E C O N O M I C S   B U L L E T I N

# The impact of outliers on transitory and permanent components in macroeconomic time series

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## *Abstract*

In this paper we investigate the effect of the outliers on the decomposition of Nelson-Plosser macroeconomic data set into permanent and transitory components from structural time series models. We show that the outliers can disturb the unobserved-components decomposition, especially the variance of trend and cycle innovations, sometimes dramatically.

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# 1 Introduction

The empirical analyses of the business cycles and growth properties of macroeconomic variables have been based on the assumption that the observed time series can be decomposed into trend and cycle components. Since the trend and cycle components are unobservable, numerous methods for trend-cycle decompositions have been proposed in the literature, such as the Beveridge-Nelson decomposition, the unobserved-component models, the Hodrick-Prescott and Baxter-King business cycle filters, among others. The unobserved-component [UC] approach allows to decompose the nonstationary time series into stochastic trend and stationary cyclical component, based on state space and the Kalman filter methodology (Harvey, 1985; Clark, 1987), in which the cyclical component is defined as stationary deviations from a stochastic trend[1]. The UC model explicitly takes the structure of the trend and various sources of shocks into consideration. The implication of the UC model decomposition for business cycle analysis is that shocks to the transitory cycle are more important for explaining the business cycle than shocks to the trend.

Recently, Perron and Wada (2006) argued that a single break trend can disturb the trend-cycle decomposition. Nevertheless, it is not certain that long-term macroeconomic series have experienced only one break. Indeed, studies have shown that numerous long-term economic series can contain more than one break as well as outliers (Balke and Fomby, 1991). Therefore, in this paper we investigate the impact of outliers on the decomposition into trend and cyclical components from the UC models within the framework of structural time series models proposed by Harvey (1985) and Harvey and Jaeger (1993). For that, we consider the Nelson-Plosser (1982) macroeconomic data set[2]. Our results show that the UC decomposition can be disturbed by the presence of outliers, especially the variance of trend and cycle innovations can be modified, sometimes

[1] It is well documented in the literature that when the business cycle filters of Hodrick-Prescott and Baxter-King are applied to integrated time series, spurious cyclical behavior are induced (Cogley and Nason, 1995; Cogley, 2001; Murray, 2003; Harvey and Trimbur, 2003).

[2] Nelson and Plosser (1982) found that they could reject the null hypothesis of a unit root for only one out of the fourteen macroeconomic time series in their data set, i.e. the unemployment rate. However, several authors pointed out that the tests employed by Nelson and Plosser had some drawbacks (low power and presence of breaks). Most of their studies tended to contradict the findings of Nelson-Plosser, i.e. there is less evidence in favor of the unit root hypothesis. Nevertheless, Darné and Charles (2008) showed that taking into account outliers confirms the findings of Nelson and Plosser (1982).

dramatically. Furthermore, taking into account the outliers does not allow to conclude if the shocks to these US macroeconomic time series are predominately permanent or transitory.

The outline of the paper is as follows. In Section 2, the methodology for decomposing integrated time series into permanent and transitory components from structural time series models is described, and the outlier methodology is briefly discussed in Section 3. Section 4 presents the decomposition of Nelson-Plosser data set and discusses the effect of outliers on this decomposition. Section 5 concludes.

## 2 Permanent and Transitory Components

Following Harvey (1985) and Harvey and Jaeger (1993), the traditional structural time series representation takes the form

$$y_t = \mu_t + \psi_t + \varepsilon_t, \qquad t = 1, \ldots, T$$

where $y_t$ is the observed series, $\mu_t$ is the trend, $\psi_t$ is the cycle, and $\varepsilon_t$ is the irregular component. The trend is a local linear trend defined as

$$\begin{aligned} \mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t & \eta_t \sim NID(0, \sigma^2_\eta) \\ \beta_t &= \beta_{t-1} + \xi_t & \eta_t \sim NID(0, \sigma^2_\xi) \end{aligned}$$

where $\beta_t$ is the slope and the normal white-noise disturbances, $\eta_t$ and $\xi_t$, are independent of each other. The stochastic cycle is generated as

$$\begin{bmatrix} \psi_t \\ \psi^*_t \end{bmatrix} = \rho \begin{bmatrix} \cos\lambda & \sin\lambda \\ -\sin\lambda & \cos\lambda \end{bmatrix} \begin{bmatrix} \psi_{t-1} \\ \psi^*_{t-1} \end{bmatrix} + \begin{bmatrix} \omega_t \\ \omega^*_t \end{bmatrix}$$

where $\rho$ is a damping factor such $0 \leq \rho \leq 1$, $\lambda$ is the frequency of the cycle in radians, and $\omega_t$ et $\omega^*_t$ are both NID$(0, \sigma^2_\omega)$. The period of a cycle corresponding to a frequency of $\lambda$ radians is $2\pi/\lambda$ years. The irregular component is NID$(0, \sigma^2)$ and the disturbances in all three components are assumed to be uncorrelated with each other, in order to identify the parameters of the model[3].

[3]Recently, Morley, Nelson and Zivot (2003) showed that when the trend and cycle innovations are allowed to be correlated, the Beveridge-Nelson decomposition and unobserved-component decomposition coincide.

The trend is equivalent to an ARIMA(0,2,1) process. However, if $\sigma_\xi^2 = 0$, it reduces to a random walk with drift. If $\sigma_\xi^2 = \sigma_\eta^2 = 0$ it becomes deterministic, that is $\mu_t = \mu_0 + \beta t$. When $\sigma_\eta^2 = 0$, but $\sigma_\xi^2 > 0$, the trend is still a process integrated of order two. A trend component with this feature tends to be relatively smooth.

The cyclical component, $\psi_t$, is stationary if $\rho$ is strictly less than one. It is equivalent to an ARMA(2,1) process in which both the MA and the AR parts are subject to restrictions (Harvey, 1985); but if $\sigma_\omega^2 = 0$, it becomes AR(2).

Unobserved-component models can be estimated in a number of ways (Harvey, 1989; Durbin and Koopman, 2001). Here, direct estimation of the structural parameters is carried out in the time domain by casting the model in state-space form. Estimation of the unknown parameters (hyperparameters), $\sigma_\eta^2, \sigma_\eta^2, \sigma_\omega^2, \rho, \lambda, \sigma^2$, can be carried out by maximum likelihood [ML]. Once this has been done, estimates of the trend, cyclical, and irregular components are obtained from a smoothing algorithm using the STAMP package (Koopman et al., 2000).

# 3 Outlier methodology

The search for outliers considers an unobserved components model in which there are two components: a regular component and an outlier component. This outlier component reflects extraordinary, infrequently occurring events or shocks that have important effects on macroeconomic time series. The model is given by

$$z_t = y_t + f(t) \tag{1}$$

$y_t$ is an ARIMA$(p, d, q)$ process and $f(t)$ contains exogenous disturbances or outliers. They are defined as

$$\begin{aligned} y_t &= \frac{\theta(L)}{\alpha(L)\phi(L)} a_t \qquad\qquad a_t \sim N(0, \sigma_a^2) \\ f(t) &= \sum_{j=1}^{m} \omega_{i,j} \nu_{i,j}(B) I_t(\tau_j) \qquad\qquad i = 1, \ldots, 4 \end{aligned} \tag{2}$$

where $\nu_{i,j}(B)$ is the polynomial characterizing the outlier occurring at time $t = \tau_j$, $\omega_{i,j}$ represents its impact on the series, $I_t(\tau_j)$ is an indicator function with the value of 1 at time $t = \tau_j$ and 0 otherwise, with $\tau_j$ the date of outlier occurring, and $m$ is the number of outliers. Following Chen and Liu (1993), we consider four types of outliers ($i = 1, \ldots, 4$): Additive outlier [AO] that causes an immediate and one-shot effect on the observed series, with $\nu_{1,j}(B) = 1$; an innovational outlier [IO] that affects temporarily the time series with the same dynamics as an innovation, with $\nu_{2,j}(B) = \theta(B)/\phi(B)$; a level shift [LS] that produces an abrupt and permanent step change in the series, with $\nu_{3,j}(B) = 1/(1-B)$; a temporary change [TC] that produces an initial effect, and this effect dies out gradually with time, with $\nu_{4,j}(B) = 1/(1-\delta B)$ where $0 < \delta < 1$. The detection[4] of the outliers is based on likelihood ratio [LR] statistics for the various types of disturbances, noted $\hat{\tau}_i(\tau_j)$ with $i = 1, \ldots, 4$.

The methods are well-developed in the field of outlier detection based on intervention analysis as originally proposed by Box and Tiao (1975). This approach requires iterations between stages of outlier detection and estimation of an intervention model. Here we employ the automatic outlier detection procedure suggested by Chen and Liu (1993), modified by Gómez and Maravall (1997) and implemented in the computer program TRAMO[5].

# 4 Decomposition of Nelson-Plosser data set

We study the 13 annual U.S. macroeconomic data set used by Nelson and Plosser (1982): Real GNP, nominal GNP, real per capita GNP industrial production, employment, GNP deflator, consumer price, nominal wages, real wages, money stock, velocity, interest rate, and stock price. The data consists of annual observations which begins between 1860 and 1909. In this paper we consider an extension of the Nelson-Plosser data set, which terminates in 1970, to include observations up to 1988. This extension was compiled by Schotman and van Dijk (1991). The logarithmic transformation is applied on the data, except for the interest rate.

The outlier detection procedure shows that outliers are identified in all the series, giving strong proof of infrequent large shocks. Most of the shocks can be due to the Great Depression, World War II and recessions. See Darné and Charles (2008) for a detailed discussion on these detected outliers in the Nelson-Plosser series.

[4]See Tolvi (2001) and Darné and Charles (2008) for detailed discussion on the outlier detection procedure.

[5]TRAMO: Time Series Regression with ARIMA Noise, Missing Observations, and Outliers.

The ML estimates for the UC models are presented in Tables 1 and 2. In all the series, the variance of the irregular component is found to be zero and that of cyclical component is positive. The zero estimates for $\sigma_\xi^2$ seem to indicate that the trend is a random walk with drift for the industrial production and the employment whereas the zero estimates for $\sigma_\eta^2$ and a positive $\sigma_\xi^2$ indicate that the trend is relatively smooth for the real (per capita) GNP, the consumer price, the real wages and the money stock[6]. The others series seem to be modelled by a local linear trend.

Note that the non-zero estimates for $\sigma_\eta^2$ and $\sigma_\xi^2$ for all the series seem to indicate that the trend is not deterministic. Therefore, this result obtained using the structural methodology strongly again supports the conclusion reached by Nelson and Plosser (1982).

When removing outliers the variance of the different components is modified, sometimes dramatically. Indeed, the GNP deflator, the nominal wages and the interest rate display a positive $\sigma_\eta^2$ but it becomes zero after correcting outliers, whereas the estimate for $\sigma_\xi^2$ becomes zero for the stock price. In many cases the variance of the cyclical component strongly decreases after correcting outliers. For the industrial production and the employment the estimates of $\sigma_\omega^2$ become zero, however $\sigma^2$ and $\sigma_\xi^2$ become positive for the industrial production and the employment, respectively. Note that the period of a cycle $(2\pi/\lambda)$ is also affected by the presence of outliers.

Furthermore, for eight of thirteen series the variance of the cycle innovation is larger than the variance of the trend innovation when the data are uncorrected, and for six series when removing outliers. Therefore, we can not conclude if the permanent shocks are or not relatively more important than transitory shocks. Note that some models can be inappropriate as suggested by an estimate of $\rho$ close to unity. However, this is not the aim of this study but could involve further investigation.

[6]This smooth trend is also called the "double-drift" trend since the drift $\mu_t$ to the random walk trend $\beta_t$ also follows a random walk. This double-drift trend specification is the most common trend specification for empirical analysis with UC models (Harvey, 1985; Harvey and Jaeger, 1993; Mills, 2003).

## 5 Conclusion

This paper studied the effect of outliers on the decomposition of Nelson-Plosser macroeconomic data set into permanent and transitory components from structural time series models. For that, we used the unobserved-component models of Harvey (1985) and Harvey and Jaeger (1993), and showed that the outliers can disturb the unobserved-component decomposition, especially the variance of trend and cycle innovations, sometimes dramatically.

Further research can be undertaken by decomposing these macroeconomic time series from unobserved-component models in which the trend and cycle models are more appropriate and specific for each macroeconomic time series. Further investigation should investigate the effect of breaks and outliers on others trend-cycle decompositions.

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Table 1: Maximum likelihood estimates of parameters for UC models.

| Series | Type | $\sigma^2_\eta$ | $\sigma^2_\xi$ | $\sigma^2_\omega$ | $\sigma^2$ | $\rho$ | $\lambda$ | $2\pi/\lambda$ |
|---|---|---|---|---|---|---|---|---|
| Real GNP | o | 0.0 | 0.09 | 19.8 | 0.0 | 0.88 | 0.38 | 16.7 |
| | c | 0.0 | 0.07 | 4.5 | 0.0 | 0.79 | 0.67 | 9.4 |
| Nominal GNP | o | 10.8 | 6.8 | 12.9 | 0.0 | 0.88 | 0.77 | 8.2 |
| | c | 5.9 | 3.8 | 5.7 | 0.0 | 0.88 | 0.80 | 7.9 |
| Real per capita GNP | o | 0.0 | 0.08 | 21.1 | 0.0 | 0.88 | 0.35 | 17.8 |
| | c | 0.0 | 0.10 | 3.8 | 0.0 | 0.80 | 0.71 | 8.8 |
| Industrial production | o | 26.7 | 0.0 | 44.1 | 0.0 | 0.77 | 0.42 | 14.9 |
| | c | 30.8 | 0.0 | 0.0 | 6.4 | 1.00 | 0.52 | 12.2 |
| Employment | o | 4.7 | 0.0 | 218.1 | 0.0 | 0.89 | 0.36 | 17.5 |
| | c | 3.9 | 0.003 | 0.0 | 0.0 | 0.60 | 0.25 | 25.6 |
| GNP deflator | o | 6.7 | 2.5 | 2.6 | 0.0 | 0.89 | 0.67 | 9.3 |
| | c | 0.0 | 1.1 | 1.8 | 0.0 | 0.76 | 0.78 | 8.1 |
| Consumer Price | o | 0.0 | 4.0 | 4.6 | 0.0 | 0.89 | 0.80 | 7.8 |
| | c | 0.0 | 3.2 | 0.9 | 0.0 | 0.84 | 1.15 | 5.5 |

o: original series, c: corrected-outliers series. All variance estimates have been multiplied by $10^4$.

Table 2: Maximum likelihood estimates of parameters for UC models (continue).

| Series | Type | $\sigma_\eta^2$ | $\sigma_\xi^2$ | $\sigma_\omega^2$ | $\sigma^2$ | $\rho$ | $\lambda$ | $2\pi/\lambda$ |
|---|---|---|---|---|---|---|---|---|
| Nominal wages | o | 2.1 | 4.8 | 7.4 | 0.0 | 0.85 | 0.77 | 8.2 |
| | c | 0.0 | 2.0 | 1.7 | 0.0 | 0.84 | 0.89 | 7.1 |
| Real wages | o | 0.0 | 0.10 | 7.6 | 0.0 | 0.83 | 0.41 | 15.3 |
| | c | 0.0 | 0.15 | 5.1 | 0.0 | 0.83 | 0.34 | 18.6 |
| Money stock | o | 0.0 | 7.0 | 4.6 | 0.0 | 0.88 | 0.71 | 8.9 |
| | c | 0.0 | 3.4 | 0.8 | 0.0 | 0.83 | 1.15 | 5.5 |
| Velocity | o | 24.8 | 0.05 | 4.9 | 0.03 | 0.85 | 0.79 | 8.0 |
| | c | 2.8 | 0.06 | 19.9 | 0.0 | 0.81 | 0.45 | 13.9 |
| Interest rate | o | 2723 | 4.6 | 153.1 | 0.0 | 0.98 | 0.53 | 11.7 |
| | c | 0.0 | 36.8 | 72.3 | 0.0 | 0.93 | 0.95 | 6.6 |
| Stock price | o | 165.0 | 0.12 | 21.5 | 0.0 | 0.92 | 0.70 | 9.0 |
| | c | 180.2 | 0.0 | 0.8 | 0.0 | 0.99 | 0.68 | 9.2 |

o: original series, c: corrected-outliers series. All variance estimates have been multiplied by $10^4$.