SEASONAL ADJUSTMENT AND MEASURING PERSISTENCE IN OUTPUT

Albert JÄGER
Robert KUNST

Forschungsbericht/
Research Memorandum Nr. 247
June 1988

ABSTRACT

This paper presents evidence on the following question: By how much does an unexpected change in real GDP of 1 percent change this series in the long-run? To shed light on the robustness of the various methods suggested in the literature to answer this question, we filter quarterly Austrian data on real GDP by three seasonal adjustment methods. Applying a variety of time series techniques to the resulting series allows us to report two main findings. First, unexpected shocks affect GDP in the long-run. This finding contradicts conventional wisdom about the generating mechanism of business cycles and confirms results by Campbell and Mankiw (1987) for U.S. data. Second, quantitative measures of persistence are not robust with respect to different seasonal adjustment methods. In addition, we present Monte Carlo evidence showing that the Census X-11 method for seasonal adjustment can be a source of spuriously high measures of persistence if seasonal differencing is the appropriate adjustment method.

1. Introduction

The nature of non-stationarity in macroeconomic time series is currently the subject of an intense debate with possibly profound implications for macroeconomic theorizing. The traditional view of nonstationarity in economy wide output measures like gross domestic product (GDP) can be described as follows: The nonstationary component of GDP, sometimes called "natural output", follows a deterministic trend. Actual GDP fluctuates around this trend, generating what is called a "business cycle". The business cycle is viewed as a highly autocorrelated but stationary movement of actual output around "natural output". Applied work embracing this vision typically starts by regressing GDP on a deterministic time trend and treats the residuals of this regression as the empirical phenomenon to be explained by business cycle theory.

Empirical work pioneered by Nelson and Plosser (1982) has led to a very different perspective on non-stationarity: The trend in GDP is envisaged as a random walk with drift. First differencing instead of subtracting a deterministic time trend is from this perspective the appropriate method to handle non-stationarity in macroeconomic time series like GDP.

If the non-stationarity in output is actually better described by a stochastic trend, we would expect that innovations change the level of the time series permanently. Shocks will be persistent. In contradistinction, the traditional view implies that shocks induce only transitory movements around a fixed trend and will consequently have no ultimate effect on the level of the time series. Acceptance of the view that non-stationarity in typical macroeconomic time series is better characterized by a stochastic trend, however, raises the question of the magnitude of persistence of unexpected shocks as formulated by Campbell and Mankiw (1987b): By how much does an innovation of 1 % in GDP increase the level of this series in the long run? It is easy to demonstrate that the realizations of a stochastic process could well follow a stochastic trend but the persistence of unexpected shocks could nonetheless be small.

Most studies measuring persistence in macroeconomic time series use U.S. data usually adjusted for seasonal fluctuations by some version of the Census X-11 method. Campbell and Mankiw (1987b) report for U.S. GNP data that a shock of 1 % increases the level of this series by more than 1 % in the long run. Campbell and Mankiw (1988) extend their work to six other important industrialized countries with similar results. Campbell and Deaton (1987) find high persistence in U.S. labor income. Using a somewhat different technique Clark (1987) finds significantly lower persistence in U.S. production series.

In this paper we first elaborate on the notion of persistence formally. In the empirical part we use several unit root tests suggested by Dickey and Fuller (1979) and Stock and Watson (1986) to test for stochastic trend in quarterly real Austrian GDP. In the next step, we investigate the persistence of innovations in GDP, using ARMA-representations and a measure of persistence suggested by Cochrane (1986). To shed light on the robustness of the results with respect to seasonal adjustment, we employ three different procedures to extract the seasonality from the raw data.

We report two main findings: First, innovations in Austrian real GDP change the level of this series permanently. This finding contradicts conventional wisdom but is consistent with the results of recent U.S. investigations. Second, seasonal adjustment matters for the quantitative importance of persistence. In particular, we find for Austrian data that Census X-11 adjusted data exhibit "excess persistence" in the sense that a 1 % innovation raises the level of the series by more than 1 %. Alternative seasonal adjustment procedures like seasonal differencing or regression on seasonal dummies produce series that exhibit lower measures of persistence. We also report the results of several Monte Carlo experiments showing that Census X-11 adjustment will in general be a source of upward bias in measures of persistence if seasonal differencing is the appropriate adjustment method.

2. Persistence

The following question is at the center of the persistence debate (Campbell and Mankiw (1987), p. 857): "By how much does a shock of 1 % at time point t affect the level of a macroeconomic time series in the long run?". The amount of the long-run change in percentage points can be taken as a heuristic definition of persistence.

To derive a more formal definition of persistence, let us first abandon the link to percentage points. Instead, we shall introduce the concept of a "unit shock" at $t=\tau$ and restrict ourselves to processes whose asymptotic reaction to such a shock is not influenced by the timing of the shock.

Assumption: Let (Y_t) be a stochastic process and Ω_t be the σ-algebra generated by the past of the process at t $\sigma(Y_t,Y_{t-1},\ldots)$. Further assume the s-step innovations $Y_{t+s}-E(Y_{t+s}|\Omega_t)$ to exist for all s and to obey stochastic properties which are independent of t.

Definition: Let (Y_t) be a process satisfying the assumption. Let Ω_τ^* denote the σ-algebra generated by the past of the same process, except for a unit shock at τ, i.e. $\sigma(Y_\tau+1,Y_{\tau-1},Y_{\tau-2},\ldots)$. The difference $E(Y_{\tau+s}|\Omega_\tau^*)-E(Y_{\tau+s}|\Omega_\tau)$ will be called the persistence at s steps and its limit as $s \to \infty$ will be called the persistence at ∞ or simply persistence.

Since Ω_τ may be thought equivalently to be generated by the one-step innovations $\epsilon_\tau=Y_\tau-E(Y_\tau|\Omega_{\tau-1})$ plus deterministic information, Ω_τ^* can be defined equivalently as being generated by the innovation sequence $(\epsilon_t+\delta_\tau{}^t)$ where $\delta_j{}^i$ denotes Kronecker's δ defined as 1 for i=j and 0 else (compare Abraham and Yatawara (1988)). Note that our definition of persistence by a "unit shock" argument is closely related to the concept of innovations outliers (see Fox (1972)). Further note that, if any of the expectations or limits are undefined, persistence will be undefined. Nevertheless, if these functionals diverge towards ∞ (or $-\infty$) we may define persistence to be infinite.

The examples for various stochastic processes in table 0 illustrate the definition. It is particularly important to remember that the persistence of any stationary series is zero and that, within the class of processes integrated of integer order, only processes integrated of order one produce finite non-zero persistence. This class of processes allows for a moving-average (MA) representation of first differences and table 0 shows that it suffices to calculate the sum of the MA coefficients to obtain an estimate for persistence. The same can be done for rational transfer (ARMA) models by calculating the sums of the AR as well as that of the MA coefficients and dividing. Measures calculated according to this strategy are called A-measures by Campbell and Mankiw (1987a).

Let us consider the three examples at the bottom of table 0. These are "seasonal" processes with an AR representation containing the factor $1-L^4$. Since for these processes the s-step persistence does not converge, their persistence is not defined. However, if the s-step persistence values approach four different limit points instead of a singular limit, we define "natural persistence" as the average of the limit points, if necessary weighted by their asymptotic frequency. Given this definition, the "seasonal random walk" $(1-L^4)Y_t=\epsilon_t$ has a natural persistence of $\frac{1}{4}$.

For practical purposes, it is more straightforward to seasonally adjust the series and to measure persistence on the adjusted series. For a seasonal process of the above specification, the correct adjustment is given by the seasonal moving average (SMA) filter

$$Y_t^s=\tfrac{1}{4}(1+L+L^2+L^3)Y_t \qquad (1)$$

(since $(1-L^4)=(1-L)(1+L+L^2+L^3)$. The adjusted series retains the AR root at 1 - the "trend" - but is free from the seasonal unit roots at $\pm i$ and -1. If Y_t is a seasonal random walk, Y_t^s has a defined persistence of 1. This motivates that the SMA filter multiplies the natural persistence by four. For this reason, in the following all measures of persistence taken from adjusted series generated through the SMA filter will be divided by four to make them comparable with the persistence of non-seasonal processes.

The SMA filter is not the only way to seasonally adjust the series. A popular alternative is to regress the data on seasonal dummies and use the residuals as adjusted data. The official alternatives are the intricate seasonal adjustment procedures of national statistical bureaus. The best known example is the Census X-11 extensively used for U.S. data. Contrary to the SMA filter, a data-independent factor to recover natural persistence does not exist for these methods. The results of this paper's Monte Carlo, but also linear approximations of the X-11 filter as suggested by Cleveland and Tiao (1976) indicate possible solutions to cope with this question.

TABLE 0: Persistence for some standard time series models

Model	Persistence at i	Persistence at ∞
white noise	0 for all i>0	0
$Y_t=\sum_0^{\infty}\theta_j\epsilon_{t-j}$	θ_i	0
random walk	1	1
$\Delta Y_t=\sum_0^{\infty}\theta_j\epsilon_{t-j}$	$\sum_0^{i}\theta_j$	$\sum_0^{\infty}\theta_j$
$\Delta_4 Y_t=\epsilon_t$	1 if 4 divides i 0 else	{0,1}
$\Delta_4 Y_t=\sum_0^{\infty}\theta_j\epsilon_{t-j}$	$\sum_{j=0}^{[i/4]}\theta_{i-4j}$	$\{\sum_0^{\infty}\theta_{k+4j}\ k=0,..,3\}$
$\Delta\Delta_4 Y_t=\epsilon_t$	[i/4]	∞

Note: Δ and Δ_4 denote $1-L$ and $1-L^4$, respectively. In cases where i-step persistences approach several limit points instead of limits, these are given in braces. [x] denotes entier(x).

3. Empirical results

The discussion in the previous section suggests the following strategy for measuring persistence in macroeconomic time series. A precondition for non-zero finite persistence is that the series is integrated of order one. As a first step we therefore use unit root tests to determine the order of integration. If the series are indeed integrated of order one, persistence can be measured either by ARMA models or via the nonparametric approach suggested by Cochrane (1986).

3.1. The Data

We examine quarterly data on Austrian real Gross Domestic Product (GDP). The seasonally unadjusted series ranges from 1964:1 to 1987:2 (94 observations). The data are taken from the data base of the Austrian Institute for Economic Research.

We employ three different procedures to extract the seasonal component from the raw data: Census X-11, filtering by the operator $(1+L+L^2+L^3)$ and regression on four seasonal dummies. Throughout the paper we use the following label conventions:

Label	Description
GDPX	Logarithm of GDP adjusted by Census X-11.
GDP4	Logarithm of GDP filtered by $\frac{1}{4}(1+L+L^2+L^3)$.
GDPS	Logarithm of GDP adjusted by seasonal dummies.
DGDPX	First difference of GDPX.
DGDP4	First difference of GDP4.
DGDPS	First difference of GDPS.

3.2. Tests for Unit Roots

Several authors have pointed out that the power of unit root tests may be low for typical economic time series with respect to interesting alternatives of roots near the unit circle (see e.g. Evans and Savin (1981,1984)). Keeping this caveat in mind we first give a short description of the tests used and then report empirical results.

Assume a finite ARMA representation of the series Y_t exists

$$\Phi^*(L)Y_t = \theta(L)\epsilon_t \qquad (2)$$

where $\Phi^*(.)$ and $\theta(.)$ are lag polynomials of order p^* and q, respectively. A unit root in the AR part

$$\Phi^*(L) = \Phi(L)(1-L) \qquad (3)$$

entails a permanent shift in the level of Y_t generated by a shock at t.

A test for a unit root of +1 in the autoregressive operator was suggested by Dickey and Fuller (1979). It relies on a simple regression of differenced on level data

$$\Delta Y_t = aY_{t-1} + \sum_{i=1}^{p} b_i \Delta Y_{t-i} + \epsilon_t \qquad (4)$$

Testing is performed via the t-statistic of the coefficient a which is not t-distributed. Fractiles are given in Fuller (1976). Sometimes an intercept is introduced to allow for drift. $p=0$ defines the original DF-statistic whereas $p>0$ gives what is sometimes called ADF (augmented DF). The significance of ADF might depend on the order p of AR lags included. Since differences of GDP seem to follow mixed ARMA models (see below), a search through lag orders up to around 8 seems reasonable.

A different track was pursued by Stock and Watson (1986) whose work on common trends generated a unit root test as a byproduct. Their procedure relies on a decomposition of the unit root process Y_t into a pure random walk component W_t and a stationary part s_t

$$Y_t = W_t + s_t \qquad (5)$$

If Y_t follows an AR model with exactly one unit root, the stationary part of the AR polynomial may be used to extract W_t.

$$(1-L)\Phi(L)Y_t = \epsilon_t \quad => \quad \Phi(L)Y_t \text{ is random walk} \qquad (6)$$

In their most recent version of the test as given in the RATS procedure "STOCKWAT.SRC", Stock and Watson do not simply difference Y_t in order to estimate $\Phi(L)$ but use an AR(1) regression instead. Presumably, this is done to improve test power. The estimated $\Phi(L)$ is then used to filter Y_t and to generate an estimate of W_t. The asymptotic properties of the statistic

$$SW = T(\Sigma W_{t-1}^2)/(\Sigma W_{t-1}\Delta W_t) = T[(\Sigma W_t W_{t-1} - TM)/(\Sigma W_{t-1}^2)-1] \qquad (7)$$

(T the sample size and M still to be explained) are known. An alternative would be to estimate what Stock and Watson call the "troublesome term M", following one of their approximation suggestions, and base the statistic on the rightmost expression. Both methods have been used here but only the results of the first one are reported since the outcomes are very similar. Again, the number of AR lags needed for estimating $\Phi(L)$ is unclear and was varied from 1 to 8.

Empirical results of unit root tests for level and first differences of the three series are displayed in tables 1a-c. The first two columns of each table contain test statistics for the augmented Dickey-Fuller (ADF) and the Stock-Watson test (SW). The last two columns are formed by versions of the two tests allowing for a linear deterministic time trend in the regression. Schwert (1987) recommends including a time trend as a prudent strategy in view of the fact that in this case the distribution of the ADF-statistic is independent of the unknown drift in the regression.

For the level of the three series, the null hypothesis of a unit root is rejected only for some lag specifications of the ADF-test. This finding strongly supports the caveat by Schwert (1987) concerning uncritical use of the popular ADF-test in case of moving average terms in the true ARMA-representation of the process. Indeed, judging from evidence on ARMA models to be presented in the next subsection, moving average terms seem to be present in the series examined.

Looking at the results for the first differences of the three series, we find that the null hypothesis of a unit root is generally rejected. According to some of the ADF-statistics, the series DGDP4 still contains a unit root. Accepting this finding would imply that the "mongrel operator"

$$1-L^4 = (1-L)(1+L+L^2+L^3) \tag{8}$$

is not sufficient for handling stochastic trend and seasonal adjustment simultaneously. According to table 0, persistence would be infinite in this case. Given the other test results, however, we interpret the overall evidence as being consistent with occurrence of exactly one factor (1-L) in the AR polynomial of the series investigated.

3.3. Parametric tests for persistence: ARMA models

From table 0 we know that for an integrated ARMA process the sum of coefficients in the MA representation, named A(1) according to

$$(1-L)Y_t = \Phi^{-1}(L)\theta(L)\epsilon_t = A(L)\epsilon_t \tag{9}$$

is persistence. After estimation of the ARMA parameters, A(1) can be calculated easily. Information criteria could be used to select the orders p and q in the ARMA(p,q) models. But we follow here the strategy of Campbell and Mankiw (1987b) and search through all possible parameter combinations (p,q) to provide for a summary picture. For this paper, the restriction $\max(p,q)\leq 3$ was imposed. It may be argued that the true model could demand for higher orders. Therefore, model orders were checked by "table methods" (EACF by Tsay and Tiao (1984) and SCAN by Tsay and Tiao (1985)) allowing for p and q up to 8. For DGDPX, EACF suggested an ARMA(1,2) model while SCAN indicated ARMA(1,1). DGDPS was identified by both procedures to follow an ARMA(3,3) model. For DGDP4, the tables suggested ARMA(0,3). Thus, the assumption of low-order ARMA models seems to be plausible.

The estimates of the ARMA coefficients critically depend on the parameter estimation procedure. In order to obtain the most reliable results, especially in the presence of suspected MA roots near the unit circle, an "exact maximum-likelihood" procedure was used here. Whereas the maximum likelihood criterion was calculated via the Mélard (1984) algorithm, a standard NAGLIB routine was used for criterion optimization. The results for the three data series are displayed in tables 2a-c.

The results in tables 2a-c illustrate the importance of taking into account seasonal adjustment for measuring persistence. For the series adjusted by the Census X-11 method in table 2a, we find that an unexpected shock of 1 % will increase the seasonally adjusted GDP in the long-run by more than 1 % if we consider the mixed ARMA-models of higher order as plausible. This result quite closely reproduces the evidence reported by Campbell and Mankiw (1987b) for U.S. data. In table 2c for the dummy adjusted GDP-series, however, we find that the persistence measure is centered around .7 whereas the series adjusted by seasonal differencing give persistence measures that center around 1 in table 2b. Seasonal adjustment procedures appear to have significant effects on measures of persistence calculated by ARMA-modeling.

3.4. Non-parametric tests

Cochrane (1986) suggests a non-parametric approach to measure persistence. If r_j is defined as the j-th autocorrelation, we may introduce a two-sided Laplace transform of the autocorrelation function by

$$r(z) = \sum_{j=-\infty}^{\infty} r_j z^j \qquad (10)$$

Cochrane's measure of persistence V is defined as r(.) evaluated at 1, i.e. the sum of all autocorrelations. Campbell and Mankiw (1987b) point out that V is related to the parametric measure A(1) via

$$A(1) = (V/(1-R^2))^{1/2} \tag{11}$$

with R^2 defined as the fraction of variance that is predictable from knowledge of the past of the process. In practice, only a finite number, say k, of autocorrelation estimates can be used, and these are weighted by the triangular Bartlett-1 kernel:

$$V_k = 1 + 2\sum_{j=1}^{k}(1-j/(k+1))r_j \tag{12}$$

and an approximation to A(1) may be evaluated from

$$A_k = (V_k/(1-r^2))^{1/2} \tag{13}$$

where r^2 is the fraction of variance explained by an ARMA(3,3) model. Campbell and Mankiw (1987b) use the estimated autocorrelation of first differences to proxy R^2 which, however, turned out to be inappropriate in our work. The values of V_k and A_k for DGDPX, DGDPS and DGDP4 for varying k are given in table 3. Again, for DGDP4 the integrated series $\frac{1}{4}(1+L+L^2+L^3)\log(GDP)$ is taken to be the seasonally adjusted series. Consequently, V is based on its first difference DGDP4. However, for calculating A(1), the result from the formula must be divided by four. To illustrate this, take the process $(1-L^4)Y_t=\epsilon_t$ as an example. A unit innovations shock at t will cause a change of $(1+L+L^2+L^3)Y_t$ by 1/4 until infinity (see section 2).

Basically, the non-parametric measures confirm the conclusions of the ARMA approach. Again, the Census X-11 adjusted data give persistence measures significantly greater than 1 whereas the A_k's for the series adjusted by seasonal differencing and dummies closely cluster around 1. Note that only the A_k's but not the V_k's from differently adjusted series are directly comparable.

The findings of this section can be summarized as follows: The evidence for Austrian GDP is consistent with the view that an innovation will raise the level of this series over a long horizon permanently. When we adjust the raw series by the Census X-11 method, the measures of persistence indicate "excess persistence" in the sense that a 1 % innovation in GDP raises the level by more than 1 %. These results are rather similar to those reported by Campbell and Mankiw (1987b). Using dummy variables for seasonal adjustment, however, gives persistence measures well below or equal to 1. Seasonally differenced data generally give persistence measures near 1. These findings are insensitive to the use of parametric ("ARMA-approach") or non-parametric ("V-measure") methods.

4. Monte Carlo Evidence

To shed more light on the role of seasonal adjustment in influencing the measurement of persistence in GDP, we conducted a small Monte Carlo experiment. The true process takes alternatively three forms:

	Process	True Persistence: A(1)
(I)	$(1-L)(1-L^4)Y_t = \epsilon_t$	∞
(II)	$(1-L^4)Y_t = (1+.86L+.63L^2+.68L^3)\epsilon_t$	.79
(III)	$(1-L^4)Y_t = \epsilon_t$	.25

$$\epsilon_t \sim N(0,1)$$

All three processes assume that seasonal differencing is the appropriate seasonal adjustment method. The first and the third process are "extreme processes" in the sense that they depict two "limit processes" for GDP both presumably inconsistent with our data. The second process is a rather crude approximation of actual GDP behavior based on the "best model" suggested by the table methods EACF and SCAN.

We generated 100 replications of these processes with 100 observations each. The raw data series are adjusted by two seasonal adjustment procedures: Fourth differences and Census X-11 method (multiplicative adjustment as implemented in the IAS-system econometric software package developed at the Institute for Advanced Studies, Vienna). We did not consider regression on seasonal dummies because it appears to be the least attractive seasonal adjustment method, leaving strong seasonal components at the beginning and the end of the series.

Tables 4a-c contain the results of the Monte Carlo experiments. As the non-parametric V_k-measures would not be comparable across the three processes (I)-(III), we have converted them into A_k-measures using the noise-signal ratios from ARMA(3,3) models fitted to the generated data series. The double integrated process (I) has a theoretical persistence of infinity. From the Monte Carlo results in table 4a we see that the estimated persistence at all window sizes is higher than 1 but smaller than 5. The magnitudes of these measures depend, however, strongly on the kernel used for estimating the V_k's. Comparing the persistence measures across the two differently adjusted processes we find that the Census X-11 adjusted process indicates higher persistence than the process (correctly) adjusted by seasonally differencing. In tables 4b and 4c, we report similar results for the processes (II) and (III). Persistence measures are higher for Census X-11 adjusted series for all window sizes.

5. Conclusion

Recent studies have concluded that fluctuations in U.S. output and other macroeconomic time series appear highly persistent. In this paper we have examined the robustness of persistence measurement with respect to different seasonal adjustment methods using quarterly data on Austrian GDP.

We find that innovations in output affect the level of this series in the long run regardless of the seasonal adjustment method. However, conclusions about the quantitative importance of persistence are affected by the choice of the seasonal adjustment method. In particular, series adjusted by the widely used Census X-11 method give persistence measures well above those for series adjusted by seasonal differencing or regression on dummies. This conclusion is also supported by Monte Carlo evidence.

The non-robustness of persistence measures should be taken into account for judgments on the extent of persistence in macroeconomic time series. In particular, the "excess persistence" results reported by Campbell and Mankiw (1987b) for U.S. GNP and Campbell and Deaton (1987) for U.S. labor income need not be robust if a different and possibly more appropriate seasonal adjustment method is applied to the raw data. Unfortunately, U.S. data series appear to be available only in seasonally adjusted form. Our results for Austrian GDP data point to persistence measures of smaller or equal to 1 as being most reasonable. Interestingly, Campbell and Mankiw (1987b) and Romer (1987) report persistence measures for yearly data (but different time ranges) also covering this range.

Acknowledgement: The authors thank Manfred Deistler and Roberto S. Mariano for helpful comments. The usual proviso applies.

TABLE 1a: Unit root test statistics for Census X-11 adjusted GDP

Level of series (GDPX)

#lags	ADF	SW	ADF_d	SW_d
1	-2.73*	-1.05	-.29	-.76
2	-3.12**	-1.26	-.67	-1.85
3	-2.88**	-1.41	-1.00	-3.19
4	-2.77*	-1.27	-.75	-2.38
5	-2.40	-1.27	-.83	-2.80
6	-2.40	-1.19	-.61	-2.30
7	-2.39	-1.20	-.61	-2.39
8	-2.94**	-1.20	-.46	-2.02

First difference of series (DGDPX)

#lags	ADF	SW	ADF_d	SW_d
1	-6.73***	-107.45***	-7.41***	-113.74***
2	-4.13***	-106.71***	-4.94***	-112.09***
3	-4.04***	-101.86***	-5.13***	-109.41***
4	-3.14**	-100.72***	-4.00***	-108.02***
5	-4.03***	-100.19***	-4.03***	-107.02***
6	-2.86**	-99.84***	-3.73**	-107.45***
7	-3.14**	-98.62***	-4.30***	-102.83***
8	-2.41*	-95.82***	-3.60**	-102.83***

Notes: ADF and SW denote augmented Dickey-Fuller and Stock-Watson test for unit roots. ADF_d and SW_d are versions of these tests including a deterministic time trend. Critical values for ADF and ADF_d are from Fuller (1976, p.373), for SW from Stock and Watson (1986, p. 24). The RATS-procedure "STOCKWAT.SRC" was employed for calculating the test statistics.

TABLE 1b: Unit root test statistics for GDP filtered by seasonal operator $\frac{1}{4}(1+L+L^2+L^3)$.

Level of Series (GDP4)

#lags	ADF	SW	ADF_d	SW_d
1	-2.69*	-1.33	-.75	-1.33
2	-2.66*	-1.56	-1.19	-3.19
3	-2.25***	-1.32	-.79	-2.12
4	-2.93*	-1.12	-.11	-.51
5	-2.64	-1.26	-.55	-1.66
6	-3.01	-1.32	-.66	-1.98
7	-2.84	-1.39	-.82	-2.21
8	-3.01	-1.35	-.66	-1.97

First difference of Series (DGDP4)

#lags	ADF	SW	ADF_d	SW_d
1	-2.70*	-18.64**	-3.65**	-29.91***
2	-2.76*	-23.31***	-3.52**	-34.61***
3	-4.02***	-24.51***	-5.18***	-30.96***
4	-2.68*	-23.84***	-3.79**	-35.70***
5	-2.48	-23.82***	-3.91**	-35.37***
6	-2.02	-22.31***	-3.40**	-33.54***
7	-2.07	-23.37***	-3.64**	-33.54***
8	-1.36	-19.96**	-2.85	-29.74***

Notes: See table 1a.

TABLE 1c: Unit root test statistics for GDP adjusted by seasonal dummies

Level of series (GDPS)

#lags	ADF	SW	ADF_d	SW_d
1	-2.09	-1.15	-.91	-2.69
2	-2.88**	-1.26	-.78	-2.38
3	-3.91***	-1.20	-.28	-1.30
4	-2.53	-1.28	-.74	-4.30
5	-2.57*	-1.47	-1.07	-5.52
6	-2.30	-1.29	-.75	-4.95
7	-2.74*	-1.13	-.20	-3.10
8	-2.58*	-1.22	-.47	-4.60

First difference of series (DGDPS)

#lags	ADF	SW	ADF_d	SW_d
1	-9.15***	-113.76***	-9.71***	-115.34***
2	-8.71***	-122.01***	-10.20***	-128.94***
3	-3.75***	-115.23***	-4.68***	-116.36***
4	-2.80*	-114.32***	-3.56**	-115.42***
5	-2.82*	-113.21***	-3.84**	-116.98***
6	-3.64***	-112.98***	-4.81***	-116.96***
7	-2.80*	-106.45***	-3.76**	-109.21***
8	-2.51*	-107.08***	-3.66**	-109.08***

Notes: See table 1a.

TABLE 2a: ARMA models for DGDPX (adjusted by Census X-11)

p	q	Φ_1	Φ_2	Φ_3	θ_1	θ_2	θ_3	A(1)	L
0	1				-.14			.859	.01167
0	2				-.20	.19		.987	.01130
0	3				-.18	.11	.15	1.079	.01117
1	1	-.32			.14			.862	.01156
1	2	.55			-.75	.28		1.175	.01116
1	3	.10			-.29	.14	.12	1.085	.01117
2	1	-.09	.10		-.06			.957	.01147
2	2	.63	-.10		-.82	.38		1.169	.01116
2	3	-.09	.32		-.07	-.23	.30	1.313	.01094
3	1	.22	.18	.12	-.39			1.278	.01108
3	2	.23	.15	.12	-.40	.07		1.350	.01111
3	3	-.08	.42	.33	-.09	-.33	-.09	1.453	.01087

Notes: p and q are AR and MA model orders; Φ_i and θ_i denote the AR and MA coefficients; A(1) is the persistence measure, see text; L is a sort of sum of squares to be minimized, see Mélard (1984).

TABLE 2b: ARMA models for DGDP4 (adjusted by seasonal differencing)

p	q	Φ_1	Φ_2	Φ_3	θ_1	θ_2	θ_3	A(1)	L
0	1				.68			.419	.02830
0	2				.25	.68		.482	.02336
0	3				.86	.63	.68	.794	.01670
1	1	.80			-.20			1.017	.02137
1	2	.64			-.14		.47	.916	.01925
1	3	-.04			.65	.69	.46	.675	.01828
2	1	.53	.03		-.22			.443	.02545
2	2	.75	-.11		-.23		.48	.877	.01918
2	3	.01	.19		.83	.41	.47	.853	.01689
3	1	.54	.28	-.04	-.23			.887	.02367
3	2	.51	.28	-.01	-.23		-.01	.869	.02337
3	3	-.35	.20	.34	1.10	.75	.57	1.053	.01525

Notes: see table 2a

TABLE 2c: ARMA models for DGDPS (adjusted by seasonal dummies)

p	q	Φ_1	Φ_2	Φ_3	θ_1	θ_2	θ_3	A(1)	L
0	1				-.39			.609	.02568
0	2				-.38	-.01		.610	.02567
0	3				-.55	.09	.27	.807	.02427
1	1	.03			-.41			.605	.02568
1	2	-.01			-.37	-.02		.605	.02567
1	3	.26			-.75	.19	.23	.908	.02388
2	1	-.12	-.11		-.20			.651	.02547
2	2	-.15	-.40		-.35	.23		.579	.02451
2	3	.26	-.81		-.71	.90	-.07	.717	.02065
3	1	-.54	-.36	-.12	.17			.579	.02476
3	2	-.17	-.46	-.05	-.36	.25		.530	.02428
3	3	-.68	-.60	-.87	.22	.46	.95	.834	.01766

Notes: see table 2a

TABLE 3: Non-parametric persistence measures

nk	DGDPX V_k	DGDPX A_k^*	DGDPS V_k	DGDPS A_k^*	DGDP4 V_k	DGDP4 A_k^*
5	1.009	1.046	.527	.934	.892	.716
10	1.147	1.115	.529	.935	1.140	.810
15	1.410	1.236	.592	.989	1.443	.911
20	1.619	1.324	.693	1.070	1.678	.982
25	1.751	1.378	.743	1.108	1.835	1.025
30	1.903	1.436	.813	1.158	1.977	1.066
35	2.014	1.477	.858	1.190	2.080	1.094
40	2.068	1.497	.885	1.209	2.120	1.104

Notes: The estimated non-explained variance from the ARMA(3,3)models used to calculate A_k (see text) are for DGDPX .923,DGDPS .608 and DGDP4 .435.

TABLE 4a: Persistence and seasonal adjustment procedures. Monte Carlo evidence

True process: $(1-L)(1-L^4)Y_t = \epsilon_t$

Window Size	Seasonal Adjustment Method	
	Seasonal Differences	X-11
5	1.79(.43)	2.75(.76)
10	2.29(.58)	3.51(1.03)
15	2.61(.71)	4.00(1.25)
20	2.82(.80)	4.33(1.40)
25	2.99(.94)	4.63(1.76)
30	3.05(.96)	4.77(1.84)

Notes: This table contains the results of a Monte Carlo experiment. It displays the mean of the A_k-measure for various sizes k. The standard deviations of the measures are given in parentheses. These measures were calculated from the corresponding V_k-measures according to formula in text. The noise-signal ratio, $1-R^2$, was taken from estimates of ARMA(3,3) processes. The results are based on 100 replications of series of length 100 taken as the last 100 observations of a generated series of size 200.

TABLE 4b: Persistence and seasonal adjustment procedures. Monte Carlo Evidence

True process: $(1-L^4)Y_t = (1+.86L+.63L^2+.68L^3)\epsilon_t$

Window Size	Seasonal Adjustment Method	
	Seasonal Differences	X-11
5	.63(.09)	.96(.12)
10	.64(.13)	.92(.16)
15	.62(.16)	.88(.20)
20	.60(.18)	.83(.23)
25	.58(.20)	.80(.25)
30	.56(.20)	.78(.26)

Notes: See table 4a.

TABLE 4c: Persistence and seasonal adjustment procedures. Monte Carlo Evidence

True process: $(1-L^4)Y_t = \epsilon_t$

Window Size	Seasonal Adjustment Method	
	Seasonal Differences	X-11
5	.25(.03)	.62(.25)
10	.23(.04)	.51(.33)
15	.22(.05)	.49(.50)
20	.21(.06)	.45(.58)
25	.21(.07)	.43(.61)
30	.20(.07)	.42(.73)

Notes: See table 4a.

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