TRENDS AND CYCLES IN REAL-TIME *

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Abstract

This paper compares the results of applying several detrending methods to the Chilean monthly economic activity index (IMACEC) 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.

Resumen

En este documento se comparan los resultados de la aplicación de distintos filtros de remoción de tendencia, aplicados a la serie del Índice Mensual de Actividad Económica de Chile (IMACEC), utilizando bases de datos en tiempo real. Se demuestra que las revisiones a los datos son extremadamente importantes, que pueden conducir a estimaciones sistemáticamente inconsistentes del componente de tendencia. A su vez, la gran mayoría de filtros utilizados en la práctica son poco robustos e inestables en estimaciones al final de la muestra.

Key words: Real-Time Data, Business Cycle, Trend, Chile.

JEL Classification: C22, C82, E32.

1. INTRODUCTION

Economic time series are customarily decomposed into three component parts:

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

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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 for economic policy.[3]

Given the realizations of z, the researcher usually takes a stance regarding the nature of E and S to filter them from the original series and obtain the cyclical component by residual. The choice of filters for the trend and seasonal components is not trivial, as the filters may substantially alter the statistical properties of the resulting series when compared to the original.[4]

While often overlooked, there is another dimension that may be important when conducting this decomposition and has to do with the data set being used. 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 y 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 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.

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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 instance, the authority may be 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").

4 The effects of applying "popular" seasonal adjustment and detrending procedures have been subjects of active research. For example, Hylleberg (1992) discusses issues related to modeling 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.

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

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

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

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. Of course, 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,

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

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

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

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

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

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:

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

where $\hat{Z}^F - \hat{Z}^Q$ 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) 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.

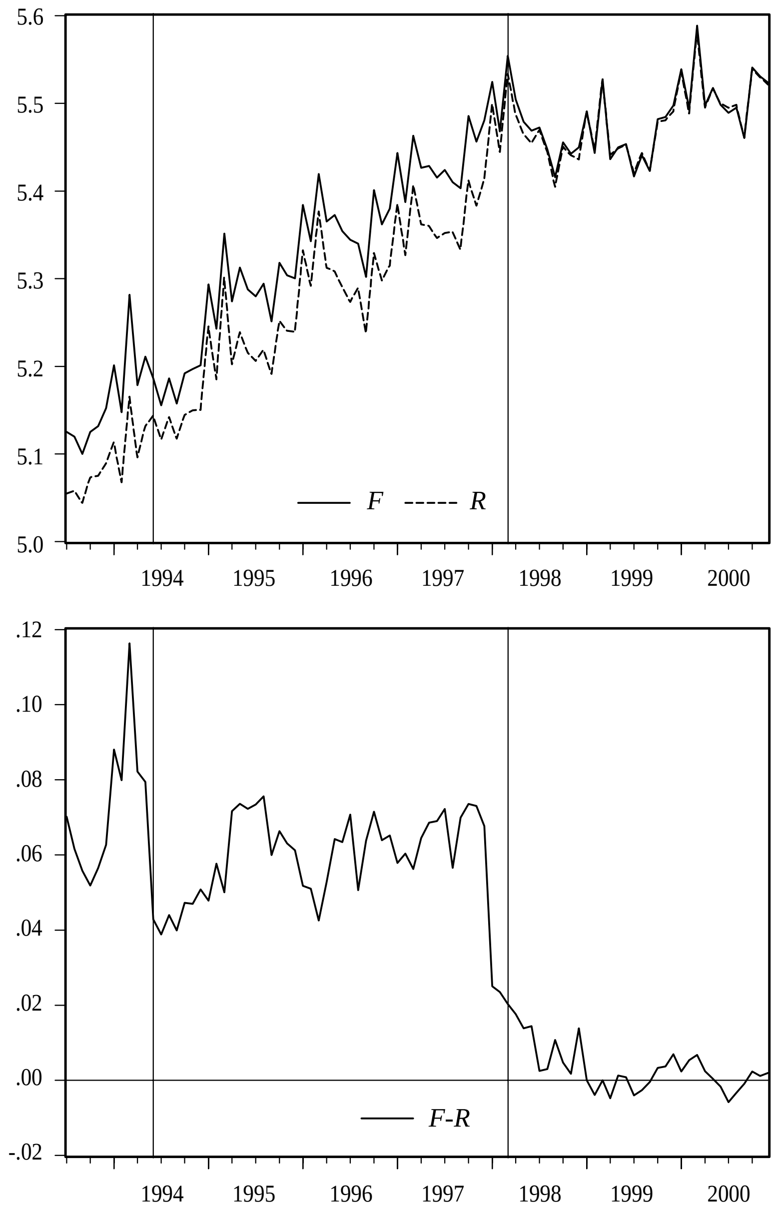
The first panel of Figure 1 presents the Final $\left(z_t^{T+2}\right)$ and Real-Time $\left(z_t^{t+2}\right)$ realizations of (the log of) IMACEC, while the bottom panel shows the difference between them.[9] The vertical lines indicate the dates at which the two major revisions on the data were made. 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% in 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

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

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

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

FIGURE 1
REAL-TIME AND FINAL (LOG OF) IMACEC (1993:07-2000:12)



the 1998:02-2001:06 period). Consequently, data revisions are extremely important for the estimation of trends and cycles using real-time data.

3. Alternative Methods

In order to evaluate the effect 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 do this at he same time. Thus, our aim is simply to assume that if a given filtering method is consistent in capturing the component it is intended to, we can compute the fraction of the revision error that is due to data revisions and the fraction that is due to the method. This allows us to provide guidelines for practitioners, with respect to the robustness of the particular method he (she) uses.

We apply the X-12-ARIMA seasonal adjustment procedure in order to remove the seasonal component of a series. Even though there are other methods available, most practitioners use X-12-ARIMA as their default procedure for filtering the seasonal component and thus we focus mainly on it.[10]

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

   (6) $$y_t = \alpha + \beta t + C_t$$

   where *a* and *b* 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;[11] 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 the presence of outliers.
3. Quadratic Trend (OLS): The third method adds a second term in the deterministic component of (6) to obtain:

   (7) $$y_t = \alpha + \beta t + \gamma t^2 + C_t$$

   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

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

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

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,…,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 modeled as:

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

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:

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

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:

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

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.[12]

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 in the presence of

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12 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 $\lambda = \sigma_C^2 / \sigma_{\Delta^2 E}^2$ if the cyclical component is a white noise process (Reeves, et al., 1996). If this is not the case, no optimality property should be attached to the HP filter (Ehlgen, 1998).

13 For example, β in (6) is $Op\ (T^{-3/2})$ while $\hat{\gamma}$ in (7) is $Op\ (T^{-5/2})$. This means that the latter parameter estimate converges faster (needs less information) than the former.

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 can never predict the occurrence of a break near the end of the sample, given that 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.

4. Results

4.1. Seasonal Component

The first step taken for decomposing (the log of) IMACEC (*z*), was to filter its seasonal component. The resulting series (denoted by y) is presented in Figure 2. From it, we gather that the Chilean economy has experienced a period of sustained growth. 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.

FIGURE 2
SEASONAL ADJUSTMENT OF (LOG OF) IMACEC (1986:01-2001:06)

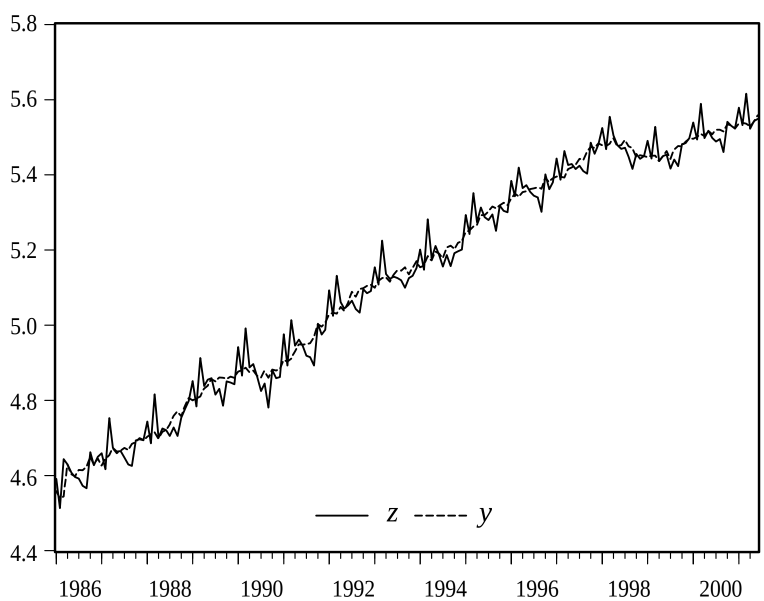
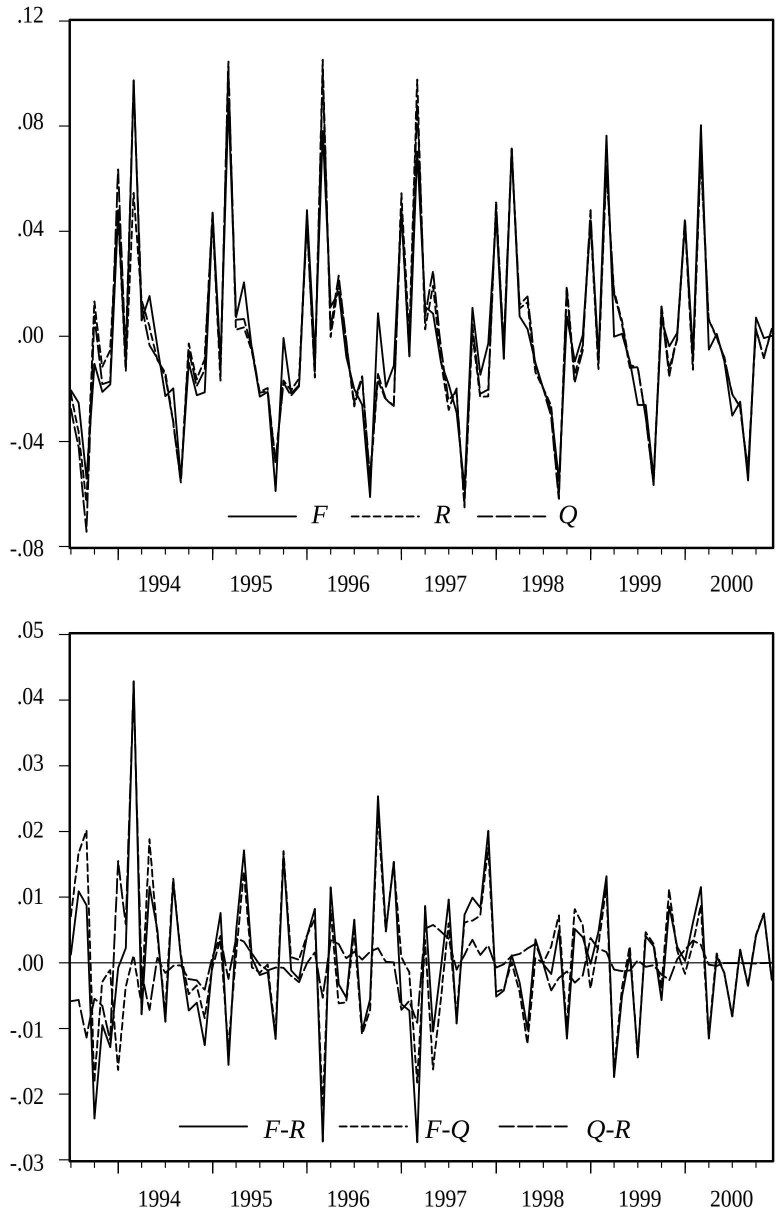


Figure 3 presents the estimates for the seasonal component obtained using the Final estimate, the Real-Time estimate and the Quasi-Real estimate. Along with them, the second panel displays the decomposition of the total revisions (*F-R*) that are due to data revisions (*Q-R*), and sample revisions (*F-Q*).

FIGURE 3
TOTAL REVISIONS IN SEASONAL COMPONENT (1993:07-2000:12)



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 seldomly 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

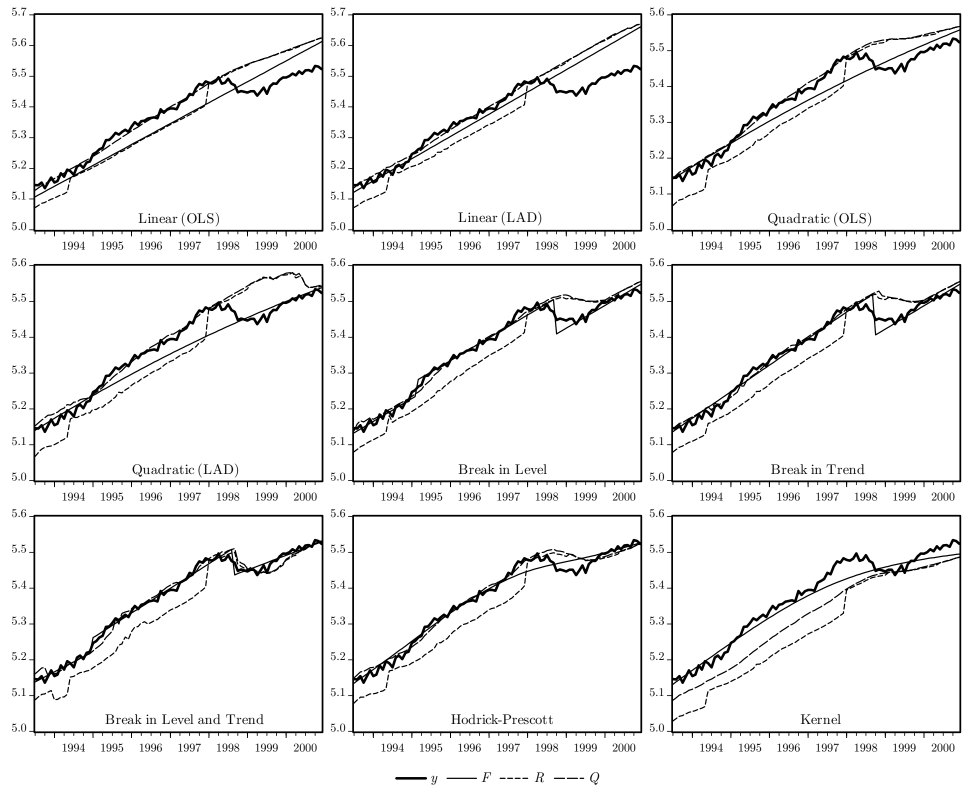
In the second stage, we filter the (log of) seasonally adjusted IMACEC (*y*) using the nine above-mentioned methodologies. Bare in mind, that each exercise assumes that the "true" trend component is consistently estimated by applying the corresponding filter. Thus, the goal of each of these decompositions is to assess the robustness of each filter and their sensitivity to both data revisions and sample extensions.

We obtained the estimates of the trend component by applying each of the nine filters (using "Final" (*F*), "Real-Time" (*R*), and "Quasi-Real" (*Q*) data sets). The results, presented in Figure 4, display several interesting features. 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 below *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, given that most of the methods 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 consider 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.

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

FIGURE 4

TREND COMPONENT (1993:07-2000:12)

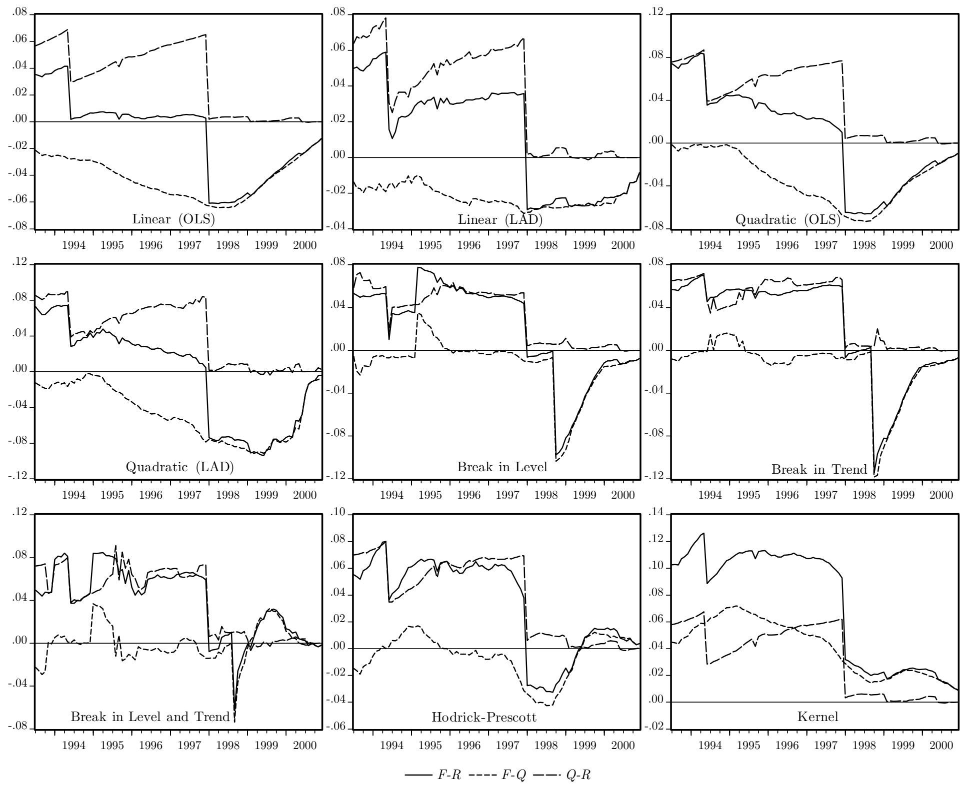


0.056 (Quadratic Trend, LAD) to 0.03 (in both Linear Trend estimators). Second, the last column of Table 1 shows that all revisions are highly persistent, having most of their first order autocorrelations exceeding 0.9. Third, while the averages of (*Q*-*R*) are always positive, averages of (*F*-*Q*) 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 difference between *F* and *Q*). Fourth, 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 inappropriate given that in the whole sample *Q* exceeds *F*.[14] Equally evident is that the Kernel filter is highly unstable, given that with it *F* always exceeds *Q*. However, none

14 As mentioned, this is due to the slow-down of y by the end of 1998.

FIGURE 5

TOTAL REVISION IN TREND COMPONENT (1993:07-2000:12)



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.

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.

TABLE 1
BREAKDOWN OF TREND REVISION STATISTICS (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	0.990
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

SD=Standard deviation, AR=First autocorrelation.

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. We must also bare in mind, that 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. Thus, 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 be actually mimicking 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

FIGURE 6
CYCLICAL COMPONENT (1993:07-2000:12)

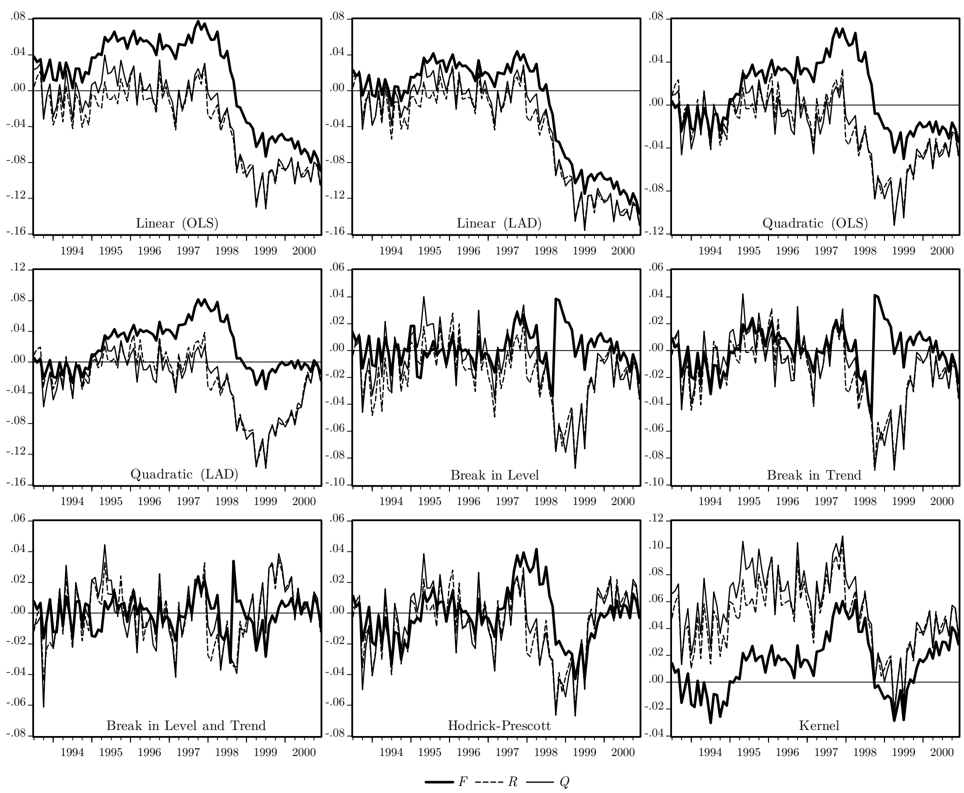


TABLE 2
CYCLES SUMMARY STATISTICS (1993:07-2000:12)

	MEAN	MEDIAN	SD	MIN	MAX	AR
			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

SD=Estándar deviation, COR=Correlation with the final estimate.

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.

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.

Finally, as in Orphanides and van Norden (1999), Table 4 constructs several indicators the measure the reliability of the business cycle estimates using real

FIGURE 7

TOTAL REVISION IN CYCLICAL COMPONENT (1993:07-2000:12)

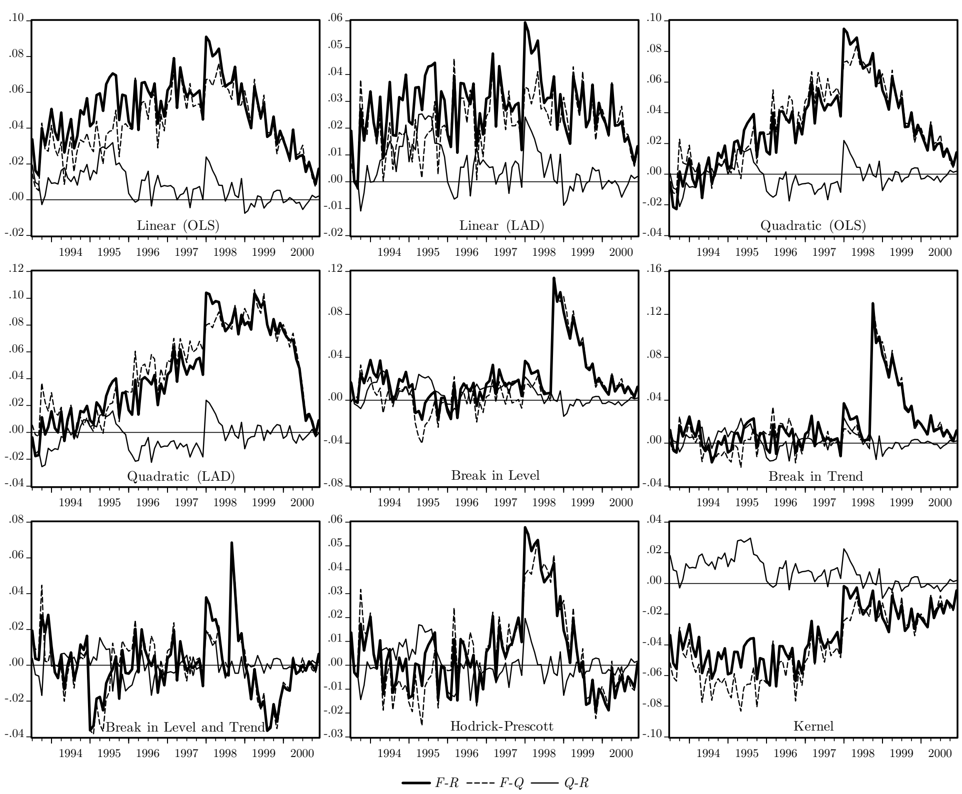


TABLE 3
BREAKDOWN OF CYCLE REVISION STATISTICS (1993:07-2000:12)

	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

SD= Standard desviation, AR=Firts autocorrelation.

TABLE 4
RELIABILITY INDICATORS OF BUSINESS CYCLE REVISIONS (1993:07-2000:12)

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

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.

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.

This last feature is of particular importance for policy-makers, given that they usually take decisions considering Real-Time data, and may incorrectly infer the magnitude and even 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, their cyclical component is as volatile as their revisions, and may present conflicting results when the Real-Time and Final estimates are compared.

References

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

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," *Documento de Trabajo* 73, Banco Central de 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, Banco Central de Chile.