Banco Central de Chile
Documentos de Trabajo

Central Bank of Chile
Working Papers

N° 130

Noviembre 2001

TRENDS AND CYCLES IN REAL-TIME

Rómulo A. Chumacero   Francisco A. Gallego

Documentos de Trabajo del Banco Central de Chile
Working Papers of the Central Bank of Chile
Huérfanos 1175, primer piso.
Teléfono: (56-2) 6702475   Fax: (56-2) 6702231

Documento de Trabajo
N° 130

Working Paper
N° 130

TRENDS AND CYCLES IN REAL-TIME

Rómulo A. Chumacero
Banco Central de Chile
Universidad de Chile

Francisco A. Gallego
Banco Central de Chile

Resumen

Este trabajo compara los resultados asociados a aplicar diferentes métodos para distinguir elementos ciclos y tendenciales al Índice Mensual de Actividad Económica chileno (IMACEC) usando datos de tiempo real. Se muestra que las revisiones de datos son extremadamente importantes y que pueden llevar a estimaciones sistemáticamente inconsistentes del componente tendencial. Además, la mayor parte de los filtros usualmente utilizados para separar el componente cíclico del de tendencia son altamente inestables y poco confiables para estimaciones al final de la muestra.

Abstract

This paper compares the results of applying several detrending methods to the Chilean monthly economic activity index (IMACEC) that arise from using real-time data sets. We show that data revisions are extremely important and that they can lead to systematically inconsistent estimates of the trend component. Furthermore, most of the filters commonly used to detrend time series in practice, are highly unstable and unreliable for end-of-sample estimation.

We would like to thank Christian Johnson, Raimundo Soto, and an anonymous referee for useful comments and suggestions. The usual disclaimer applies.
E-mails: rchumace@bcentral.cl ; fgallego@bcentral.cl.

1 Introduction

Economic time series are customarily decomposed into three component parts:

$$z_t = E_t + S_t + C_t \tag{1}$$

where E is the trend component, S is the seasonal component, and C is the cyclical component.[1] This decomposition is important because it can be applied to analyze the characteristics of the fluctuations of a series around its long-run trend,[2] or because the decomposition by itself is considered to be relevant.[3]

Given the realizations of z, the researcher usually takes a stance regarding the nature of E and S and filters them from the original series in order to obtain the cyclical component as a residual. The choice of filters for the trend and seasonal components is not a trivial task, as filters may substantially alter the statistical properties of the resulting series when compared

[1] Some times, the cyclical component is further decomposed into a regular (systematic) and an irregular (unsystematic) component. Here we will not follow such practice.

[2] This is the approach followed by Kydland and Prescott (1982) and by subsequent papers on the RBC tradition.

[3] For ecxample, policy-makers are often interested in having estimates of the trend component of GDP (also referred to as “potential output”) or the phase of the cycle (also referred to as “output gap”).

to the original.[4]

While often overlooked, there is another dimension that may be important when conducting this decomposition. Researchers rely on data sets that contain information of the variables at the moment in which the decomposition is being undertaken. However, the information that is available for any given time, may be different in the future due to data revisions. That is, the data set that is used is not the final (revised) data available today, but rather the original, unrevised data available to economic agents who were around at the time. We refer to each data set corresponding to the information set at a particular date as a "vintage" and to the collection of such vintages as a real-time data set (Croushore and Stark, 2001).

This paper analyzes the effects on the decomposition of the Chilean Monthly Activity Index (IMACEC) into the three components mentioned above, that are due to both data revisions and the properties of statistical methods applied to obtain them. The document is organized as follows: Section 2 presents the definitions of the variables used. Section 3 briefly describes the statistical methods used for decomposing the series. Section 4

[4] The effects of applying "popular" seasonal adjustment and detrending procedures have been subject of active research. For example, Hylleberg (1992) discusses issues related to modelling seasonality and Soto (2000) shows the effects of several of these procedures on Chilean macroeconomic time series. Gallego and Johnson (2001) present several detrending methods and apply them to the Chilean GDP.

presents the results of applying these methods. Finally, Section 5 provides the main conclusions.

2 Data and Concepts

Following Orphanides and van Norden (1999), our aim is to better understand the reliability and statistical accuracy of methods commonly used to decompose (1), by measuring the degree to which estimates of each component at any point in time vary as data are revised and as data about the subsequent evolution of z becomes available.

Formally, let z_t^v be the value of z published at time v for an observation at time t. Due to publication lags, we require $t < v$.[5] The full series, published at any point in time v, can be written as the column vector $Z^v = \left[z_1^v, z_2^v, \ldots, z_{v-2}^v\right]'$.

Define the **last-value function** $\ell\left(Z^v\right) : \mathbb{R}^{v-2} \rightarrow \mathbb{R}$, which selects the last observation of the column vector. Then, for any arbitrary function $f\left(X\right) : \mathbb{R}^N \rightarrow \mathbb{R}^N$, we define $\ell\left[f\left(X\right)\right]$ as the last observation of the column vector of $f\left(X\right)$. In our case $f\left(\cdot\right)$ will be the filter applied to z in order to obtain the seasonal, trend, and cyclical components.

[5] The publication lag for the first observation of IMACEC is of two months.

A "Final" (F) estimate is defined as:

$$\widehat{Z}^F = f\left(Z^{T+2}\right) \tag{2}$$

where $T+2$ is the "final" vintage of data available (in our case, this is the series as published in 2001:09 for observations until 2001:06). This estimate simply takes the last available vintage of data we have available, and applies the filter $f(\cdot)$. The resulting series constitutes the "Final" estimate. This is the typical way in which decomposition methods are employed.[6]

The "Real-Time" (R) estimate is constructed in two stages. First, we apply $f(\cdot)$ to every vintage of data available. Earlier vintage series are shorter since the series on which they are based end earlier. Next, we use these different vintages to construct a new series which consists entirely of the first available estimate of the series for each point in time. That is,

$$\widehat{Z}^R = \left\{\ell\left[f\left(Z^3\right)\right], \ell\left[f\left(Z^4\right)\right], \ldots, \ell\left[f\left(Z^{T+2}\right)\right]\right\}' \tag{3}$$

This series represents the most timely estimate which researchers could have at any point in time. The difference between the Final and Real-Time

[6] For example, this procedure is extensively used for the estimation of monetary policy rules and forecasts of future inflation.

estimate $(F - R)$ gives us the Total Revision at each point in time. This difference has two sources, one of which is the ongoing revision of published data.

To isolate the importance of this factor, define the "Quasi-Real" (Q) estimate. Like the Real-Time estimate, it is constructed in two steps. The first step is to construct an ensemble of "rolling" estimates. That is, we begin by taking the Final vintage of the series but use only the observations up to period t in order to compute the Quasi-Real estimate for t. Next, we extend the sample period by one observation and repeat the procedure. We continue in this way until we have used the full sample. The second step is the same as that used to construct the Real-Time series; we collect the first available estimate at each point in time from the various series we constructed in the first step. This sequence is the Quasi-Real series:

$$\widehat{Z}^{Q} = \left\{ \ell \left[f \left(Z_3^{T+2} \right) \right], \ell \left[f \left(Z_4^{T+2} \right) \right], \ldots, \ell \left[f \left(Z_T^{T+2} \right) \right] \right\}' \tag{4}$$

The difference between the Quasi-Real and the Real-Time series $(Q - R)$ is mainly due to the effects of data revisions, since estimates in the two series at any particular point in time are based on data samples covering the same time period.

Thus, we can decompose the Total Revision of an estimate as:

$$\underbrace{\widehat{Z}^F - \widehat{Z}^R}_{\text{Total Revision}} = \underbrace{\widehat{Z}^F - \widehat{Z}^Q}_{\text{Sample Revision}} + \underbrace{\widehat{Z}^Q - \widehat{Z}^R}_{\text{Data Revision}} \tag{5}$$

where $\widehat{Z}^F - \widehat{Z}^Q$ indicate the changes in an estimate that are due to applying $f(\cdot)$ to the full sample and to partial samples. This difference can be used to assess the stability of a particular filter given that it closely resembles stability tests of recursive estimates.[7]

As mentioned in the Introduction, we focus our attention on the Chilean Monthly Activity Index (IMACEC).[8] This index provides a monthly estimate of Chilean GDP and is constructed by covering roughly 90% of total GDP. The remaining 10% is not considered because of lags in the availability of information in some sectors.

As discussed above, the publication lag of the first observation for the IMACEC is of two months. However, due to changes in the base year in September of 1993 (from a 1977 to a 1986 base year), a consistent data set can be constructed beginning on that month's vintage (thus, covering the period 1986:01-1993:07). The final vintage (as published on August 2001)

[7] This difference also measures the importance of having additonal information when applying a particular filter.

[8] Venegas and Zambrano (2000) present a detailed description of the construction of this index.

covers the period 1986:01-2001:06.

Data revisions of the IMACEC are made in two stages. First, monthly revisions of the initial data are continuously made and incorporate more information is it becomes available. In the second stage, major and discrete revisions take place. These revisions correspond to re-calculations of the total GDP. After these major revisions are published, the final series is not modified. In our sample period, two major revisions have taken place (August 1994 and March 1998). Thus, observations covering the period 1998:02-2001:06 are not definitive, and have only had initial revisions.

The first panel of Figure 1 presents the Final (z_t^{T+2}) and Real-Time (z_t^{t+2}) realizations of (the log of) IMACEC, while the bottom panel shows the difference between them.[9] The vertical lines indicate the dates at which the two major revisions on the data were made. From it, it is apparent that the Real-Time realizations of IMACEC persistently under-estimated their final values. This difference is always positive and numerically important (about 6.4% on average, and fluctuating between 2.5% and 12.3%) when considering the period up to the second major revision, and with alternate signs of minor significance when the series is revised in the adjacent months (the average difference is of 0.4% in the 1998:02-2001:06 period). Consequently, data

[9] In the remainder of this paper we will use the (natural) logarithm of IMACEC instead of its level.

revisions are not minor factors, and their effects on the estimation of trends and cycles using real-time data should be considered.

[Insert Figure 1 here]

3 Alternative Methods

In order to evaluate the effects that data revisions have on (1), we consider several statistical methods that are routinely used to obtain the seasonal and trend components of a series. Recalling that we want to decompose the difference between Real-Time and Final estimates in a component that is mainly due to data revisions, and another that combines the effect of the filter and additional information, we must be careful on the interpretation of the results.

To evaluate the merits of each filter, each exercise assumes that the particular method being employed can consistently estimate the seasonal and trend component. Of course, it cannot be the case that several methods can do this at the same time. However, our aim is simply to provide guidelines to practitioners that use different filtering method with respect to the sensitivity of each method to data revisions and to the properties of the filter itself.[10]

[10] In this sense, the objective of this paper is not to provide a uniform "metric" that

Even though there are other methods available, we apply the X-12-ARIMA seasonal adjustment procedure to remove the seasonal component of a series. This choice is mainly due because most practitioners use it as their default procedure.[11]

Once we obtain a seasonally adjusted series ($y_t = z_t - S_t$), we focus on the estimation of the trend component. We consider nine detrending methods:

1. Linear Trend (OLS): This method assumes that y can be decomposed into a cyclical component and a linear function of time

$$y_t = \alpha + \beta t + C_t \tag{6}$$

   where α and β are obtained by OLS (Ordinary Least Squares).

2. Linear Trend (LAD): Even tough the OLS estimators of α and β are consistent under general conditions;[12] in finite samples, they may be heavily influenced by outliers. Thus, we also obtain estimators for α and β with the Least Absolute Deviation (LAD) estimator, which is more robust in presence of outliers.

would help the practitioner to choose the proper filter to use.

[11] Findley, et al (1998) present a detailed description of this procedure and the differences with its predecessor (X-11-ARIMA).

[12] In fact, the estimate of β is super-consistent.

3. Quadratic Trend (OLS): The third method adds a second term in the deterministic component of (6) to obtain:

$$y_t = \alpha + \beta t + \gamma t^2 + C_t \tag{7}$$

   This allows the flexibility to detect a slowly changing trend in a simple way.

4. Quadratic Trend (LAD): As was the case with the first method, OLS estimates may again be heavily influenced by outliers, thus we also obtain the trend component of (7) using the LAD estimator.

5. Breaks in Level: An increasingly popular way to characterize economic time series allows for the possibility of structural changes. The simplest of such methods considers that a time series with m breaks ($m+1$ regimes) in its level can be characterized as:

$$y_t = \alpha_j + \beta t + C_t, \qquad t = T_{j-1}, \ldots, T_j \tag{8}$$

   for $j = 1, \ldots, m+1$. The number of breaks and their dates (m and T_j respectively) are endogenously estimated following Bai and Perron (1998).

6. Breaks in Trend: This method is capable of detecting changes in the trend component of a series and is modelled as:

$$y_t = \alpha + \beta_j t + C_t, \quad t = T_{j-1}, \dots, T_j \tag{9}$$

Again, m and T_j are endogenously estimated.

7. Breaks in Level and Trend: In this case we allow for breaks in both the level and the trend of a series to obtain:

$$y_t = \alpha_j + \beta_j t + C_t, \quad t = T_{j-1}, \dots, T_j \tag{10}$$

8. Hodrick-Prescott: Hodrick and Prescott (1997) proposed one of the most popular methods for detrending macroeconomic (commonly referred to as the HP filter). It decomposes y into a growth component and a cyclical component by solving the following minimization problem:

$$\{E_t\}_{t=1}^{T} = \arg\min \sum_{t=2}^{T-1} \left\{ (y_t - E_t)^2 + \lambda \left(E_{t+1} - 2E_t + E_{t-1}\right)^2 \right\} \tag{11}$$

where λ is called the "smoothness parameter" which penalizes the variability of the growth component. The larger the value of λ, the smoother the growth component and the greater the variability of the cyclical component. As λ approaches infinity, the growth component corresponds to a linear trend. For monthly data, Hodrick and Prescott propose setting λ equal to 14400.

As noted by Reeves, et al (1996), the justification for choosing this value is weak, given that if the HP filter is viewed as the result of a signal extraction problem, the optimal value of λ should be equal to $\lambda = \frac{\sigma_C^2}{\sigma_{\Delta^2 E}^2}$ if the cyclical component is a white noise process. If this is not the case, no optimality property should be attached to the HP filter (Ehlgen, 1998).

9. Kernel: The last method used in order to obtain the trend component considers a Gaussian kernel regression that used t as its independent variable.

Having different convergence properties, each method has its strengths and weaknesses.[13] The first four methods can consistently estimate the values of the parameters that characterize the deterministic trends and are robust to several distributional assumptions regarding the cyclical component. Nevertheless, the methods that use the LAD estimator may perform better

[13] For example, $\widehat{\beta}$ in (6) is $O_p\left(T^{-3/2}\right)$, while $\widehat{\delta}$ in (7) is $O_p\left(T^{-5/2}\right)$. This means that the latter parameter estimate converges faster (needs less information) than the former.

in the presence of outliers. Of course, these methods may display undesirable features if, for example, breaks in level and/or trend were present in the sample. In such case, we expect to assess the stability of the parameters by evaluating the difference between the Final and Quasi-Real estimates.

The methods that assume a break in level and/or trend have problems in obtaining the Real-Time and Quasi-Real estimates around the period in which a break occurs. This happens because the filters can never predict the occurrence of a break near the end of the sample, as it needs to estimate the values of the parameters after the break.

Finally, the last two methods (Hodrick-Prescott and Kernel) have problems in tracking down the trend component at the endpoints of the sample. This feature is relevant for this exercise, given that the Real-Time and Quasi-Real estimates are obtained using the last-value function operator.[14]

[14] Of course, these methods are not the only ones available. For example, X-12-ARIMA also provides estimates of the trend component along with the seasonal component. Furthermore, other filters such as Baxter and King (1995) are also used in practice. Both methods display the same undesirable feature of the HP and Kernel filters with respect to end points. In particular, given that these methods take the form of moving averages, they sacrifice information from the beggining and the end of the data set; thus seriously limiting their usefulness for analyzing contemporaneous data.

4 Results

4.1 Seasonal Component

The first step taken for decomposing (the log of) IMACEC (z), is to filter its seasonal component. The resulting series (denoted by y) is presented in Figure 2 which shows that the Chilean economy has experienced a period of sustained growth during the sample period. In fact, using the Final vintage, the average annual growth rate of this series is of 6.4%. Equally evident, is an important decrease on the economic activity in the last quarter of 1998.

[Insert Figure 2 here]

Figure 3 presents the estimates for the seasonal component obtained using the Final estimate, the Real-Time estimate and the Quasi-Real estimate. Along with them, the second panel displays the decomposition of the total revisions ($F-R$) that are due to data revisions ($Q-R$), and sample revisions ($F-Q$).

[Insert Figure 3 here]

The results indicate that while the seasonal adjustment may modify the stochastic properties of the resulting series (y), this method is relatively robust in terms of obtaining the seasonal component (the levels and volatilities of the component parts of the Total revisions are similar). In fact, the total revisions seldom exceed 2%. The only exception (when the total revision exceeds 4%) is around the period in which the first major revision on the data was made (1994). In this case, data revisions ($Q - R$) are exclusively responsible for the discrepancy between the Real-Time and Final estimate. Apart from this instance, neither the filter nor the data revisions modify the seasonal pattern of the series.

4.2 Trend Component

In the second stage, we filter the (log of) seasonally adjusted IMACEC (y) using the nine above-mentioned methodologies assuming that the "true" trend component is consistently estimated by applying the corresponding filter.

The trend components of each filter are displayed in Figure 4 (using "Final" (F), "Real-Time" (R), and "Quasi-Real" (Q) data sets), the most salient features of which are: First, using the Final vintage, the resulting trend components differ substantially across methods. For example, estimates for December 2000 range from 5.50 (Kernel) to 5.66 (Linear Trend, LAD), implying with the former method that the actual realization of y was slightly above its trend; while with the later, the economy was almost

14% below its trend. Second, regardless of the detrending method and as a consequence of the under-estimation of z up to1998, R is always bellow F in that period. Third, there are usually two discrete increases that coincide with the major revisions of z. Fourth, the robustness of most of these filters is called into question because of the slowdown on economic activity by the end of 1998, as most of them predict a higher level for R than for F in that period. Finally, when comparing the differences between the Linear Trend estimator using OLS and LAD, we observe that the former penalizes the abrupt decrease of y by the end of 1998 by decreasing the implied long-run growth rate with the Final estimate, while the LAD estimator is not as sensitive the this decline and ends up with a higher growth rate. However, when Quadratic Trends are considered, the LAD estimator predicts a more important slow-down in the long run, given that it considers that the realizations of y in 2000 coincide with the implied trend, while the OLS estimator considers that for that period, y is actually below its trend. The three models that incorporate breaks in levels and/or trends conclude that there is evidence of at least one break during the sample period; the latest of which is dated in the last quarter of 1998. Of these three models, the one that displays only breaks in level is preferred.

[Insert Figure 4 here]

These points are confirmed in Figure 5 and Table 1 which show the relative importance of $(F-Q)$ and $(Q-R)$ in accounting for $(F-R)$. First, averages of Total Revisions range from 0.073 (Kernel) to -0.010 (Linear Trend, OLS) with positive medians that always exceed their means; thus, irrespective of the method, Real-Time trends always under-estimated the Final estimate more than 50% of the times. The volatilities of the Total Revisions are also important, ranging from 0.056 (Quadratic Trend, LAD) to 0.03 (in both Linear Trend estimators). Second, the last column of Table 1 shows that all revisions are highly persistent, having most of their first order autocorrelations exceeding 0.9. Third, while the averages of $(Q-R)$ are always positive, averages of $(F-Q)$ are usually negative (the sole exception being the Kernel estimate). These facts signal the importance of the under-estimation of the level of y until major revisions are conducted (thus the difference between Q and R), and the influence of the significant decrease in economic activity by the end of 1998 (thus the difference between F and Q). Third, as mentioned above, the difference between F and Q may show not only how relevant is the additional information that is gained from increasing the sample size, but also the adequacy of a given filter. In particular, systematic differences between both estimates can be viewed as evidence of instability of a filter. In that regard, the Linear and Quadratic

Trend models are shown to be inappropriate given that in the whole sample Q exceeds F.[15] Equally evident is that the Kernel filter is also highly unstable, given that with it F always exceeds Q. However, none of these features are evident when considering the models that incorporate breaks or in the HP filter. The models with breaks are remarkably stable up to the point in which a break occurs and tend to adjust the Final and Quasi-Real estimates in at most a year.

[Insert Figure 5 here]

[Insert Table 1 here]

Summarizing, the implications of these exercises for obtaining estimates of the trend component are: First, the trend component is extremely sensitive to the data set being used; in all cases discrepancies that range between 6% and 12% can be expected when using Real-Time data. Second, simple models of deterministic trends (linear, quadratic, or Gaussian kernel) appear to be inconsistent with the data, given that there is important evidence of instability in their estimates (due mainly to the slow-down by the end of 1998). Finally, models that incorporate breaks (particularly in levels) and the HP filter do not display such instability.

[15] As mentioned, this is due to the slown-down of y by the end of 1998.

4.3 Cyclical Component

Focusing on the cyclical component of a series may be misleading, given that it is obtained as a residual from the difference between the original series and the seasonal and trend components. As discussed above, the trend component of the series is seriously distorted (independently of the method) when Real-Time data is used. Nevertheless, one of our objectives is to focus on the properties of the cyclical component that is customarily obtained by practitioners following the practice outlined above; thus, we now focus on its analysis.

As some practitioners are interested in evaluating whether or not the economy is above or below its long-run trend in a particular point in time, it may be the case that while the precise level of the trend component is not consistently estimated using Real-Time data, its cyclical component may mimic its ex-post counterpart.

Real-Time, Final and Quasi-Real estimates of the cyclical component are presented in Figure 6 and Table 2 (again called F, R, and Q respectively). Up to 1997, the Final estimates using linear and quadratic trends is consistent with the Chilean economy displaying a prolonged boom, while the Real-Time estimates consider that it was evolving roughly about its trend. Beginning on 1998, the HP filter provides conflicting results, given that if

Real-Time data were used, the filter predicts the beginning of a recession, while the Final estimates considers that to be the case only by the end of that year. Similar conflicting results (in terms of signs) are also present in other filters. Interestingly, the filters that do a better job on tracking down the trend component (models with breaks and the HP filter) are also the ones the show the lowest correlation between the Real-Time and Final estimates.

[Insert Figure 6 here]

[Insert Table 2 here]

Figure 7 and Table 3 show the behavior of the breakdown of cycle revisions. Contrary to what happens with the revisions of the trend component, the main factor behind the discrepancy between the Final and Real-Time estimate of the cycle is not due to data revisions $(Q - R)$ but to the instability of the filter $(F - Q)$. Furthermore, the volatility of the total revisions is primarily due to the instability of the filter and not because of data revisions. Once again, the revisions are systematic and persistent, although not as much as in the case of the trend component.

[Insert Figure 7 here]

[Insert Table 3 here]

Finally, as in Orphanides and van Norden (1999), Table 4 constructs several indicators the measure the reliability of the business cycle estimates using real time data. The first column reproduces the correlations between the Final and Real-Time estimates of the cycle which show that the methods that better capture the trend component of the series (models with breaks and HP) are also the ones in which the Real-Time estimates have the lowest correlations with the Final estimates of the cycle. Furthermore, it is precisely with these methods that the volatility of the revisions of the cyclical component exceeds the magnitude of the cycle itself (second column). Finally, irrespectively of the method used, Real-Time and Final estimates have conflicting signs with respect to the phase of the cycle between 25% and 50% of the times.

[Insert Table 4 here]

This last feature may be of particular importance for practitioners that take decisions considering Real-Time data, given that they may be incorrectly assessing not only the magnitude but also the sign of the phase of the cycle.

5 Concluding Remarks

This paper evaluates the reliability of alternative detrending methods applied to the Chilean Monthly Activity Index (IMACEC), paying special attention to the accuracy of Real-Time estimates. We show that data revisions are extremely important and that estimates of the trend component are usually inconsistently estimated when we compare the Real-Time and ex-post revisions estimates. Furthermore, several methods are not only sensitive to data revisions, but show signs of being unstable.

Even though some detrending methods appear to be more robust than others for estimating the trend component (models with breaks in levels and the HP filter), their cyclical component is as volatile as their revisions, and present conflicting results when the Real-Time and Final estimates are compared. In particular, irrespective of the method used, not only the magnitude but also the sign of the phase of the cycle is inconsistently estimated between 25% and 50% of the times.

References

Bai, J. and P. Perron (1998), "Estimating and Testing Linear Models with Multiple Structural Changes," *Econometrica* 66, 47-78.

Baxter, M. and R. King (1995), "Measuring Business Cycles Approximate Band-Pass Filters for Economic Time Series," *NBER Working Papers* 5022, National Bureau of Economic Research.

Croushore, D. and T. Stark (2001), "A Real-Time Data Set for Macroeconomists," *Journal of Econometrics* 105, 111-30.

Ehlgen, J. (1998), "Distortionary Effects of the Optimal Hodrick-Prescott Filter," *Economics Letters* 61, 345-49.

Findley, D., B. Monsell, W. Bell, M. Otto, and B. Chen (1998), "New Capabilities and Methods of the X-12-ARIMA Seasonal Adjustment Program," *Journal of Business & Economic Statistics* 16, 127-52.

Gallego, F. and C. Johnson (2001), "Teorías y Métodos de Medición del Producto de Tendencia: Una Aplicación al Caso de Chile," *Economía Chilena* 4, 27-58.

Hylleberg, S. (1992), *Modelling Seasonality*, Oxford University Press.

Hodrick, R. and E. Prescott (1997), "Post-War U.S. Business Cycless: An Empirical Investigation," *Journal of Money, Credit, and Banking* 29, 1-16.

Kydland, F. and E. Precott (1982), "'Time-to-Build' and Aggregate Fluctuations," *Econometrica* 50, 1345-70.

Orphanides, A. and S. van Norden (1999), "The Reliability of Output Gap Estimates in Real-Time," *Manuscript*, Board of Governors of the Federal Reserve System.

Reeves, J., C. Blyth, C. Triggs, and J. Small (1996), "The Hodrick-Prescott Filter, a Generalisation, and a New Procedure for Extracting an Empirical Cycle from a Series," *Manuscript*, The University of Auckland.

Soto, R. (2000), "Ajuste Estacional e Integración en Variables Macroeconómicas," *Working Paper* 73, Central Bank of Chile.

St-Amant P. and S. van Norden (1997), "Measurement of the Output Gap: A Discussion of Recent Research at the Bank of Canada," *Manuscript*, Bank of Canada.

Venegas, J. and C. Zambrano (2000), "Indicador Mensual de Actividad

Económica: IMACEC Base 1986: Nota Metodológica", *Serie de Estudios Económicos* 42, Central Bank of Chile.

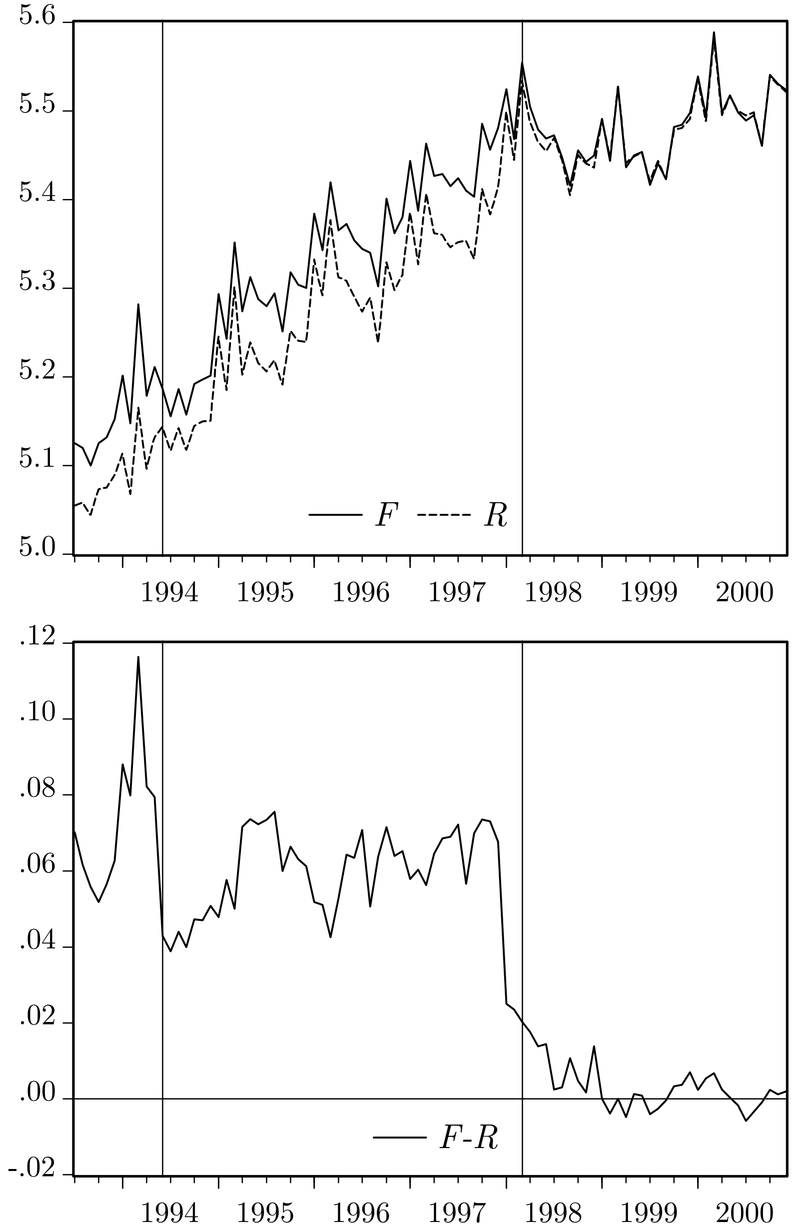

Figure 1: Real-Time and Final (log of) IMACEC (1993:07-2000:12)

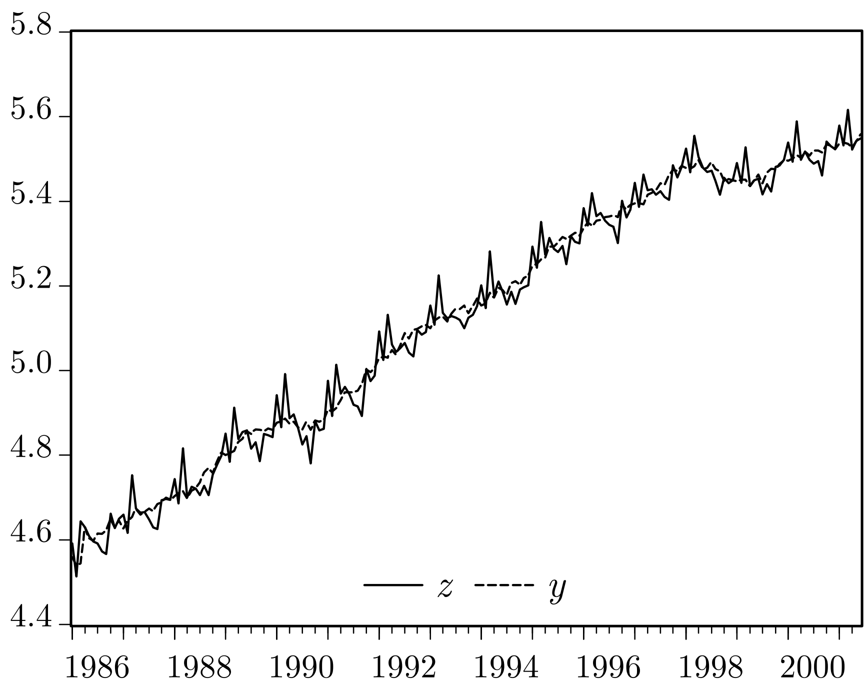

Figure 2: Seasonal adjustment of (log of) IMACEC (1986:01-2001:06)

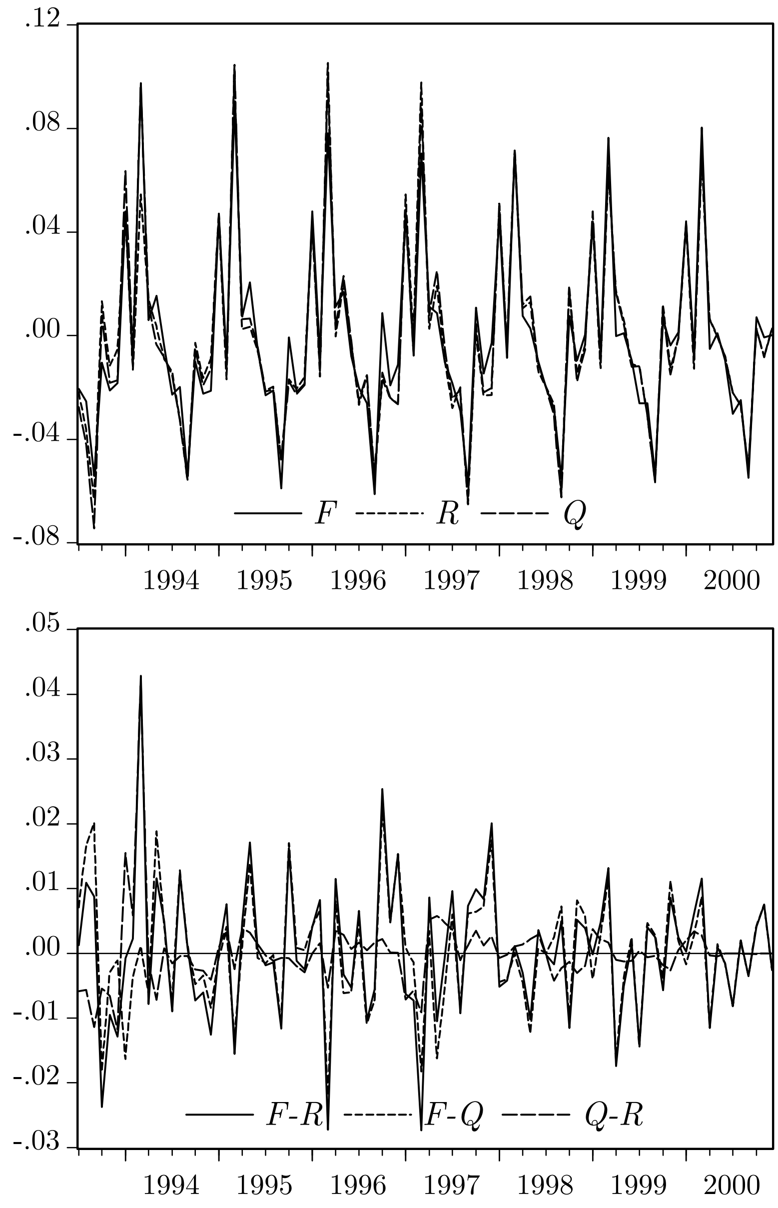

Figure 3: Total revisions in seasonal component (1993:07-2000:12)

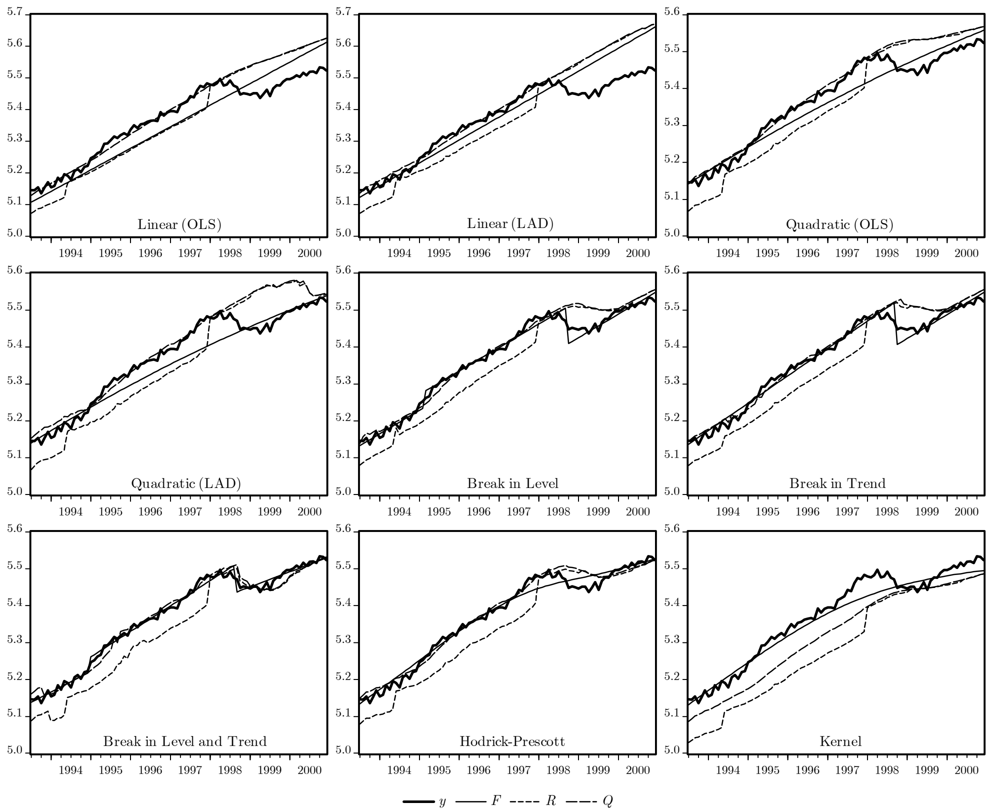

Figure 4: Trend component (1993:07-2000:12)

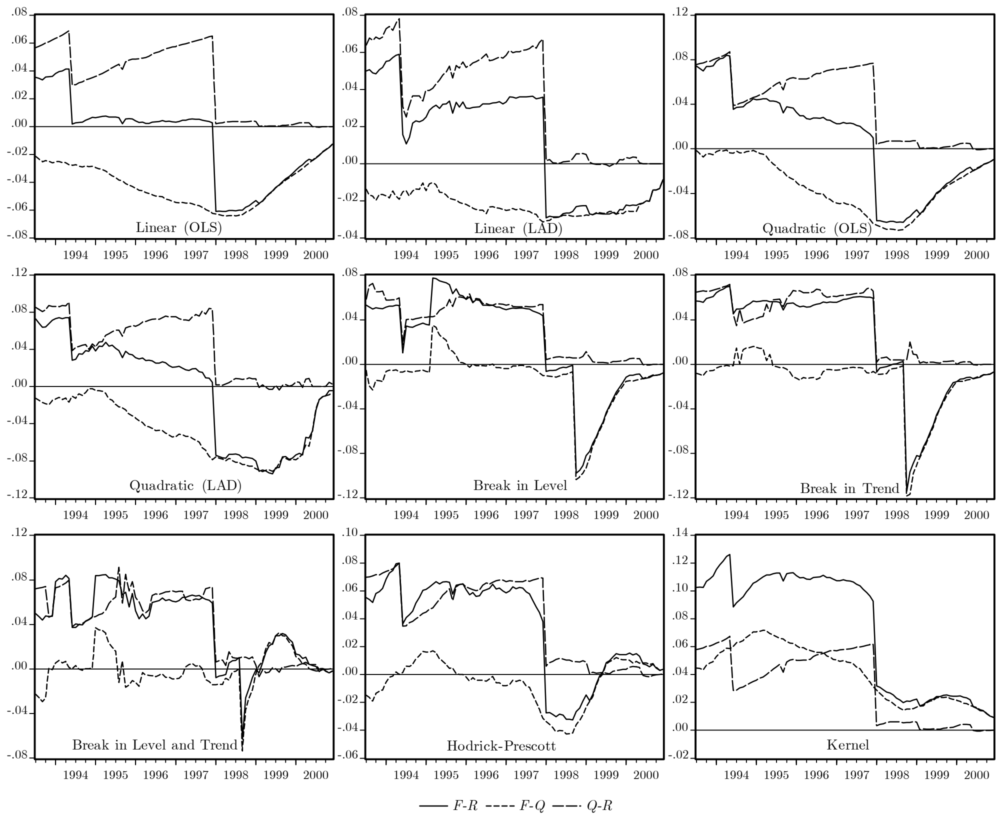

Figure 5: Total revision in trend component (1993:07-2000:12)

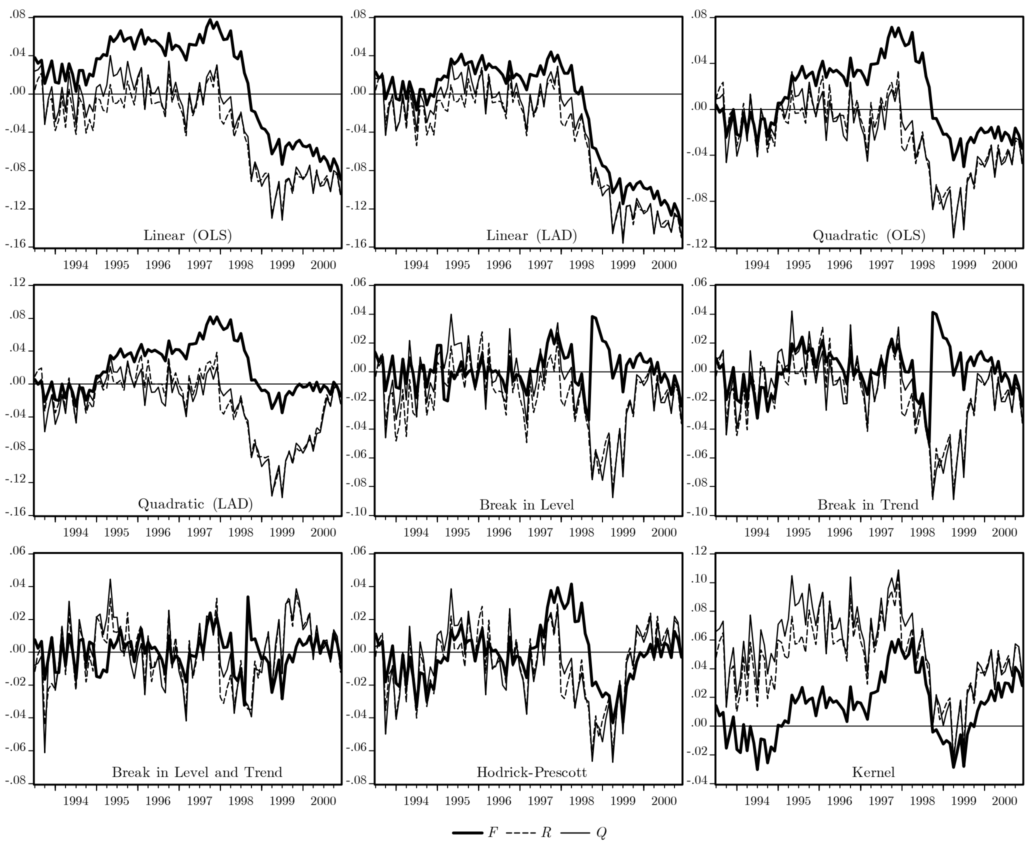

Figure 6: Cyclical component (1993:07-2000:12)

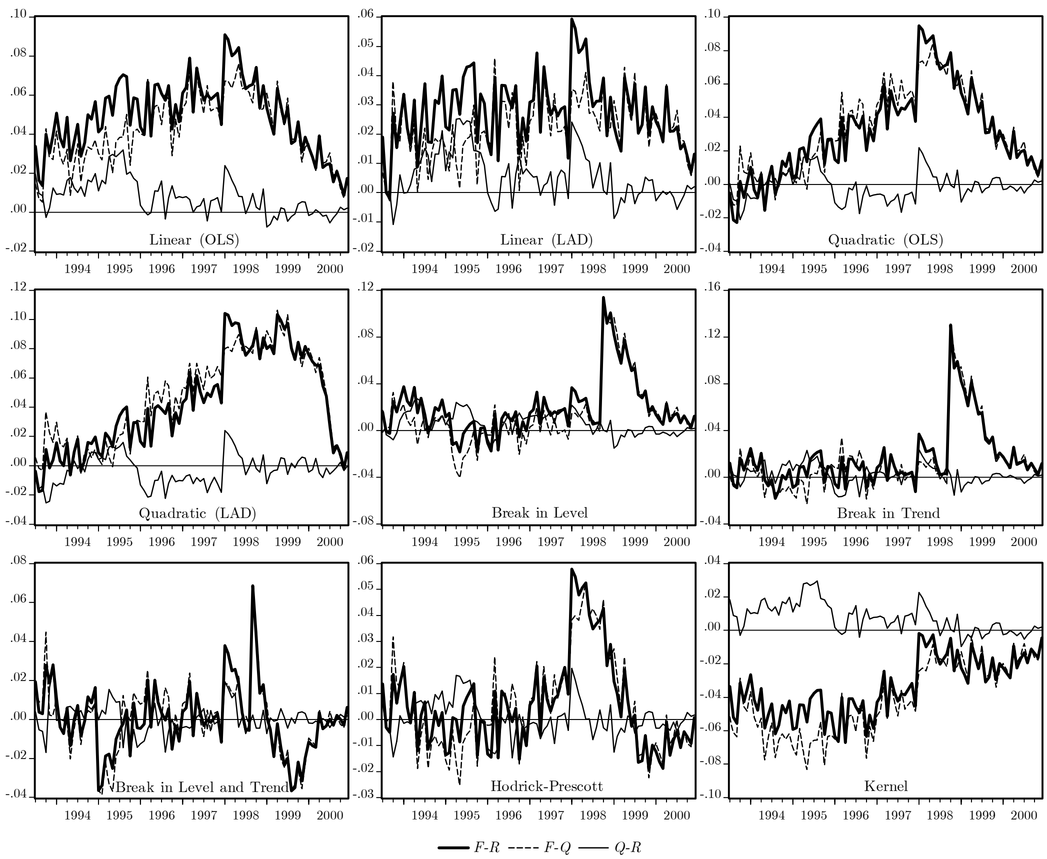

Figure 7: Total revision in cyclical component (1993:07-2000:12)

	MEAN	MEDIAN	SD	MIN	MAX	AR
			Linear Trend (OLS)			
$F-R$	-0.010	0.003	0.030	-0.060	0.041	0.965
$F-Q$	-0.042	-0.042	0.015	-0.064	-0.013	0.996
$Q-R$	0.032	0.038	0.026	0.000	0.069	0.953
			Linear Trend (LAD)			
$F-R$	0.012	0.028	0.030	-0.029	0.059	0.961
$F-Q$	-0.022	-0.024	0.006	-0.031	-0.009	0.953
$Q-R$	0.034	0.040	0.028	-0.001	0.078	0.951
			Quadratic Trend (OLS)			
$F-R$	0.008	0.023	0.045	-0.066	0.084	0.978
$F-Q$	-0.033	-0.033	0.024	-0.073	-0.001	0.996
$Q-R$	0.041	0.049	0.032	-0.001	0.087	0.958
			Quadratic Trend (LAD)			
$F-R$	-0.004	0.020	0.056	-0.094	0.074	0.982
$F-Q$	-0.046	-0.048	0.030	-0.091	-0.002	0.990
$Q-R$	0.042	0.048	0.034	-0.004	0.091	0.951
			Break in Level			
$F-R$	0.020	0.040	0.045	-0.098	0.077	0.953
$F-Q$	-0.014	-0.007	0.026	-0.103	0.035	0.900
$Q-R$	0.033	0.043	0.025	-0.001	0.072	0.953
			Break in Trend			
$F-R$	0.022	0.053	0.047	-0.114	0.070	0.951
$F-Q$	-0.014	-0.007	0.027	-0.118	0.016	0.879
$Q-R$	0.037	0.047	0.029	-0.001	0.072	0.959
			Break in Level and Trend			
$F-R$	0.039	0.046	0.032	-0.063	0.085	0.905
$F-Q$	0.000	0.000	0.017	-0.073	0.037	0.767
$Q-R$	0.039	0.048	0.031	-0.007	0.091	0.933
			Hodrick-Prescott			
$F-R$	0.033	0.053	0.035	-0.033	0.080	0.967
$F-Q$	-0.005	-0.002	0.016	-0.043	0.017	0.984
$Q-R$	0.039	0.047	0.030	-0.002	0.080	0.959
			Kernel			
$F-R$	0.073	0.102	0.043	0.009	0.126	0.983
$F-Q$	0.041	0.046	0.020	0.009	0.072	0.997
$Q-R$	0.032	0.038	0.025	-0.001	0.067	0.955

Table 1: Breakdown of Trend Revision Statistics (1993:07-2000:12). SD=Standard deviation, AR=First autocorrelation.

	MEAN	MEDIAN	SD	MIN	MAX	COR
			Linear Trend (OLS)			
F	0.014	0.035	0.049	-0.089	0.078	1.000
Q	-0.028	-0.012	0.047	-0.132	0.040	0.935
R	-0.035	-0.022	0.042	-0.127	0.030	0.930
			Linear Trend (LAD)			
F	-0.017	0.009	0.056	-0.137	0.044	1.000
Q	-0.039	-0.014	0.058	-0.156	0.035	0.983
R	-0.045	-0.023	0.054	-0.152	0.029	0.977
			Quadratic Trend (OLS)			
F	0.009	0.005	0.031	-0.050	0.071	1.000
Q	-0.024	-0.021	0.031	-0.112	0.033	0.670
R	-0.023	-0.019	0.031	-0.107	0.034	0.650
			Quadratic Trend (LAD)			
F	0.019	0.008	0.030	-0.035	0.082	1.000
Q	-0.028	-0.015	0.040	-0.139	0.035	0.624
R	-0.024	-0.013	0.041	-0.133	0.039	0.596
			Break in Level			
F	0.002	0.001	0.013	-0.034	0.039	1.000
Q	-0.011	-0.001	0.026	-0.088	0.040	0.110
R	-0.017	-0.014	0.023	-0.082	0.028	0.134
			Break in Trend			
F	0.001	0.001	0.016	-0.049	0.041	1.000
Q	-0.013	-0.009	0.026	-0.089	0.042	0.158
R	-0.016	-0.011	0.024	-0.089	0.031	0.219
			Break in Level and Trend			
F	0.000	0.002	0.011	-0.032	0.033	1.000
Q	0.000	-0.001	0.019	-0.061	0.045	0.400
R	0.000	-0.001	0.018	-0.044	0.035	0.371
			Hodrick-Prescott			
F	-0.001	-0.002	0.018	-0.043	0.041	1.000
Q	-0.007	-0.005	0.022	-0.067	0.039	0.619
R	-0.007	-0.004	0.021	-0.063	0.030	0.589
			Kernel			
F	0.013	0.015	0.021	-0.030	0.061	1.000
Q	0.055	0.056	0.028	-0.026	0.109	0.647
R	0.047	0.051	0.025	-0.021	0.106	0.729

Table 2: Cycles Summary Statistics (1993:07-2000:12). SD=Standard deviation, COR=Correlation with the final estimate.

	MEAN	MEDIAN	SD	MIN	MAX	AR
			Linear Trend (OLS)			
$F-R$	0.049	0.049	0.018	0.009	0.091	0.735
$F-Q$	0.042	0.041	0.017	0.005	0.076	0.707
$Q-R$	0.008	0.007	0.009	-0.008	0.032	0.728
			Linear Trend (LAD)			
$F-R$	0.028	0.028	0.012	-0.002	0.059	0.339
$F-Q$	0.022	0.021	0.011	-0.003	0.046	0.213
$Q-R$	0.006	0.005	0.008	-0.011	0.025	0.667
			Quadratic Trend (OLS)			
$F-R$	0.031	0.031	0.026	-0.023	0.095	0.868
$F-Q$	0.033	0.029	0.025	-0.015	0.084	0.870
$Q-R$	-0.002	-0.002	0.008	-0.021	0.022	0.661
			Quadratic Trend (LAD)			
$F-R$	0.043	0.039	0.033	-0.018	0.104	0.910
$F-Q$	0.046	0.050	0.031	-0.005	0.106	0.908
$Q-R$	-0.003	-0.003	0.010	-0.026	0.024	0.712
			Break in Level			
$F-R$	0.019	0.015	0.025	-0.018	0.114	0.739
$F-Q$	0.013	0.008	0.028	-0.040	0.114	0.792
$Q-R$	0.006	0.005	0.010	-0.015	0.027	0.719
			Break in Trend			
$F-R$	0.017	0.011	0.026	-0.018	0.130	0.726
$F-Q$	0.014	0.008	0.028	-0.023	0.128	0.764
$Q-R$	0.003	0.002	0.008	-0.017	0.234	0.572
			Break in Level and Trend			
$F-R$	0.000	-0.001	0.018	-0.037	0.069	0.556
$F-Q$	0.000	0.002	0.018	-0.039	0.055	0.595
$Q-R$	0.000	-0.000	0.008	-0.018	0.026	0.319
			Hodrick-Prescott			
$F-R$	0.006	0.003	0.018	-0.019	0.058	0.745
$F-Q$	0.006	0.001	0.018	-0.025	0.052	0.757
$Q-R$	0.000	0.000	0.007	-0.015	0.020	0.600
			Kernel			
$F-R$	-0.034	-0.035	0.017	-0.067	-0.002	0.713
$F-Q$	-0.041	-0.045	0.022	-0.083	-0.002	0.817
$Q-R$	0.007	0.007	0.009	-0.010	0.030	0.739

Table 3: Breakdown of Cycle Revision Statistics (1993:07-2000:12). SD=Standard deviation, AR=First autocorrelation.

Method	COR	NS	OPSIGN	XSIZE
Linear Trend (OLS)	0.930	0.376	0.500	0.567
Linear Trend (LAD)	0.977	0.212	0.378	0.500
Quadratic Trend (OLS)	0.650	0.841	0.367	0.611
Quadratic Trend (LAD)	0.596	1.100	0.300	0.578
Break in Level	0.134	1.848	0.389	0.744
Break in Trend	0.219	1.637	0.378	0.656
Break in Level and Trend	0.371	1.591	0.344	0.578
Hodrick-Prescott	0.589	1.015	0.300	0.500
Kernel	0.729	0.803	0.256	0.722

Table 4: Reliability Indicators of Business Cycle Revisions (1993:07-2000:12). COR=Correlation of the Real-Time and Final estimates, NS=Ratio of standard deviation of the Revision and the standard deviation of the Final estimate. OPSIGN=Frequency with which the Real-Time and Final estimates have opposite signs, XSIZE=Frequency with which the absolute value of the Revision exceeds the absolute value of the Final estimate.

Documentos de Trabajo Banco Central de Chile	Working Papers Central Bank of Chile
NÚMEROS ANTERIORES	PAST ISSUES

La serie de Documentos de Trabajo en versión PDF puede obtenerse gratis en la dirección electrónica: http://www.bcentral.cl/Estudios/DTBC/doctrab.htm. Existe la posibilidad de solicitar una copia impresa con un costo de $500 si es dentro de Chile y US$12 si es para fuera de Chile. Las solicitudes se pueden hacer por fax: (56-2) 6702231 o a través de correo electrónico: bcch@condor.bcentral.cl

Working Papers in PDF format can be downloaded free of charge from: http://www.bcentral.cl/Estudios/DTBC/doctrab.htm. Printed versions can be ordered individually for US$12 per copy (for orders inside Chile the charge is Ch$500.) Orders can be placed by fax: (56-2) 6702231 or e-mail: bcch@condor.bcentral.cl

DTBC-129 Noviembre 2001
Alternative Monetary Rules in the Open-Economy: A Welfare-Based Approach
Eric Parrado y Andrés Velasco

DTBC-128 Noviembre 2001
Price Inflation and Exchange Rate Pass-Through in Chile
Carlos José García y Jorge Enrique Restrepo

DTBC-127 Noviembre 2001
A Critical View of Inflation Targeting: Crises, Limited Sustainability, and Agregate Shocks
Michael Kumhof

DTBC-126 Noviembre 2001
Overshootings and Reversals: The Role of Monetary Policy
Ilan Goldfajn y Poonam Gupta

DTBC-125 Noviembre 2001
New Frontiers for Monetary Policy in Chile
Pablo S. García, Luis Oscar Herrera y Rodrigo O. Valdés

DTBC-124 Noviembre 2001
Monetary Policy under Flexible Exchange Rates: An Introduction to Inflation Targeting
Pierre-Richard Agénor

DTBC-123 Noviembre 2001
Targeting Inflation in an Economy with Staggered Price Setting
Jordi Galí

DTBC-122 Noviembre 2001
Market Discipline and Exuberant Foreign Borrowing
Eduardo Fernández-Arias y Davide Lombardo

DTBC-121 Noviembre 2001
Japanese Banking Problems: Implications for Southeast Asia
Joe Peek y Eric S. Rosengren

DTBC-120 Noviembre 2001
The 1997-98 Liquidity Crisis: Asia versus Latin America
Roberto Chang y Andrés Velasco

DTBC-119 Noviembre 2001
Politics and the Determinants of Banking Crises: The Effects of Political Checks and Balances
Philip Keefer

DTBC-118 Noviembre 2001
Financial Regulation and Performance: Cross-Country Evidence
James R. Barth, Gerard Caprio, Jr. y Ross Levine

DTBC-117 Noviembre 2001
Some Measures of Financial Fragility in the Chilean Banking System: An Early Warning Indicators Application
Antonio Ahumada C. y Carlos Budnevich L.

DTBC-116 Noviembre 2001
Inflation Targeting in the Context of IMF-Supported Adjustment Programs
Mario I. Blejer, Alfredo M. Leone, Pau Rabanal y Gerd Schwartz

DTBC-115 Noviembre 2001
A Decade of Inflation Targeting in Chile: Developments, Lessons, and Challenges
Felipe Morandé

DTBC-114 Noviembre 2001
Inflation Targets in a Global Context
Gabriel Sterne

DTBC-113 Noviembre 2001
Lessons from Inflation Targeting in New Zealand
Aaron Drew