the period 1999:3-2000:4, the seasonal ECM has the lower prediction error, even accounting for the Y2K effect, an unexpected shock for all money demand specifications.

The estimated demand is a valuable instrument to guide monetary policy, even if uses the interest rate –instead of monetary aggregates- as instrument. In the future, this type of models should be upgraded, and extended to monthly data. Then, the convenience of alternative instruments in the conduction of monetary policy should be evaluated, comparing the volatility and forecasting power of money demand models with the growth and inflation models associated with interest rates policy.

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ENDNOTES

1 Sriram (1999) evaluates 32 recent studies on money demand in 15 countries and finds that 25 studies use GDP as their scale variable (others use absorbtion, national income or industrial production).

2 Chumacero (2000) shows that in most general equilibrium analytic models interest rates must be stationary. Although conceptually correct, this paper adopts a more pragmatic view. Cochrane (1988) shows that the series true underlying process may be irrelevant in finite samples. Due to data limitations, using the best available statistical description is more appropriate. In this case, interest rates are best characterized as I(1).

3 Table 3 presents the best specification at each frequency. Complete results are available upon request.

4 The 1982-83 recession in Chile is one of the deepest depressions in history for a market economy, with GDP falling by 18% in only two years. In comparison, European countries during the Big Depression contracted by less than 15% in four years.

5 These results are similar to those found by Bohl (2000) and Herwartz and Reimers (2000) for the German case and Shen and Huang (1999) for Taiwan.

6 Details on these estimations and the complete data are available upon request to the authors.

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