Continuous Time Models to Extract a Signal in Presence of Irregular Surveys*

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Abstract

A typical statistical problem arises when a time series consists of observations collected with two different timing intervals. This is a frequent case in Statistical Offices, when the frequency of their surveys changes. In these cases, the classical tools to deal with signal extraction, such as the Hodrick-Prescott filter, are used on the most recent homogeneous span, losing the information deriving from the previous period. To use all the available information we exploit the fact that the Hodrick-Prescott filter has a state-space representation in a continuous time support, which provides the possibility to deal with different spans. In this paper we investigate the advantages of the continuous time models to extract a trend from a time series with respect to the Hodrick-Prescott filter in presence of irregular surveys. The flexibility of this model will be underlined with Monte Carlo experiments and an application on real data.

Keywords: Hodrick-Prescott filter, smoothing parameter, cubic spline, state-space model.

1 Introduction

In many situations statistical data are collected with different timing, producing time series with different frequency. For example, a survey could be recorded with quarterly timing until the period t and with monthly timing from period $t+1$ onwards. This is a frequent situation in data collected by National Statistical Institutes following the revision of corresponding surveys. Clearly, the analysis of time series, in particular the extraction of a signal, such as a trend or a cycle, is affected by the non homogeneity of data, because the classical filtering operators work with equally spaced data. In this way, the dynamics of the period dropped in the analysis is not considered, with the risk to lose an important set of information. The possibility to use the complete span of observations could be guaranteed by continuous time models (see, for example, Harvey, 1990, ch. 9); in fact, they are defined on a continuous time support and, for their estimation, the constraint to have equally spaced observations is not required. Nevertheless, this kind of models has not been frequently used by statisticians in their analysis. This fact is even more surprising for one of the most frequently used method to extract a signal from a time series, the Hodrick-Prescott (HP) filter. The filter has a model based interpretation, which can be easily generalized to the continuous time case. This result is well known in literature. For example, King and Rebelo (1993) show that the filter has a model-based interpretation, considering the series observed as generated by the sum of an IMA(2,0) stochastic trend and an orthogonal white-noise. As a result the HP filter solution is equivalent to find the minimum mean square error estimator of the growth component g_t and the cyclical component c_t. Harvey and Jaeger (1993) use the Kalman filter to obtain these estimators. Kaiser and Maravall (2001) note that the previous specifications for the growth component and the cycle imply an IMA(2,2) model for the overall series and obtain the HP filter as a Wiener-Kolmogorov filter, using its properties to improve its performance.

Given a model-based interpretation, the HP filter can be expressed in a state-space form and generalized to a continuous time support, using well-known results about the relationship between cubic splines and state-space models (Wahba, 1978, Wecker and Ansley, 1983, Koopman et al., 1999, Koopman and Harvey, 2003).

This specification provides the possibility to extract a signal with a method equivalent to the HP filter in the discrete case, using data recorded with different timing. The main purpose of this paper is an empirical evaluation of the eventual improvement obtained using the continuous time state space model (CTSS hereafter) with respect to the HP filter used only on the homogeneous span. This evaluation will be conducted via Monte Carlo experiments and an application on real quarterly data, supposing that the first i years were recorded annually.

In addition, the use of a CTSS model provides the possibility to work with more flexible models. In particular, the HP filter requires the choice of a smoothing parameter λ which "balances" the trade-off between the goodness of fit of the model to the observations and the degree of smoothness. HP (1997) suggest to fix the smoothing parameter equal 1600 for quarterly data; this result is obtained from empirical considerations about the U.S. quarterly GNP series (1950:Q1-1979:Q2) and eliminates the frequencies of 32 quarters or greater, but it has been adopted as the default value in many applications and in computer routines. This constraint is an open problem and it has been considered perhaps the main weakness of the HP filter because the smoothing parameter has not an intuitive interpretation (Wynne and Koo, 1997). Recently Maravall and del Río (2001) and Pedersen (2001) suggest alternative methods to calculate the smoothing parameter, the former using the relationship between the HP filter and the Butterworth filter; the latter minimizing a metric in the frequency domain that compares the cyclical component derived by HP and the cyclical component obtained by an ideal filter. Ravn and Uhlig (2002) propose alternative methods, considering the continuous time case. From our point of view, all these approaches have the limit to consider the smoothing parameter extraneous to the data generating process of the observed series; in fact it is fixed or calculated in a separate step with respect to the extraction of the components. In the continuous time formulation the smoothing parameter is part of the data generating process of the series, in the sense that it is present directly in the state-space representation and can be easily estimated. This consideration is supported by Monte Carlo experiments, available on request and present in the preliminary version of the paper.

In section 2 the relationship between the HP representation and the cubic splines is recalled: this leads to the specification of the CTSS model. In section 3, a comparison of the HP filter and the CTSS model is performed in terms of Monte Carlo experiments to evaluate the performance of the two alternative models in presence of irregular surveys; in the same section, a graphical illustration of this performance on the Italian series of workers in building sector will be provided. Concluding remarks follow.

2 Hodrick-Prescott Filter and Cubic Splines

The filter proposed by Hodrick and Prescott (1997) has a long tradition as a method to extract the trend (or the cyclical) signal from a time series. They suppose that an observed time series y_t (generally considered by taking logarithms) is the sum of two unobserved components: a growth component g_t and a cyclical component c_t:

$$y_t = g_t + c_t, \qquad t = 1, \ldots, T. \tag{1}$$

The purpose is to extract the trend component g_t and to obtain the cyclical component as a residual. We suppose that $c_t = y_t - g_t$ has zero mean in the long period. Assuming the sum of the squares of the second difference of g_t as a measure of its smoothness, a logical solution to this problem would be to solve the minimization problem:

$$\min_{\{g_t\}_{t=1}^{T}} \left[\sum_{t=1}^{T} (y_t - g_t)^2 \right]$$

subject to the constraint:

$$\sum_{t=1}^{T} \left(\nabla^2 g_t\right)^2 \leq \nu$$

where ∇^2 is the second order difference and ν is a known constant. This is equivalent to solve the following unconstrained programming problem:

$$\min_{\{g_t\}_{t=1}^{T}} \left[\sum_{t=1}^{T} (y_t - g_t)^2 + \lambda \sum_{t=1}^{T} \left(\nabla^2 g_t\right)^2 \right] \tag{2}$$

where λ is a positive known constant that controls the degree of smoothness of the series (the larger the value of λ, the smoother is the series obtained). We can call this parameter smoothing parameter.

Deriving (2) with respect to g_t after simple algebra, we obtain the growth filter:

$$G(B) = \frac{1}{\lambda (1-B)^2 (1-B^{-1})^2 + 1}$$

where B denotes the backward operator.

The specification of λ plays a crucial role in extracting the trend, but HP suggest to fix it to 1600 for quarterly series (see section 1).

We consider the problem in a continuous time support; more specifically we suppose that the index t in (2) varies in $[\alpha,\omega]$ and g_t is generated by a Wiener process. Of course, in application to real time series data, there are just T observations not necessarily equally spaced; we stress this point saying that the observation y_t is recorded at time τ_t.

There is a correspondence between this model and smoothing polynomial splines. The smoothing polynomial spline $g(t)$ of degree $2m-1$ satisfies this condition (Wecker and Ansley, 1983):

$$\min_{g(t)} \left\{ \sum_{i=1}^{n} [y(\tau_t) - g(\tau_t)]^2 + \lambda \int_a^\omega \left[g^{(m)}(t) \right]^2 dt \right\} \tag{3}$$

among all functions whose first $m-1$ derivatives are continuous and the $m-th$ derivative square integrable, with λ arbitrary; $g^{(m)}$ denotes the $m-th$ derivative of the function g. It is immediate to note that (2) corresponds to the problem of minimization in (3) in a continuous time domain when $m = 2$. In other terms, the extraction of the growth component in (1) for the discrete case is equivalent to the search of the optimal cubic polynomial spline in the problem (3) in the continuous case (Harvey and Jaeger, 1993). Moreover, Wecker and Ansley (1983) show that (3) can be formulated as a dynamic linear system.

Now, let us consider the linear trend component defined in a continuous time support (Harvey, 1990):

$$\frac{d}{dt} \begin{bmatrix} g(t) \\ g^{(1)}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} g(t) \\ g^{(1)}(t) \end{bmatrix} dt + dW(t) \tag{4}$$

where $dW(t) \to N\left(\mathbf{0}, \begin{bmatrix} 0 & 0 \\ 0 & k^2 dt \end{bmatrix}\right)$ and $W(t)$ is a Brownian motion. Considering the dates τ_t in which the data are recorded, the corresponding discrete time state-space form for (1)-(4) is (see Carter and Kohn, 1997, Koopman et al., 1999, section 3.4, and Koopman and Harvey, 2003, section 5.2):

$$\begin{cases} y(\tau_t) = \mathbf{f}'\alpha(\tau_t) + c(\tau_t) \\ \alpha(\tau_t) = \mathbf{G}_t \alpha(\tau_{t-1}) + k\mathbf{u}(\tau_t) \end{cases} \tag{5}$$

where:

$$\alpha(\tau_t) = \begin{bmatrix} g(\tau_t), & g(\tau_t)^{(1)} \end{bmatrix}', \quad \mathbf{f} = \begin{bmatrix} 1, & 0 \end{bmatrix}', \quad \mathbf{G}_t = \begin{bmatrix} 1 & \delta_t \\ 0 & 1 \end{bmatrix},$$

$c(\tau_t) \sim IIN(0, \sigma_c^2)$, and the precision parameter k is linked to the smoothing parameter λ by:

$$\lambda = \frac{\sigma_c^2}{k^2}.$$

.

The disturbances $\mathbf{u}(\tau_t) = [u_1(\tau_t), u_2(\tau_t)]'$ are bivariate independent normally distributed variables with zero mean and variance matrix:

$$\mathbf{V}_t = \begin{bmatrix} \delta_t^3/3 & \delta_t^2/2 \\ \delta_t^2/2 & \delta_t \end{bmatrix}.$$

Note that uncorrelated disturbances in continuous time imply correlation among corresponding discrete disturbances.

The variable δ_t represents the time distance between two contiguous observations; formally $\delta_t = \tau_t - \tau_{t-1}$. Of course, when the observations are equally spaced, $\delta_t = 1$ for each t.

Filtering and smoothing (5) with the well-established techniques for dynamic models (Harvey, 1990, ch.9), we can obtain the unobserved signal g_t.

The classical HP filter, with equally spaced observations, can be seen as a particular case of (5), constraining the first element of the vector α_t to be deterministic, imposing a smooth trend. In other terms, the model, in an extensive form, will be:

$$\begin{array}{lcl} y(\tau_t) & = & g(\tau_t) + c(\tau_t), \\ g(\tau_t) & = & g(\tau_{t-1}) + g(\tau_{t-1})^{(1)}, \\ g(\tau_t)^{(1)} & = & g(\tau_t)^{(1)} + ku(\tau_t). \end{array}$$

Clearly, in this case the covariance matrix $\mathbf{V}$ collapses to the variance of u_t. As noted by Harvey and Jaeger (1993), it is not reasonable to suppose that all the series have a smooth trend; they support their consideration with stylized facts, so the constraint imposed in the previous equation could be unrealistic.

3 Extracting the Signal in Presence of Irregular Surveys

A particular advantage in the use of CTSS model is the possibility to consider time series recorded with different frequency. In this case, the classical HP filter will be used only for the homogeneous span dropping the observations at the other frequency. In the CTSS model (5), the use of the variable δ_t provides the possibility to take into account this situation.[1] For example, let us suppose that the variable y_t is recorded quarterly until time i and monthly from time $i + 1$. In this case, the variable δ_t would be defined:

$$\delta_t = \begin{cases} 3 & \text{if } t \leq i \\ 1 & \text{if } t > i \end{cases}$$

Similarly, if the variable y_t is recorded annually until the time i and quarterly, from time $i + 1$, the variable δ_t would be defined:

$$\delta_t = \begin{cases} 4 & \text{if } t \leq i \\ 1 & \text{if } t > i \end{cases}$$

The extension to other irregular surveys is straightforward.

3.1 Monte Carlo Evaluation

To evaluate this property, we perform several Monte Carlo simulations, under the hypothesis that the data are generated under the model (1). We recall that King and Rebelo (1993) show

[1] We are supposing that the data are referred to stock variables; the same considerations are valid for flow variables with few modifications (see Harvey, 1990)

that the data can be seen as the sum of an IMA(2,0) model (component g_t) and a white noise (component c_t). So, we can generate separately the two components by the models:

$$\begin{aligned} \nabla^2 g_t &= \varepsilon_t^{(g)}, \qquad \varepsilon_t^{(g)} \sim NID(0, k^2) \\ c_t &= \varepsilon_t^{(c)}, \qquad \varepsilon_t^{(c)} \sim NID(0, \sigma_c^2) \end{aligned}$$

and $\lambda = \sigma_c^2/k^2$. Referring the considerations of Hodrick and Prescott (1997) about the variances of the components, we can fix the value of k^2 to 1/64 and obtain the value of σ_c^2 in correspondence of different values of λ. In particular, we choose the values of three different smoothing parameters, compatible with three cycles of reference (the values are taken by Table 5 of Maravall and del Río, 2001):

1) $\lambda = 179$ for quarterly series, $\lambda = 14400$ for monthly series, which correspond cycles of length 5.7 years;

2) $\lambda = 1600$ for quarterly series, $\lambda = 129119$ for monthly series, which corresponds cycles of length 9.9 years;

3) $\lambda = 6199$ for quarterly series, $\lambda = 501208$ for monthly series, which corresponds cycles of length 13.9 years.

We generate quarterly and monthly series of 10 years, using the various λ specifications; for each simulation we generate 1000 series. We perform the following experiment: from each series we extract the trend with CTSS using the model (5), with the correct HP filter and with the HP filter fixing λ to the default value (we choose the most frequently used values, that are 1600 for quarterly series and 14400 for monthly series). The use of the true λ in the HP filter is clearly a theoretical situation, because the researcher does not know a priori it; but this is a useful benchmark to compare the CTSS model and the HP filter with fixed λ. The results are compared with the true trend using RMSE and Theil index; the first one would indicate how distant from the true signal are the estimated signals, whereas the second would stress the ability of the methods to track turning points in the series. In Table 1 the means and the standard deviations of the indices calculated on these simulations are showed, with the maximum likelihood estimated parameters in the CTSS procedure. The first row for each group of simulations ($t = 0$) show that the performance of the CTSS model is similar to that of the HP filter with true smoothing parameter and better of the HP with default value (a part the case with λ generator equal 6199).

Now, we consider as annual the initial i years of the series ($i = 1, 2, 3, 4, 5$); in other terms we drop the second, the third and the fourth observation of the initial i years and then estimate the trend with the model (5), using the appropriate specification for the variable δ_t; then we estimate the trend with the HP filter with the true λ and with the default value using only the second part of the series (that with quarterly data) and compare the results, using only the common second part of the series. The same experiment is performed using the monthly simulated series, and considering quarterly the first i years ($i = 1, ..., 5$). The results are showed in the rest of Table 1. It is interesting to note that the performance of the CTSS model is always better then the case of HP filter with default values (a part the case of $\lambda = 6199$ with only an annual data) and its performance becomes better then the HP filter with the true smoothing parameter, increasing the number of irregular observations. In fact, when the first part of the time series is annual and the second quarterly, we can note that, a part the case of brief cycles (true λ equal to 179), is sufficient to have 2 or 3 additional annual observations to obtain a better performance with respect to the use of the true HP filter; in the case of initial quarterly and then monthly series, it is always sufficient that the first 2 years are quarterly to obtain improvement in the extraction of the trend. Note also that the estimations of σ_c and k varies slowly, but this is sufficient to adapt the trend to its correct dynamics.

3.2 An Empirical Illustration

As an application to compare the behavior of the two approaches, we have considered the same experiment of the previous section on a real time series. In the quadrant a of Figure 1 is represented the Italian seasonally adjusted quarterly series of workers in building sector (I 1993-IV 2002). We have extracted the trend with the default HP filter and the CTSS model, obtaining the profiles in quadrant b of Figure 1; let us note the similarity of the two trends, denoting a turning point at the end of 1997- beginning of 1998. Then, we have considered as annual data the first i years, dropping the data relative to the second, third and fourth quarters until time i (i =1993, 1994, 1995, 1996); the trend components are estimated using only the quarterly span for the HP filter (partial information) and both the annual and quarterly spans for the CTSS model (mixed information). In Figures 2 and 3 the various trends extracted with partial and mixed information are compared with the corresponding trend obtained with the full information (that one with the complete quarterly series). It is evident that the reduced information leads the HP filter progressively to get worse and worse, not long capturing the turning point after that two initial years are dropped (quadrants b and d of Figure 3). Vice versa, the CTSS model, using both the quarter and annual spans, is able to detect the curvature of the trend, also when the data from 1993 to 1996 are considered annual (quadrant c of Figure 3).

4 Final Remarks

In this paper we have used a continuous time state space model for the extraction of unobserved signals in time series; this approach generalizes the Hodrick-Prescott filter, using the well-known results for cubic spline models. The main advantage of this methodology underlined in the paper is the possibility to work with irregular surveys. Another appealing characteristic is its flexibility; in particular we have pointed out that the smoothing parameter is estimated and not fixed, but other aspects are relevant, such as its general form which provides the specification of structural models for the signals. For example, a stationary ARMA structure can be hypothesized for the dynamics of the cyclical component; another possibility would be to add a trigonometric function to represent the cycle (see, for example, Harvey, 1989, Harvey and Jaeger, 1993). In addition, in a similar way for the irregular surveys, the presence of the variable δ_t in model (5) allows for the presence of missing data.

Our Monte Carlo experiments suggest that the CTSS approach, in the presence of irregular surveys, approximates the true signal and performs generally better then the classical HP filter. In particular, it is noted that the true HP filter fails when only a part of the series is used to extract the signal, not being able to capture the turning points, whereas the CTSS model, using the full information available, can modify the smoothing parameter, detecting turning points also at the beginning of the homogeneous time interval. In the cases of equal data sets, the CTSS model has a performance, in terms of detection of turning points and distance from the true signal, very similar to that obtained with the true filter.

Note that recently many algorithms to improve the filter extraction of the CTSS model have been developed; for example, the efficient MCMC method of Carter and Kohn (1997), which works also dropping the Normal hypothesis about disturbances; the Koopman and Harvey (2003) algorithm for computing implicit weights for the observations; the Koopman and Durbin (2003) procedure for diffuse initial state-space vectors. In particular, the use of the Carter and Kohn procedure could be very useful in the case of few observations, being based on Bayesian procedures. We have experimented this methodology only in the application on the Italian data in section 3.2, because for the Monte Carlo experiments the cumbersome calculations implied by the Carter and Kohn method would be prohibitive. The results obtained are very similar with respect to those deriving from the classical maximum likelihood method.

Tabella 1: Results of Monte Carlo experiment for several smoothing parameters λ and irregural time series: means of estimated σ_c, k, RMSE, Theil (standard deviations in parentheses)

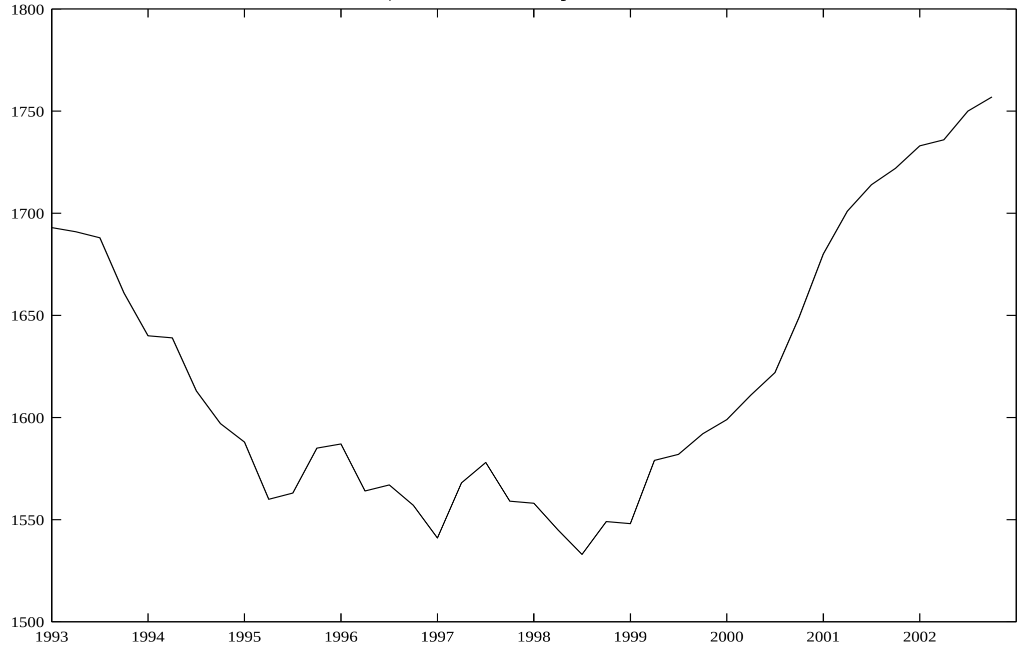
	CTSS				HP true		HP default	
	σ_c	k	RMSE	Theil	RMSE	Theil	RMSE	Theil
annual for t years and then quarterly (λ default = 1600)								
λ generator=179								
t=0	1.647	0.115	0.602	0.046	0.570	0.044	0.706	0.053
	(0.202)	(0.074)	(0.175)	(0.065)	(0.163)	(0.061)	(0.218)	(0.067)
t=1	1.648	0.113	0.588	0.045	0.575	0.044	0.709	0.052
	(0.210)	(0.074)	(0.183)	(0.066)	(0.175)	(0.064)	(0.232)	(0.070)
t=2	1.645	0.113	0.592	0.046	0.581	0.045	0.711	0.053
	(0.222)	(0.076)	(0.195)	(0.073)	(0.188)	(0.074)	(0.240)	(0.081)
t=3	1.645	0.114	0.596	0.047	0.588	0.046	0.706	0.054
	(0.235)	(0.079)	(0.208)	(0.083)	(0.195)	(0.084)	(0.246)	(0.090)
t=4	1.641	0.113	0.600	0.049	0.596	0.047	0.693	0.054
	(0.248)	(0.082)	(0.220)	(0.103)	(0.208)	(0.099)	(0.246)	(0.101)
t=5	1.636	0.113	0.608	0.051	0.602	0.049	0.666	0.054
	(0.265)	(0.087)	(0.239)	(0.121)	(0.231)	(0.113)	(0.251)	(0.119)
λ generator=1600								
t=0	4.911	0.111	1.450	0.109	1.356	0.104		
	(0.581)	(0.118)	(0.520)	(0.153)	(0.495)	(0.147)		
t=1	4.906	0.111	1.432	0.108	1.377	0.104		
	(0.607)	(0.128)	(0.544)	(0.159)	(0.541)	(0.156)		
t=2	4.896	0.110	1.422	0.107	1.402	0.108		
	(0.640)	(0.127)	(0.580)	(0.173)	(0.573)	(0.187)		
t=3	4.896	0.112	1.426	0.110	1.430	0.111		
	(0.676)	(0.130)	(0.620)	(0.203)	(0.594)	(0.212)		
t=4	4.887	0.109	1.437	0.115	1.471	0.117		
	(0.709)	(0.129)	(0.660)	(0.247)	(0.642)	(0.245)		
t=5	4.870	0.110	1.474	0.120	1.519	0.124		
	(0.745)	(0.141)	(0.705)	(0.286)	(0.716)	(0.308)		
λ generator=6199								
t=0	9.656	0.120	2.552	0.193	2.360	0.180	2.469	0.190
	(1.140)	(0.177)	(1.045)	(0.282)	(0.962)	(0.262)	(0.986)	(0.280)
t=1	9.645	0.123	2.535	0.191	2.417	0.183	2.515	0.191
	(1.184)	(0.198)	(1.077)	(0.296)	(1.052)	(0.283)	(1.070)	(0.296)
t=2	9.619	0.128	2.520	0.191	2.478	0.192	2.570	0.200
	(1.252)	(0.203)	(1.156)	(0.325)	(1.137)	(0.345)	(1.141)	(0.357)
t=3	9.625	0.128	2.518	0.195	2.567	0.202	2.635	0.207
	(1.320)	(0.207)	(1.231)	(0.376)	(1.204)	(0.400)	(1.193)	(0.408)
t=4	9.602	0.126	2.539	0.203	2.703	0.217	2.736	0.220
	(1.389)	(0.205)	(1.293)	(0.454)	(1.313)	(0.462)	(1.305)	(0.472)
t=5	9.569	0.129	2.615	0.214	2.855	0.234	2.869	0.235
	(1.449)	(0.233)	(1.382)	(0.530)	(1.454)	(0.596)	(1.448)	(0.597)

Table 1 (continued)

	CTSS				HP true		HP default	
	σ_c	k	RMSE	Theil	RMSE	Theil	RMSE	Theil
quarterly for t years and then monthly (λ default=14400)								
λ generator=14400								
t=0	14.863	0.110	3.040	0.043	2.910	0.042		
	(0.976)	(0.070)	(0.858)	(0.060)	(0.803)	(0.060)		
t=1	14.868	0.111	2.956	0.042	2.936	0.042		
	(1.013)	(0.074)	(0.872)	(0.062)	(0.854)	(0.063)		
t=2	14.869	0.110	2.948	0.041	2.957	0.041		
	(1.043)	(0.073)	(0.940)	(0.063)	(0.922)	(0.063)		
t=3	14.883	0.108	2.956	0.041	3.009	0.042		
	(1.103)	(0.074)	(1.005)	(0.061)	(1.008)	(0.067)		
t=4	14.875	0.106	2.971	0.040	3.026	0.042		
	(1.168)	(0.074)	(1.065)	(0.062)	(1.053)	(0.067)		
t=5	14.874	0.105	2.995	0.041	3.078	0.042		
	(1.227)	(0.076)	(1.144)	(0.069)	(1.157)	(0.072)		
λ generator=129119								
t=0	44.459	0.101	7.392	0.105	6.972	0.101	7.804	0.113
	(2.892)	(0.113)	(2.656)	(0.150)	(2.450)	(0.150)	(2.460)	(0.168)
t=1	44.472	0.101	7.231	0.104	7.076	0.102	7.884	0.114
	(2.981)	(0.118)	(2.649)	(0.156)	(2.557)	(0.159)	(2.628)	(0.176)
t=2	44.473	0.100	7.159	0.101	7.223	0.102	7.972	0.112
	(3.079)	(0.118)	(2.807)	(0.160)	(2.784)	(0.164)	(2.819)	(0.179)
t=3	44.496	0.099	7.139	0.099	7.366	0.103	8.122	0.114
	(3.247)	(0.119)	(2.997)	(0.159)	(3.049)	(0.168)	(3.071)	(0.191)
t=4	44.455	0.099	7.198	0.098	7.493	0.103	8.190	0.113
	(3.427)	(0.122)	(3.192)	(0.160)	(3.257)	(0.168)	(3.201)	(0.188)
t=5	44.446	0.098	7.291	0.101	7.779	0.108	8.402	0.116
	(3.593)	(0.120)	(3.438)	(0.180)	(3.560)	(0.198)	(3.482)	(0.207)
λ generator=501218								
t=0	87.542	0.107	12.909	0.185	12.137	0.177	15.182	0.220
	(5.682)	(0.169)	(5.248)	(0.276)	(4.875)	(0.272)	(4.883)	(0.328)
t=1	87.560	0.110	12.724	0.184	12.378	0.181	15.339	0.221
	(5.849)	(0.182)	(5.294)	(0.293)	(5.103)	(0.291)	(5.217)	(0.344)
t=2	87.561	0.111	12.625	0.179	12.800	0.182	15.522	0.219
	(6.033)	(0.179)	(5.554)	(0.302)	(5.586)	(0.302)	(5.586)	(0.351)
t=3	87.596	0.112	12.588	0.176	13.158	0.184	15.806	0.222
	(6.370)	(0.181)	(5.849)	(0.299)	(6.176)	(0.311)	(6.082)	(0.375)
t=4	87.518	0.117	12.668	0.176	13.703	0.189	15.947	0.221
	(6.754)	(0.184)	(6.213)	(0.304)	(6.639)	(0.319)	(6.346)	(0.369)
t=5	87.508	0.115	12.871	0.181	14.588	0.204	16.391	0.227
	(7.087)	(0.185)	(6.668)	(0.344)	(7.218)	(0.384)	(6.882)	(0.406)

Figura 1: Workers in Building Sector: QI 1993- QIV 2002

a) Seasonal Adjusted Series



b) Trend Component

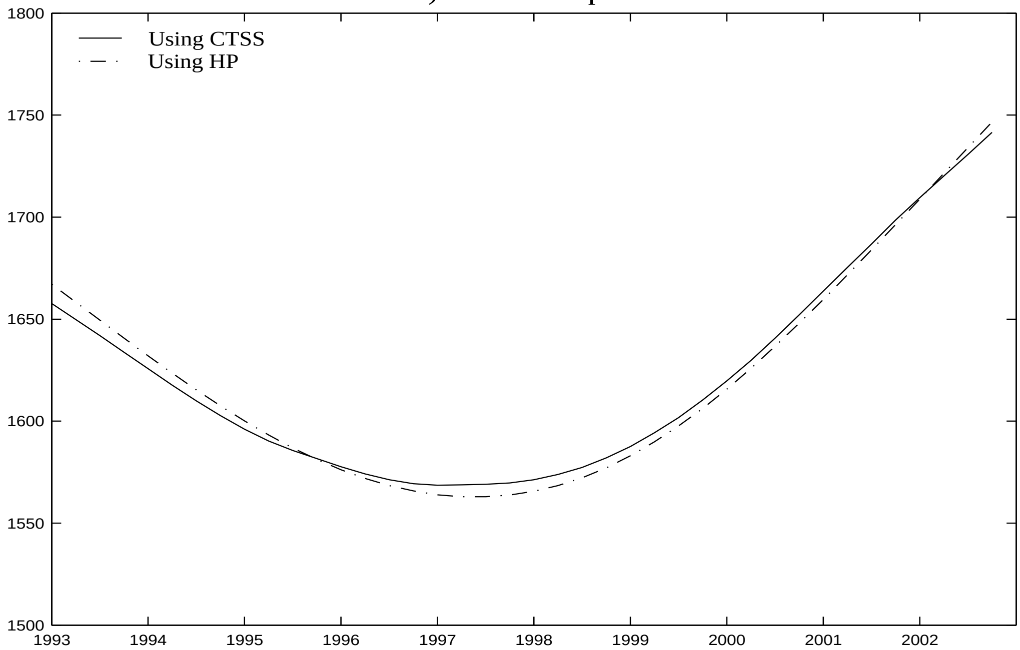


Figure 2: Workers in Building Sector − Trend extraction after removing 1993 and 1994

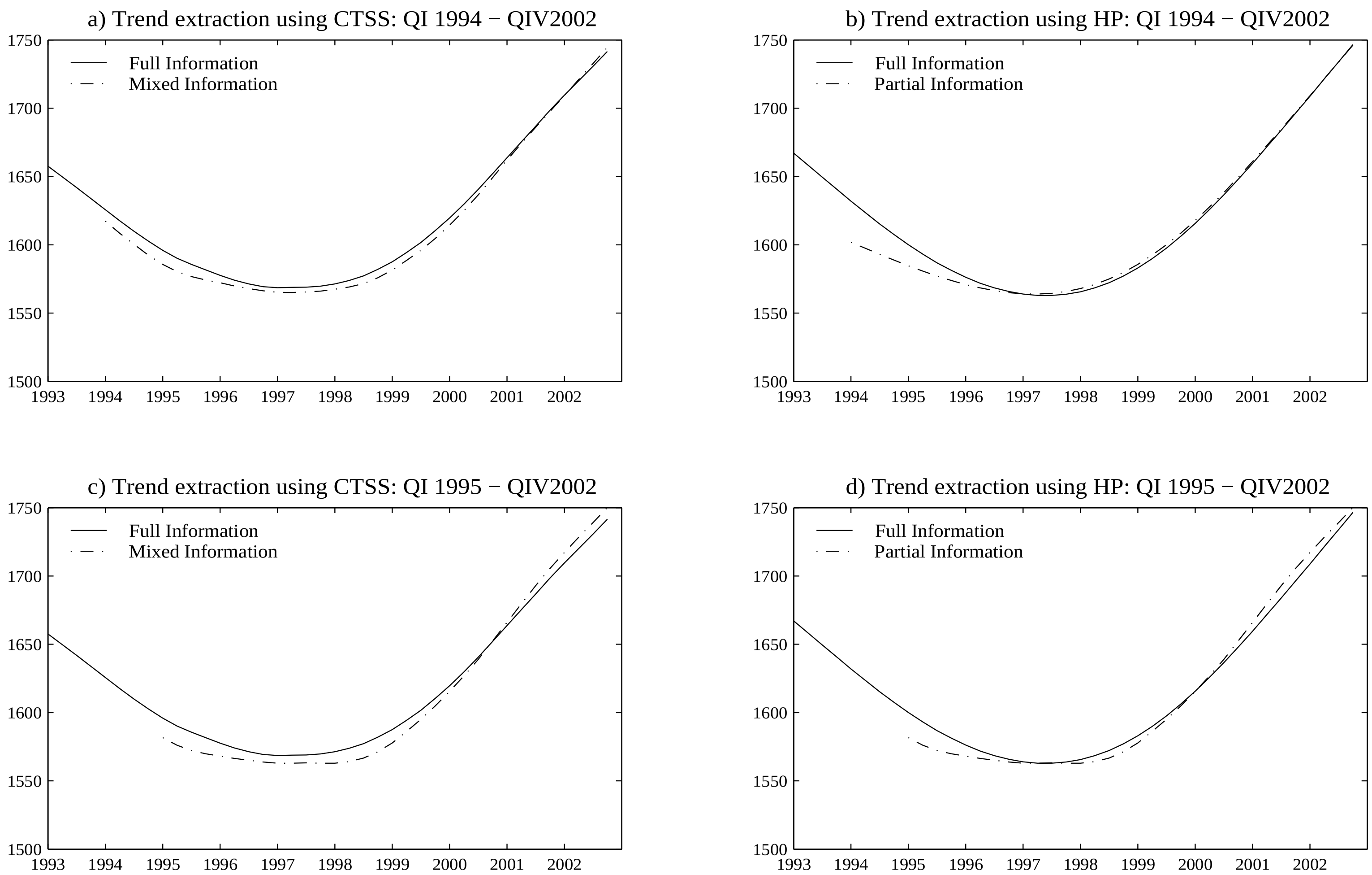
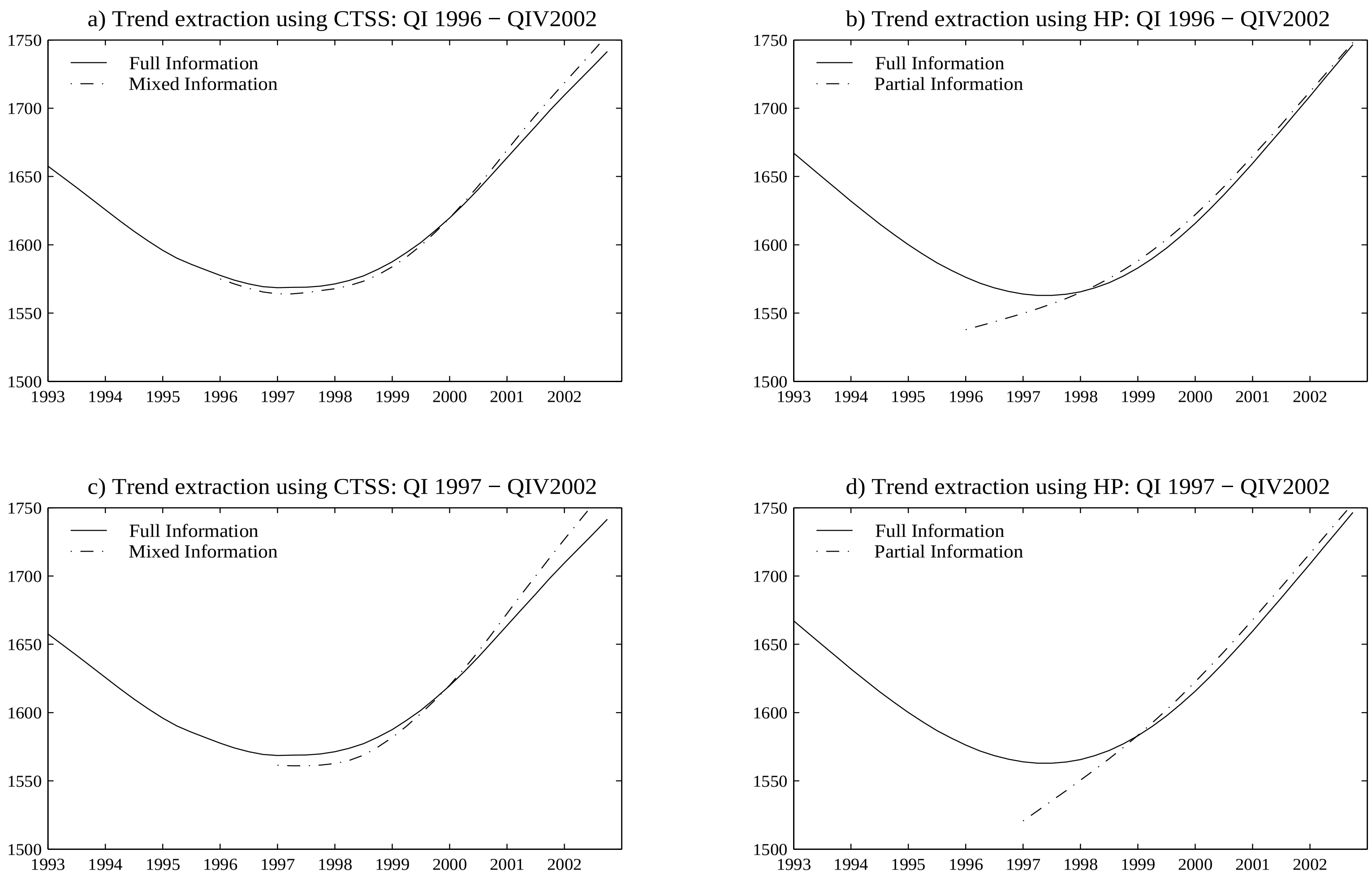


Figure 3: Workers in Building Sector − Trend extraction after removing 1995 and 1996



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