A TIME SERIES APPROACH TO SMALL AREA ESTIMATION

Richard B. Tiller, U.S. Bureau of Labor Statistics
2 Massachusetts Avenue, N. E., Washington, DC 20212

Abstract: The time series approach to small area estimation offers important advantages not only in achieving efficiency gains over the direct survey estimator but also in facilitating analysis of the characteristics of the true underlying series. In this paper, signal extraction is applied to state labor force data taken from the Current Population Survey (CPS). Because of this survey's complex design, the behavior of the observed sample estimates differ in important ways from that of the true values. An overlapping sample design and changes in reliability induce strong positive autocorrelation and heteroscedasticity in the sampling errors. Along with high variability due to small sample sizes, theses characteristics greatly complicate analysis. It is shown that signal extraction achieves major reductions in variability and that the trend and noise component can be seriously confounded by not controlling for the dynamics of the sampling error.

Key words: Signal extraction; structural models; correlated sampling error; seasonal adjustment.

1. Introduction

Much of the small area estimation literature deals with the problem of how to improve the reliability of data drawn from small samples for a large number of areas but collected for only one or a few points in time. In this context, cross-sectional modeling has often been an effective way to improve on the direct survey estimator. However, many of the most interesting population characteristics behave in a highly dynamic way over time. To provide data users with up-to-date information requires periodic sampling at frequent intervals. Often these periodic surveys are designed to provide reliable national statistics but the sample is spread too thin geographically to provide acceptable reliability for small areas. An alternative way of reducing variance in the survey estimator is to pool data across time rather than over areas using signal extraction techniques developed in the time series literature. Scott and Smith (1974) were among the first to suggest this approach to survey data.

In recent years, there have been a number of applications of signal extraction techniques to small area estimation, see, e.g., Bell and Hillmer (1990), Binder and Dick (1989), Pfeffermann (1991), and Tiller (1992). This approach provides a powerful unifying framework for analyzing time series data generated from periodic surveys. The conventional sampling approach treats the underlying population values as fixed and seeks to develop an efficient sample design but is too costly to provide reliable statistics for small areas. In contrast, traditional time series analysis treats the population as stochastic and provides a method for estimating the population values from a noisy series. Most time series applications assume that sampling error, if present, is approximately white noise. However, most periodic sample data are generated from complex designs that produce sampling errors with complicated forms of autocorrelation. By accounting for variation due to the stochastic behavior of the population and the sample design, the signal extraction approach not only can achieve efficiency gains over the sample estimator but also improve on the time series analysis by more effectively accounting for the dynamics of the sampling error.

In this paper, signal extraction is applied to state labor force data taken from the Current Population Survey (CPS). Because of this survey's complex design, the behavior of the observed sample estimates differ in important ways from that of the true values. Section 2 discusses those features of the CPS design that have an important effect on the properties of the sampling error. In Section 3 a time series model, consisting of a signal and noise component that represent the true population values and sampling errors, respectively, is fit to employment data from the Nebraska CPS sample. Section 4 presents the conclusions.

2. The Current Population Survey

The CPS is a nationwide monthly sample of about 59,000 households designed to produce estimates of employment and unemployment and other labor force characteristics of the population. While estimates of key labor force variables with acceptable reliability are produced for the nation as a whole, at the state level these same statistics have much higher variability. In the discussion to follow, we focus on those features of the design that have an important effect on the time series properties of the sampling error.

An important characteristic of the State CPS estimator is its changing reliability over time which results in heteroscedastic sampling errors. This occurs because of redesigns, sample size changes, and variation in labor force levels. The CPS is redesigned and a new sample selected each decade to make use of decennial census data to update the sampling frame and estimation procedures. Most recently, a state-based design was phased in during 1984/85 along with improved procedures for non interviews, ratio adjustments and compositing. This redesign had a major effect on the state variances. Special sample supplementations under the old national design have also had an effect on the reliability of selected state samples in the late 1970's and early 1980's. Even with a fixed design and sample size, the error variance will be changing because it is a function of the size of the labor force characteristics of the population being measured.

In those states that experience major fluctuations in their labor force, we can expect the variance to follow a similar pattern.

The second key characteristic of the CPS is the complex pattern of sample overlaps generated by a multi-stage rotating sample design. Once selected, PSUs, consisting of a county or groups of contiguous counties, remain in sample for 10 or more years. Within sampled PSUs, USUs, compact clusters of about 4 housing units, are rotated in and out of the sample over a period of 16 months. USUs selected for the sample are systematically assigned to 8 separate panels or rotation groups. The panels are introduced into the sample once a month for 8 months using a 4-8-4 scheme; i.e., each panel is interviewed for 4 months, dropped for 8 months, and then interviewed for 4 additional months. Each rotation group may be treated as an independent random sample of the state population.

This rotation scheme generates significant overlaps. Each month three-fourths of the sample from the previous month is interviewed, one-eighth of the sample is interviewed for the first time and one-eighth is resuming interviews after being out of sample for 8 months. Also, each month one half of the households being interviewed were interviewed in the same month a year ago. Figure 1 shows the proportion of the sample consisting of USUs in the current sample that were also in the sample k months ago. For example, 75% of the USUs in sample this month were in sample last month, 50% were in two months ago, etc. Note that samples from 4 to 8 months and over 15 months apart have no USUs in common.

The use of a rotation system requires the periodic replacement of the sample. To cover a decade under the 4-8-4 scheme, 15 samples are needed. A key feature of the replacement scheme is that successive samples are generated in a dependent way. Once an initial sample of USUs is selected, replacements are obtained from nearby addresses. For each original USU, the 14 succeeding ones needed to cover the decade are usually taken from the same neighborhood.

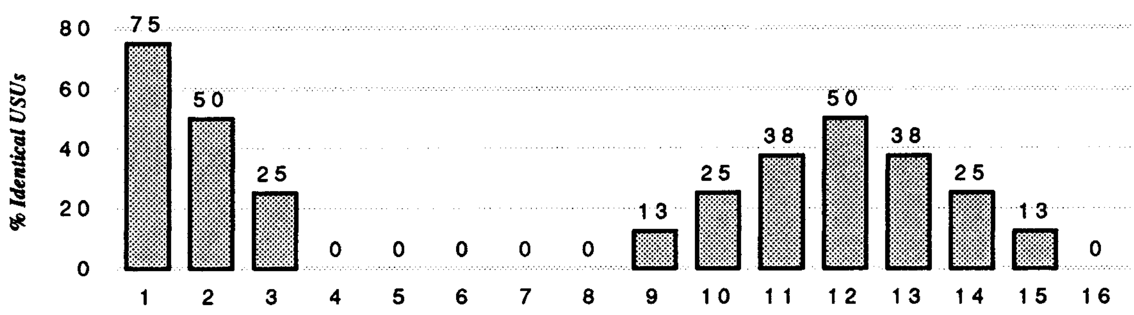
Since the labor force characteristics of state populations are positively correlated over time, we can expect the sample overlaps to induce autocorrelation in the sampling errors as well. In fact, the strong effect of the rotating panel on the sampling error correlations is used to improve the precision of estimation by means of compositing (Bureau of the Census, 1978).

A few empirical studies of the CPS autocorrelation structure at the national level (Train, Cahoon, and Makens, 1978, Lent, 1991) have been done using conventional designed based estimation methods. Because of the large processing costs involved, these studies are infrequently conducted and limited to a small number of time series observations.

Recently Dempster and Hwang (1991) have investigated the autocorrelation structure of the CPS at the state level. Using 48 months of data for each of the eight rotation groups, the authors used a mixed model to compute state-specific autocorrelations for employment and unemployment. Their model consists of 4 variance components, representing variance among streams (rotation groups), variance among different samples of USUs within a stream, variance between the first and the second year within a sample within a stream, and a residual variance. The use of the aggregate rotation group data is not as efficient as an analysis based directly on the sample unit data but has an important advantage in cost and provides information on error correlations at long lags.

The results for the state of Missouri, which are fairly typical of most states, are shown in Figure 1. The effect of the 4-8-4 rotating panel design is clearly revealed, the autocorrelation is highest at the low lags and falls at higher lags as the proportion of identical USUs common to both samples. While employment is more strongly autocorrelated than unemployment, the overall pattern is the same for both. Note the strong peak at the 12-month lag corresponding to the 50% overlap in identical housing units from year to year. Also, after a lag of 15 months when there is no longer any overlap of identical housing units, the autocorrelations fail to completely dampen out. Since replacement USUs are rotated into the sample from the same neighborhood, postive autocorrelations beyond 15 months can be expected. Because the stream variance is fixed in the Dempster and Hwang model, there is no decay in the correlations between different USUs in the same stream. This seems to be unrealistic since over a 10 year span neihgboorhood characteristics may change and general economic conditions are likely to change as well. In the example described

Figure 1. Overlap of Identical USUs



later in this paper, autocorrelations beyond 15 lags are assumed to slowly decay.

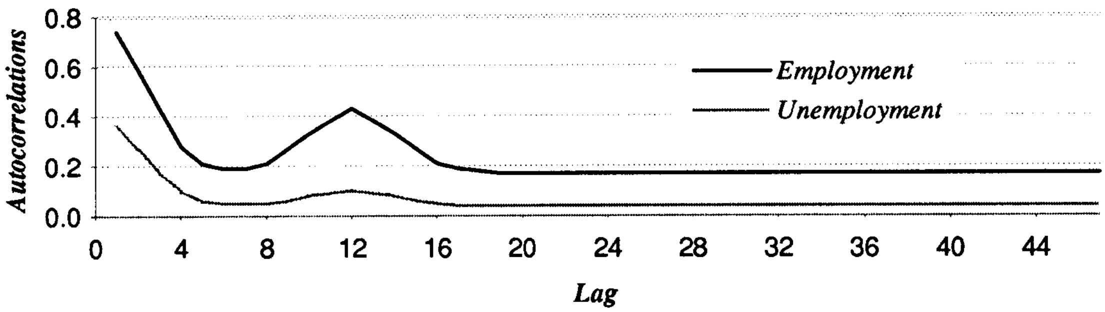
Both the heteroscedastic and autocorrelated properties, just discussed, have important implications for time series modeling. The next section describes how the special structure of the sampling error is accounted for in the time series modeling.

model assumptions, it is also a design consistent estimator from a sample survey point of view (Bell and Hillmer, 1990).

To illustrate the signal-plus-noise approach to CPS data we consider the employment-to-population ratio estimates in Nebraska from January 1976 to December 1991. This variable is defined as

CPSEP = 100*CPS Employment / Population.

Figure 2 CPS Autocorrelations for Missouri



3. Signal-Plus-Noise Modeling

Let the observed series $y(t)$, be the sum of a signal, $\theta(t)$, and a noise process, $N(t)$,

$$y(t) = \theta(t) + N(t).$$

Signal extraction is the process of separating the signal from the noise process when only their sum is directly observable. It requires specification of the stochastic processes generating the unobserved components of the time series. From this specification is derived an estimator of the unobserved components that has certain desirable statistical properties.

The typical economic time series is characterized by strong trend and seasonal variation and a white noise residual. The basic approach is to specify plausible a priori properties for both the signal and noise along with a sufficient number of constraints to ensure identification. Accurate estimation of the signal follows because the ratio of the signal to noise variance is high over those frequencies accounting for most of the variation in the signal.

The state CPS data, subject to large sampling errors with strong positive autocorrelations, do not conform to the typical economic series. For the CPS, the signal to noise ratio will be relatively weak in the low frequency range that accounts for most of the variation in the signal resulting in a substantial increase in the mean squared error of the estimated signal (see Hausman and Watson, 1985).

However, when the time series arise from a design based survey, information is available on the behavior of the noise that can aid in the identification of the signal and thus reduce the mean squared error of the estimated signal. Given a model for $\theta(t)$ and design-based information on the covariance structure of $N(t)$, the observed sample series may be decomposed into its signal and noise components. While this estimator is optimal given the

To implement the signal-plus-noise approach, the signal is represented by a 3 variance structural time series components model (Harvey 1989) and the noise component is represented as an ARMA process with parameters determined from the variance-covariance structure of the CPS sampling error.

First, we consider the sampling error characteristics of this variable. To capture the autocorrelated and heteroscedastic structure of $e(t)$, we express the noise component in multiplicative form as

$$N(t) = \gamma(t) N'(t) \tag{3.1}$$

with $\gamma(t)$ representing the heteroscedastic part of the CPS

$$\gamma(t) = \sigma_{N'}^{-1}\, \sigma_{e(t)} \tag{3.2}$$

where $\sigma_{e(t)}$ is the standard deviation of the sampling error, and $N'(t)$ representing the autocorrelated part of the CPS, parameterized in ARMA form as

$$(1-.98L)N'(t) = (1-.36L-.08L^2-.14L^3-.32L^4+.01L^5 +.02L^6+.03L^7-.03L^8)(1+.23L^{12})\upsilon_{N'}(t) \tag{3.3}$$

The time varying standard deviation, $\sigma_{e(t)}$, was estimated using the method of generalized variance functions. The estimated values range from 1.2 to 1.8 percentage points and the CVs vary between 1.6 and 3.0 percent. While the sampling error may appear to be low in an absolute sense, only 10% of the monthly changes are as large as two standard deviations of month to month change in the CPS. The behavior of the CPS standard deviations will be discussed in more detail below.

The autocorrelation structure is represented by equation (3.3). An ARMA(1,8)(0,1)$_{12}$ multiplicative seasonal model was fit to these autocorrelations. The autoregressive operator picks up the slowly decaying autocorrelations at high lags due to long- term sample overlaps. An autoregressive root close to unity usually suggests first differencing, but in this case the variance of N' can not be infinite. An eighth order MA term is included to account for the sharp drop and leveling out of the correlations in lags 1 through 8 as identical USUs are rotated into and then out of the sample. The seasonal MA operator accounts for the transitory seasonality induced by the 50% overlap of identical USUs from year to year.

For this series we estimate two types of models: Model 1 incorporates sampling error and Model 2 ignores it. Several varieties of Model 2 will be examined to clarify the effects of ignoring sampling error. In each case, the model of the signal is held constant so that the models differ only in how the noise component is specified.

The signal is specified as the sum of stochastic trend (T), seasonal (S) and irregular (I) components

$$\theta(t) = T(t) + S(t) + I(t) \tag{3.4}$$

$$T(t) = T(t-1) + R(t-1) + \upsilon_T(t) \tag{3.5}$$

$$R(t) = R(t-1) + \upsilon_R(t) \tag{3.6}$$

$$S(t) = \sum_j S_j(t), \quad p = \{12, 6, 4, 2\} \tag{3.7}$$

$$S_j(t) = \cos(\omega_j) S_j(t-1) + \sin(\omega_j) S_j^*(t-1) + \upsilon_{s_j}(t)$$

$$S_j^*(t) = -\sin(\omega_j) S_j(t-1) + \cos(\omega_j) S_j^*(t-1) + \upsilon_{s_j}^*(t)$$

$$\omega_j = 2\pi p_j^{-1}, \quad p = \{12, 6, 4, 2\}$$

$$I(t) = \upsilon_I(t) \tag{3.8}$$

Each of the components contains a white noise shock, $\upsilon_i(t)$ with its own variance, $\sigma^2_{\upsilon_i}$. The trend is represented as a local approximation to a linear trend with adaptive level (3.5) and slope (3.6) components. The seasonal component (3.7) consists of the 12 month frequency and three of its harmonics, specified to have a common variance. The irregular is specified as white noise.

The signal-plus-noise model described above is transformed into state space form. The unknown parameters of the variance components of the signal are estimated by maximum likelihood using the Kalman filter (KF) algorithm (Harvey,1989). Given these parameter values, the filter also calculates the expected values of the signal and noise components at each point in time conditional on the observed data up to the given time point. It also calculates the conditional variances so that standard errors of each component can be computed. As more data become available, previous estimates are updated by a process called smoothing (Maybeck, 1979).

Since time series are typically influenced by exogenous disturbances that affect specific observations, an additive outlier component was added to the model.

$$O(t) = \sum_j \lambda_j w_j(t), \quad t_j = \{Aug90, Sept\ 90\} \tag{3.9}$$

$$w_j(t) = \begin{cases} 1, & t = t_j \\ 0, & t \neq t_j \end{cases}$$

Two outliers were identified, as indicated in (3.9). Outliers are defined in terms of the one-step ahead errors in predicting the actual CPS observations generated by the Kalman filter recursions. Those errors that were at least three times their standard deviations were designated as outliers. The estimated parameters for this model appear in Table 1 under the column labeled Model 1.

Table 1. Parameter Estimates and Diagnostics

A. Parameter Estimates	*Model 1*	*Model 2a*	*Model 2b*
Trend			
Level ($\sigma^2_{V_T}$)	.11	.94	.55E-01
Slope ($\sigma^2_{V_R}$)	.54E-07	.91E-06	.10E-05
Seasonal ($\sigma^2_{V_s}$)	.19E-05	.19E-07	.19E-06
Irregular			
Variance ($\sigma^2_{V_I}$)	.13	.16	.97
Coefficient (α_I)	.00	.00	.63
Noise			
With sampling error	*yes*	*no*	*no*
Standard Deviation	*1.2-1.8*	*.40*	*1.27*

B. Diagnostics	*Model 1*	*Model 2a*	*Model 2b*
Ljung-Box[-12]	15.9	18.1	15.7
Ljung-Box[-24]	21.4	24.3	22.2
Heteroscedasticity			
With time	.99	2.0*	1.9*
Cusum of Squares	-	*	*
Bera-Jarque Normality	.72	3.8	4.9
Skewness	-.12	-.30	-.30
Excess Kurtosis	.19	.30	.50

**significant at .05 level*

Part B of Table 1 presents the results of a battery of diagnostic tests performed on the one-step-ahead predictions of the actual CPS estimates generated from the KF. Conditional on the parameters, these predictions should behave as normally distributed white noise variables. The usual tests for various departures from these properties are shown (Harvey, 1989). A residual seasonality test, based on the periodogram of the prediction errors, was also performed to detect significant variance at one or more of the seasonal frequencies. Based on these tests Model 1 appeared to be performing adequately.

Figure 3 plots the estimated signal (solid line) and the CPS (dotted line) in the upper panel, the estimated sampling error in the middle panel and the standard deviation of the CPS (gray line) and the standard deviation of the signal (black line) in the lower panel. As expected, the signal has a much smoother appearance than the sample estimates. The heteroscedasticity of the sample data is readily apparent. Prior to 1980 the signal did not track the CPS as closely as after 1980 (upper panel), a reflection of larger fluctuations in the estimated sampling errors (middle panel) which is explained by the large values of the standard deviations in the CPS (gray line in the bottom panel). Note the downward shift in the standard deviation (SD) of the CPS occurring in 1980 and again in 1985. The first corresponded to a supplement to the Nebraska sample under the old national design which resulted in a 10% drop in the SD. The drop of 12% in 1985 resulted from the introduction of a new state design.

The efficiency gains due to modeling depend on the amount by which the variance of the error in estimating the signal can be reduced over the survey estimator. To assess these gains, the SDs were estimated for the smoothed estimates of the signal conditional on the estimated parameters (black line in bottom panel). The signal SDs always lies below that for the CPS, averaging about 76% of the latter or an efficiency gain of 24%. Also note that the long run difference in SDs has narrowed as a result of the previously mentioned sample supplemenation and redesign, resulting in a narrowing of the difference between the signal and sample estimates. This last result is a reflection of the design consistency property of the estimator of the signal: as sample size increases, the estimator of the signal will differ little from the sample estimator (Bell and Hillmer, 1990).

Figure 4 shows estimated subcomponents of the observed CPSEP series. The smoothness of the signal is due to a slowly changing trend (upper panel), a stable seasonal pattern (second panel) and a small irregular component (third panel). The estimated outlier effects are shown in the bottom panel.

Table 2 presents estimates of the relative contribution of the components of CPSEP to the variance of change over different length intervals. The contribution of the sampling error

Table 2. Variance Components of Change in CPSEP*

% Noise	% Signal			
	Total	Trend	Seasonal	Irregular
48.5	51.5	1.2	45.8	4.5
38.2	61.8	1.8	59.1	0.9
67.0	33.0	30.3	0.0	2.7
5.6	94.4	44.5	49.9	-
1.0	99.0	38.1	60.9	-
2.0	98.0	98.0	0.0	-
57.6	42.4	0.3	42.1	-
40.0	60.0	0.6	59.4	-
85.0	15.0	15.0	0.0	-

A variance component is defined as $\sum_t \{y(t) - y(t-j)\}^2 \quad j = 1, 3, 12.$

to month-to-month variation in CPSEP is substantial, accounting for at least half of the total variation. It is also substantial for year-to year variation, a reflection of the strong autocorrelation induced by the rotating sample design. (The decline in the relative contribution at the 3-month interval is due to the strong seasonal nature of the signal rather than a reduction in the amplitude of the noise.)

While variance reduction is an important benefit of signal-plus-noise modeling, Table 2 also suggests that accounting for the dynamics of the noise is also very important. We investigate this issue next by estimating models that ignore the structure of the sampling error. Model 2a specifies the noise component to be white noise, a common assumption in time series decomposition. For this model (3.1) is replaced by

$$N(t) \approx NID(0, \sigma_a). \tag{3.1a}$$

As shown below, Model 2a produces clearly unsatisfactory results and this would likely suggest to a time series analyst a need for a correlated noise component. Accordingly, Model 2b assumes the noise is a first order autoregressive process,

$$\begin{aligned} (1 - \alpha_1)N(t) &= \upsilon_b(t) \\ \upsilon_{b(t)} &\approx NID(0, \sigma_b) \end{aligned} \tag{3.1b}$$

The noise parameters were estimated directly from the aggregate time series ignoring the sampling error information. The results are shown in Table 1. Model 2a has a trend level variance almost 9 times larger than Model 1. The white noise irregular component, acting as a proxy for the noise, has a SD of .40, only a fifth to a third the size of the CPS SD. Allowing for a correlated irregular in Model 2b, results in a small value for the trend variance, .06, and an SD of the noise equal to 1.3,

$\left(\text{i.e.}, \sqrt{\sigma^2_{v_b} / (1 - \alpha_1^{\,2})}\right)$. In both cases the models, by specifying a fixed noise variance, fail to capture the heteroscedasticity of the CPS as indicated by the diagnostics.

Futher evidence that the stochastic properties of the signal are substantially affected by ignoring sampling error is provided by the behavior of the variance components of change presented in Table 2. Under the white noise assumption of Model 2a, the relative contribution of the trend component to short run fluctuations of less than 12 months is unusually high for what should be a low frequency component. Moreover, the contribution of the noise component is unusually low and the seasonal variance not much changed, indicating that much of the autocorrelated sampling error is absorbed into the trend.

Under the Model 2b assumption of a first-order autoregressive noise component, about half of the trend variance over a 12-month span appears to be absorbed into the noise component, resulting in an over smoothed trend. These results are illustrated by Figure 5 which compares the Model 1 trend with Model 2a and 2b respectively.

It is also important to note that the Ljung-Box statistics (Table 1b) indicates no residual autocorrelation for either Model 2a or 2b. Theses models appear to explain the autocorrelation in the CPS series even though their assumptions about the noise component are incorrect and result in biased estimates of the variance components for the signal.

We note that the seasonal component is not much affected by ignoring sampling error. The seasonal pattern is not much different and remains very stable for all 3 models as shown in Table 1. This is also evident in Table 2 where the seasonal contributions are of roughly equal magnitude for all 3 models.

These results may also have important implications for the practice of seasonal adjustment of time series with large and strongly autocorrelated errors. The conventional assumptions about the noise component, non-autocorrelated and constant variance, are likely to have a significant impact on the reliability of the seasonal adjustment . Model based approaches to seasonal adjustment, however, can be adapted to account for sampling error, as illustrated by this study. On the other hand, non-model based approaches appear to be too inflexible.

A related study by Hausman and Watson (1985) reached similar conclusions from their study of the effects of measurement error on X-11 when adjusting national CPS unemployment rate data. The consequences of ignoring sampling error are even more severe when dealing with employment series at the state level where the relative size of the sampling error is higher and the autocorrelations stronger.

Another point to consider is the effect of the specification of the noise component on the signal extraction variances. The assumption that the variances of the noise component in (3.1a) and (3.1b) are constant imply that the variance of the signal will reach a steady-state. However, the true noise variance is heteroscedastic indicating that no such steady-state will be approached. The effect of this misspecification appears to be a downward bias in the SD of the signal (see Figure 6). The SD for Model 1 has been at a level of around .98 since 1984. In contrast, Model 2a and 2b reach steady-state values of .35 and .60 respectively. (The large spike in the Model 2a variances indicates a greater sensitivity to the August and September 1990 outliers.) Unlike Model 1, these latter two models are not design consistent.

4. Conclusions

This study applied the time series approach to survey data containing sampling error with high variance and strong autocorrelation. Specifically, a signal plus noise model was fit to employment data taken from the Nebraska CPS sample. The results indicated the potential for significant gains in efficiency over the sample estimator and the pitfalls in not properly accounting for the influence of the sampling error. When sampling error was ignored, bias in key variance components substantially altered the stochastic properties of the signal and the estimates of the signal extraction variances had a large downward bias. Moreover, diagnostic testing did not reveal any serious lack of fit to the data. In short, the use of sample design information in the estimation of unobserved components of time series can be very important in guarding against serious distortions in the estimated signal caused by making inappropriate assumptions about the noise component.

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Figure 3. CPS and Signal for Nebraska's Employment-to -Population Ratio

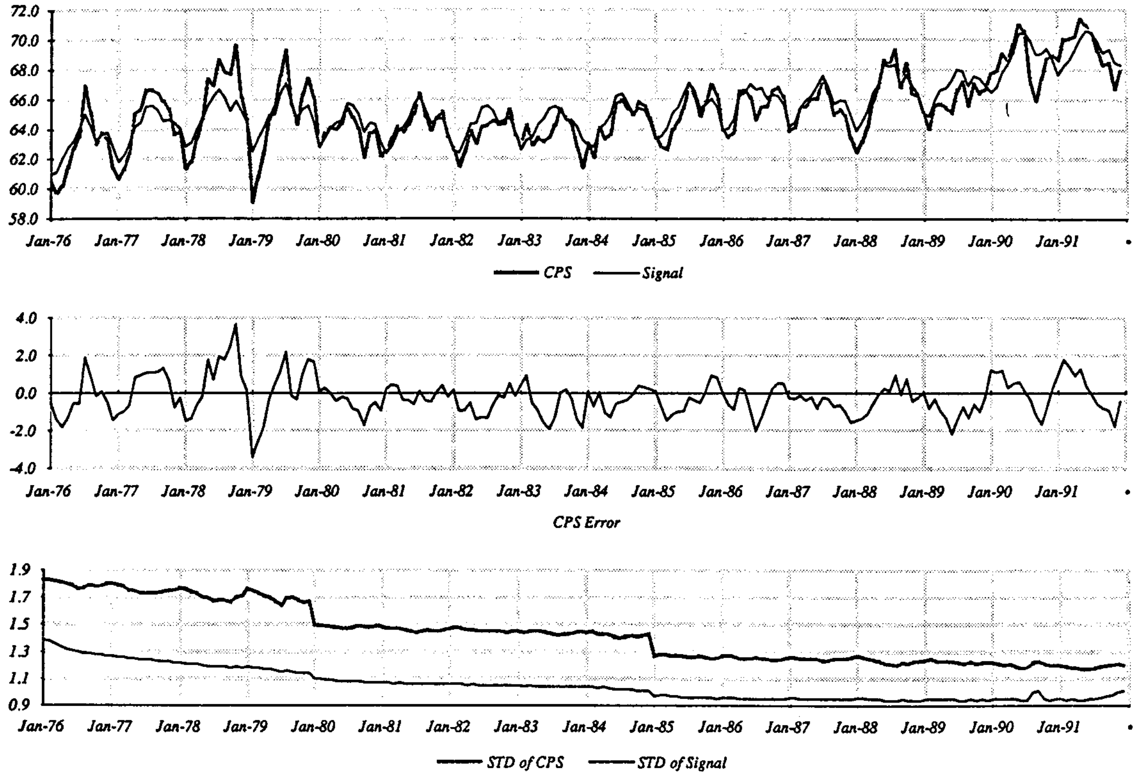


Figure 4. Time Series Components

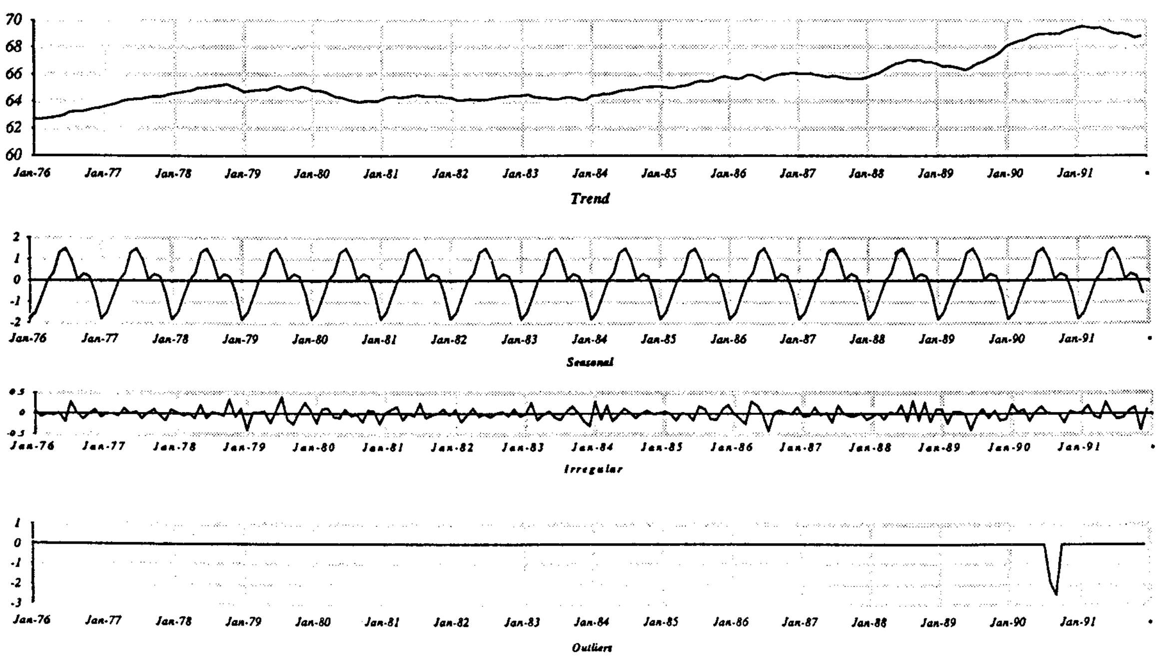
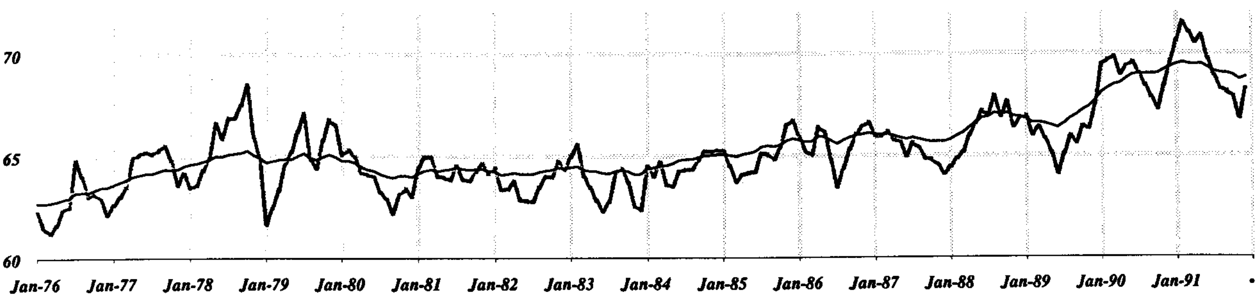


Figure 5. Trend Components



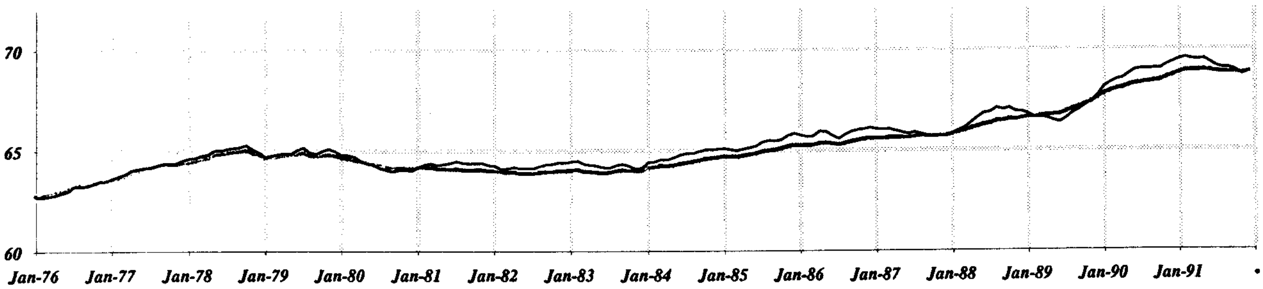


Figure 6. Standard Deviations of the Estimated Signal