*Econometrics Journal* (2003), volume **6**, pp. 79–98.

# The effects of institutional and technological change and business cycle fluctuations on seasonal patterns in quarterly industrial production series

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Received: February 2003

**Summary** Changes in the seasonal patterns of macroeconomic time series may be due to the effects of business cycle fluctuations or to technological and institutional change or both. We examine the relative importance of these two sources of change in seasonality for quarterly industrial production series of the G7 countries using time-varying smooth transition autoregressive models. We find compelling evidence that the effects of gradual institutional and technological change are much more important than the effects attributable to the business cycle.

**Keywords:** *Nonlinear time series, Seasonality, Smooth transition autoregression, Structural change, Time-varying parameter.*

## 1. INTRODUCTION

Seasonal fluctuations are an important source of variation in many macroeconomic time series. When monthly or quarterly series are modelled, it is often assumed that the seasonal pattern of the series is constant over time, in which case it may be characterized by seasonal dummy variables, see Miron (1996) and Miron and Beaulieu (1996), among others. On the other hand, it has been known for a long time that seasonality in a series may change over time. As Kuznets (1932) remarked:

> For a number of years statisticians have been concerned with the problem of measuring changes in the seasonal behaviour of time series.

The possible causes for such time-variation in seasonal patterns have also been a longstanding object of interest. After examining a number of employment series from various countries and regions, Gjermoe (1931) wrote (in Norwegian):

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> The strength of seasonal fluctuations has to do with the *level* of business activity. A month in a year of low employment is more affected by seasonality than the same month in a year of high employment (emphasis in original).

In fact, Gjermoe (1926) had already made a similar point.

The possibility that seasonality is affected by the business cycle has been reconsidered in the more recent literature. For example, Canova and Ghysels (1994) and Franses (1996, pp. 86–87) find that the seasonal pattern in quarterly US output growth is affected by the (NBER-dated) business cycle. In particular, it is found that the summer slowdown is less pronounced around business cycle peaks. A similar conclusion is reached by Cecchetti and Kashyap (1996) and Matas-Mir and Osborn (2001), using an international data set of monthly production series at the industry-level. Cecchetti *et al.* (1997) and Krane and Wascher (1999) document the same effect of the business cycle on seasonal patterns in US production, inventories and employment, which is attributed to the fact that during a boom the presence of capacity constraints forces firms to produce a larger fraction of output in off-peak seasons.

Business cycle fluctuations are not the only possible reason for changes in the seasonal pattern of output or employment series. In particular, technological change and changes in institutions and habits may cause changes in seasonality as well. As an example of the former, in the construction industry it has become possible to keep a construction site going year-round in countries where, a few decades ago, work was interrupted for the winter months. As to the latter type of change, the increase in paid leisure over the last few decades has gradually changed people's vacation habits. At least in some Scandinavian countries it has become customary to spend a week of the annual holiday in the winter. Yet another example may be the increasingly efficient use of capital and just-in-time production techniques. Many factories in Europe no longer close down for the summer vacation but keep the production process running without interruption. In all these examples, the result may have been that the seasonal pattern of, for example, output and consumption series has changed over time.

Our aim is to compare the effects on seasonality of gradual institutional and technological change with the effects attributable to the business cycle. As for the former, there do not seem to exist reliable aggregate measures for these changes. We allow for the possibility that the aggregate change is steady and continuous and simply use time as a proxy variable for it. This means that we in fact contrast 'Kuznets-type' unspecified changes in seasonality with 'Gjermoe-type' changes caused by fluctuations in economic activity. The main question we ask is: which of the two types is more prominent in practice, if any? We shall investigate the problem using quarterly industrial production series of the world's leading market economies, the G7 countries.

In this work, the logarithmic time series are differenced once in order to achieve stationarity, and the differenced series are used for modelling. For most countries, these first differences, or quarterly growth rates, are dominated by seasonal variation that almost completely inundates the other features of the series, see Figures 2 and 3 in what follows. The models we are going to build are constructed strictly to investigate the main research question formulated above about reasons for time-variation in seasonal patterns of industrial production series. Because most of the variation captured by the parameters will be seasonal variation, models based on first differences are not likely to be appropriate tools in forecasting industrial production several quarters ahead. A typical forecaster would rather begin his analysis by transforming the original quarterly series into annual differences which emphasize the low-frequency variation he is most likely interested in, build a linear or nonlinear model for them and use that for forecasting.

The plan of the paper is as follows. In Section 2, we describe the output series for the G7 countries, focusing on the properties of their seasonal cycles. In Section 3, we present our main statistical tool, the time-varying smooth transition autoregressive (TV-STAR) model. In Section 4, we use Lagrange multiplier (LM) tests derived from the TV-STAR framework for addressing the question of whether the changes in the seasonal patterns in the output series are due to the effects of business cycle fluctuations or to technological and institutional change or both. For all series except the US, we find convincing evidence that 'Kuznets-type' unspecified change is much more important than 'Gjermoe-type' business cycle-induced change. In contrast to previous research our analysis suggests that, for the US, seasonality does not vary over the business cycle nor has it changed over time. In Section 5, we specify and estimate TV-STAR models to gain further insight into when and how seasonality in the quarterly output series has changed. Section 6 contains final remarks. Material that for space reasons has been omitted from the paper is available at the website `http://swopec.hhs.se/hastef/abs/hastef429.htm`.

## 2. PRELIMINARIES

### *2.1. Data*

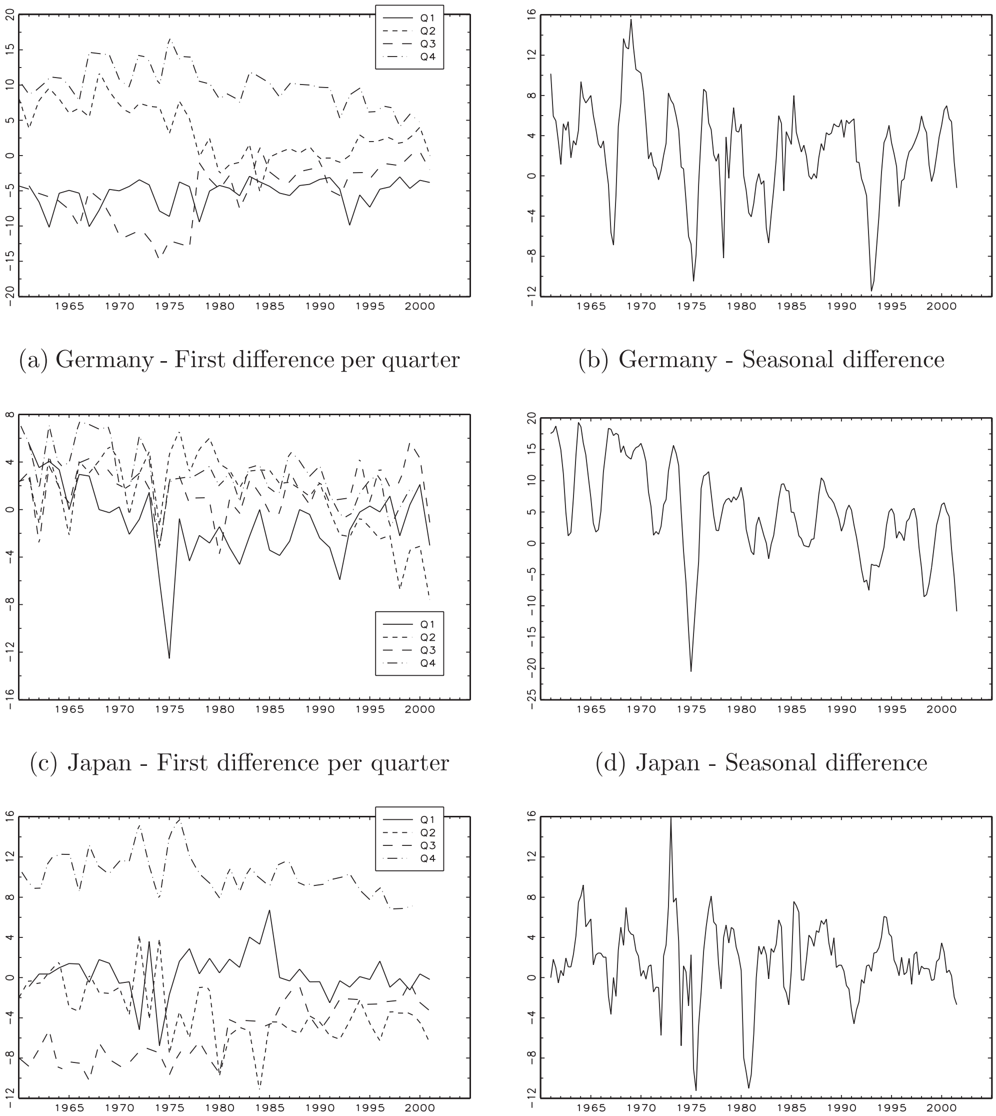
Our data set consists of quarterly seasonally unadjusted industrial production volume indexes for the G7 countries, taken from the OECD *Main Economic Indicators*. The sample period runs from 1960.1 until 2001.3, except for Canada for which the series is available only from 1961.1. Obvious outliers in 1963.1 and 1968.2 for France and in 1969.4 for Italy are replaced by the average of the index values in the same quarter of the previous and the following year.

Seasonal variation is a dominant component in the German and the UK series, and the same is true for France, Italy and Canada. A regression of the quarterly growth rates on the four seasonal dummies confirms this: the coefficients of determination lie between 0.68 (Canada) and 0.92 (France). They are lower for Japan (0.21) and the US (only 0.06).

A common feature for Canada and three European countries, Germany, France and the UK, is that the seasonal variation in the industrial output series appears to have dampened over time; see also Figure 1. In particular, the drop in output in the third and fourth quarters peak have become less pronounced, which was also documented by Canova and Hansen (1995). The Japanese and the US series do not show a third-quarter summer holiday slack in production. In the US, the quarterly growth in the 1990s was actually highest in the third quarter and lowest in the fourth quarter.

### *2.2. Deterministic and stochastic seasonality*

In the case of nonstationary time series, time-varying seasonal patterns may often be conveniently characterized by seasonal unit roots, see Hylleberg (1994). Autoregressive models of seasonally differenced data are capable of generating series in which the seasonal pattern evolves over time. In realizations from such models 'summer may become winter' or, in general, seasons may gradually 'trade places'. Structural time series models offer another way of modelling stochastically time-varying seasonality; see Harvey (1989, Ch. 6) and Harvey and Scott (1994). In this approach, the time series is divided into components, of which the seasonal one is represented by a linear combination of trigonometric functions with stochastic coefficients. If these coefficients have zero variance, seasonality is deterministic.




(a) Germany - First difference per quarter
(b) Germany - Seasonal difference
(c) Japan - First difference per quarter
(d) Japan - Seasonal difference
(e) UK - First difference per quarter
(f) UK - Seasonal difference

**Figure 1.** Industrial production for Germany, Japan and the UK.

Neither one of these alternatives, seasonal differencing or decomposing the time series, is directly applicable to our situation. The reason is that we intend to consider two types of time-varying seasonality, variation due to technological and institutional change (‘unspecified change’) and variation induced by cyclical fluctuations in economic activity, simultaneously. This requires a model within which we can distinguish these two different sources of variation on the seasonal pattern from each other and thus compare their relative importance. For this reason we employ the TV-STAR model of Lundbergh *et al.* (2003), to be discussed in the next section, for our investigation. The paper that comes closest to ours as far as the modelling approach is concerned is Matas-Mir and Osborn (2001). These authors use a threshold autoregressive model in which the seasonal pattern, characterized by seasonal dummy variables, switches according to a business cycle indicator. Structural changes in seasonality are also accounted for by allowing linear trends in the coefficients of the seasonal dummy variables. An important aspect in which our approach differs from the one in Matas-Mir and Osborn (2001) is that the TV-STAR model allows for more flexible nonlinear trends in seasonality, as will become clear in the following.

## 3. THE TV-STAR MODEL

We use the TV-STAR model to investigate the source of changes in seasonality in the G7 output series, because it is capable of describing business cycle nonlinearity and structural change in the characteristics of a time series variable simultaneously. To suit our purposes, we augment the model by seasonal dummies, such that for our quarterly time series it has the following form:

$$\Delta y_t = [(\boldsymbol{\phi}_1'\mathbf{x}_t + \boldsymbol{\delta}_1'\mathbf{D}_t)(1 - G_1(w_t)) + (\boldsymbol{\phi}_2'\mathbf{x}_t + \boldsymbol{\delta}_2'\mathbf{D}_t)G_1(w_t)][1 - G_2(t^*)] + [(\boldsymbol{\phi}_3'\mathbf{x}_t + \boldsymbol{\delta}_3'\mathbf{D}_t)(1 - G_1(w_t)) + (\boldsymbol{\phi}_4'\mathbf{x}_t + \boldsymbol{\delta}_4'\mathbf{D}_t)G_1(w_t)]G_2(t^*) + \varepsilon_t, \qquad (1)$$

where $y_t$ is the log-level of the industrial production index, $w_t$ a stochastic transition variable, $\Delta$ denotes the first differencing operator, defined by $\Delta_k y_t \equiv y_t - y_{t-k}$ for all $k \neq 0$ and $\Delta \equiv \Delta_1$, $\mathbf{x}_t = (1, \widetilde{\mathbf{x}}_t')'$, $\widetilde{\mathbf{x}}_t = (\Delta y_{t-1}, \ldots, \Delta y_{t-p})'$, $\mathbf{D}_t = (D^*_{1,t}, D^*_{2,t}, D^*_{3,t})' \equiv (D_{1,t} - D_{4,t}, D_{2,t} - D_{4,t}, D_{3,t} - D_{4,t})'$, $D_{s,t}$, $s = 1, \ldots, 4$ are seasonal dummy variables, with $D_{s,t} = 1$ when time $t$ corresponds with season $s$ and $D_{s,t} = 0$ otherwise, and $t^* \equiv t/T$ with $T$ denoting the sample size. The transition functions $G_j(s_t) \equiv G_j(s_t; \gamma_j, c_j)$, $j = 1, 2$, are assumed to be given by the logistic function

$$G_j(s_t; \gamma_j, c_j) = (1 + \exp\{-\gamma_j(s_t - c_j)/\sigma_{s_t}\})^{-1}, \qquad \gamma_j > 0, \qquad (2)$$

where the transition variable $s_t = w_t$ ($j = 1$) or $s_t = t^*$ ($j = 2$), and $\sigma_{s_t} = [\mathrm{var}(s_t)]^{1/2}$ makes $\gamma_j$ scale-free. As $s_t$ increases, the logistic function changes monotonically from 0 to 1, with the change being symmetric around the location parameter $c_j$, as $G_j(c_j - z; \gamma_j, c_j) = 1 - G_j(c_j + z; \gamma_j, c_j)$ for all $z$. The slope parameter $\gamma_j$ determines the smoothness of the change in the value of the logistic function. As $\gamma_j \to \infty$, the logistic function $G_j(s_t; \gamma_j, c_j)$ approaches the indicator function $\mathtt{I}[s_t > c_j]$ and, consequently, the change of $G_j(s_t; \gamma_j, c_j)$ from 0 to 1 becomes instantaneous at $s_t = c_j$. When $\gamma_j \to 0$, $G_j(s_t; \gamma_j, c_j) \to 0.5$ for all values of $s_t$.

The TV-STAR model distinguishes four regimes corresponding with combinations of $G_1(w_t)$ and $G_2(t^*)$ being equal to 0 or 1. The transition variable $w_t$ in (1) is assumed to be a lagged seasonal difference, $w_t = \Delta_4 y_{t-d}$, for certain $d > 0$. As this variable tracks the business cycle quite closely for our quarterly industrial production series (see panels (b), (d) and (f) of Figure 1), and because the logistic function $G_j(s_t)$ is a monotonic transformation of $s_t$, the regimes associated with $G_1(\Delta_4 y_{t-d}) = 0$ and 1 will roughly correspond with recessions and expansions, respectively. Thus, using $\Delta_4 y_{t-d}$ as transition variable ensures that the TV-STAR model allows for 'Gjermoe-type' change in the seasonal pattern of $y_t$.[1] On the other hand, the function $G_2(t^*)$ enables the model to describe 'Kuznets-type' unspecified change as well.

The reason for defining the elements of $\mathbf{D}_t$ as $D^*_{s,t} \equiv D_{s,t} - D_{4,t}$, $s = 1, 2, 3$, is that it effectively separates the deterministic seasonal fluctuations from the overall intercept. For example, the coefficients in $\boldsymbol{\delta}_1 = (\delta_{11}, \delta_{12}, \delta_{13})'$ measure the difference between the intercept in the first three quarters of the year and the overall intercept, given by the first element of $\boldsymbol{\phi}_1$, in the regime $G_1(\Delta_4 y_{t-d}) = 0$ and $G_2(t^*) = 0$. The difference for the fourth quarter $\delta_{14}$ is obtained as $\delta_{14} = -\sum_{s=1}^{3} \delta_{1s}$. This parameterization makes it easy, for example, to test constant seasonality while allowing for a business cycle influenced intercept under the null hypothesis, cf. Franses (1996, pp. 86–87).

The general TV-STAR model in (1) allows both the dynamics and the seasonal properties of the growth rate of industrial production to vary both over the business cycle and over time. By imposing appropriate restrictions on either the autoregressive parameters or the seasonal dummy parameters or on both, more restrictive models can be obtained. Of particular interest here are models in which seasonality only varies either over time or over the business cycle. A model in which seasonality is constant over time is obtained if $\boldsymbol{\delta}_1 = \boldsymbol{\delta}_3$ and $\boldsymbol{\delta}_2 = \boldsymbol{\delta}_4$ in (1). Similarly, a model in which seasonality is constant over the business cycle is obtained by setting $\boldsymbol{\delta}_1 = \boldsymbol{\delta}_2$ and $\boldsymbol{\delta}_3 = \boldsymbol{\delta}_4$. When $\boldsymbol{\delta}_1 = \boldsymbol{\delta}_2 = \boldsymbol{\delta}_3 = \boldsymbol{\delta}_4$, seasonality is linear and constant over time. Imposing analogous restrictions on $\boldsymbol{\phi}_i$, $i = 1, \ldots, 4$ results in models with constant but nonlinear, linear but time-varying, and linear and constant autoregressive dynamics, respectively. If both the seasonal patterns and the autoregressive dynamic structure are constant either over time or over the business cycle, the TV-STAR model reduces to a STAR or TV-AR model, respectively. All these restrictions are testable, as will be discussed in the next section. Often a useful restricted TV-STAR model is an additive one, containing a nonlinear and a time-varying component. For example, a model in which the seasonal dummy coefficients vary over time and the autoregressive parameters enter nonlinearly can be written as

$$\Delta y_t = \boldsymbol{\phi}_1^{*\prime}\mathbf{x}_t + \boldsymbol{\delta}_1^{*\prime}\mathbf{D}_t + \boldsymbol{\phi}_2^{*\prime}\mathbf{x}_t G_1(w_t) + \boldsymbol{\delta}_2^{*\prime}\mathbf{D}_t G_2(t^*) + \varepsilon_t. \tag{3}$$

In Section 5 we will use this form for the models for the industrial production series.

On the other hand, the TV-STAR model (1) is restrictive in the sense that it requires any nonlinearity or structural change to be common across the autoregressive dynamics and seasonal dummies. But then, model (3) does not contain that restriction because $G_1$ only controls the lag structure and $G_2$ the seasonal component. A potential limitation of both models (1) and (3) is that they only allow for a single change in the seasonal pattern over time. The model can be generalized in a straightforward fashion to accommodate multiple changes by including additional time-varying components. For example, an additive model in which the autoregressive parameters enter nonlinearly and the seasonal dummy coefficients change over time following a mixture of two patterns is given by

$$\Delta y_t = \boldsymbol{\phi}_1^{*\prime}\mathbf{x}_t + \boldsymbol{\delta}_1^{*\prime}\mathbf{D}_t + \boldsymbol{\phi}_2^{*\prime}\mathbf{x}_t G_1(w_t) + \boldsymbol{\delta}_2^{*\prime}\mathbf{D}_t G_2(t^*) + \boldsymbol{\delta}_3^{*\prime}\mathbf{D}_t G_3(t^*) + \varepsilon_t. \tag{4}$$

[1] It may be argued, however, that GNP is a more representative and more commonly used indicator of the business cycle than industrial production. In fact, we repeated our tests described in Section 4 using lagged seasonal differences of GNP instead of $\Delta_4 y_{t-d}$ as the transition variable. The results were very similar to the ones obtained by using $\Delta_4 y_{t-d}$ and therefore are omitted.

## 4. CHANGES IN THE SEASONAL PATTERN AND THEIR CAUSES

### *4.1. Testing linearity and parameter constancy in the TV-STAR framework*

The question posed in the Introduction about the causes of fluctuations in the seasonal pattern is addressed within the framework of the TV-STAR model (1), in particular by testing hypotheses about the coefficients of the model. In the previous section, it was emphasized that linearity or parameter constancy in the TV-STAR model (1) may be achieved by imposing equality restrictions on certain coefficient vectors $\boldsymbol{\delta}_i$ and/or $\boldsymbol{\phi}_i$. Note, however, that linearity or parameter constancy of both the seasonal pattern and the dynamic autoregressive structure also results if the smoothness parameter $\gamma_j$ in the corresponding transition function $G_j$ is set equal to zero. This is an indication of an identification problem present in the model: the TV-STAR model is only identified under the alternative, not under the null hypothesis. For a general discussion, see Hansen (1996). In this paper, we follow the approach of Lundbergh *et al.* (2003) and circumvent the identification problem by approximating the transition functions by their first-order Taylor expansions, see also Luukkonen *et al.* (1988).

Let the null hypothesis of interest be $\mathsf{H}_0 : \gamma_1 = \gamma_2 = 0$, which is to be tested against the alternative hypothesis $\mathsf{H}_1 : \gamma_1 > 0$ and/or $\gamma_2 > 0$. Under $\mathsf{H}_0$, model (1) reduces to a seasonality-augmented linear autoregressive model, which we assume to be stationary and ergodic. Furthermore, we assume that the moment condition $\mathsf{E}[(\Delta y_t)^2(\Delta_4 y_t)^2] < \infty$ is satisfied, which is necessary for the asymptotic inference to be valid. In testing $\mathsf{H}_0$, we only assume that $d \in \{1, \ldots, r\}$ in (1), that is, the true delay $d$ is unknown but assumed to be no greater than $r$. A convenient way to parameterize this assumption is by setting $w_t = \sum_{i=1}^{r} a_i \Delta_4 y_{t-i}$, with $a_d = 1$ and $a_i = 0$ for all $i \neq d$; see Luukkonen *et al.* (1988) for further details. In this case, after rearranging terms the first-order Taylor expansion of (1) around $\mathsf{H}_0$ becomes

$$\Delta y_t = \boldsymbol{\phi}_1^{*\prime}\mathbf{x}_t + \boldsymbol{\delta}_1^{*\prime}\mathbf{D}_t + \sum_{i=1}^{r}(\boldsymbol{\phi}_{2,i}^{*\prime}\mathbf{x}_t + \boldsymbol{\delta}_{2,i}^{*\prime}\mathbf{D}_t)\Delta_4 y_{t-i} + (\boldsymbol{\phi}_3^{*\prime}\mathbf{x}_t + \boldsymbol{\delta}_3^{*\prime}\mathbf{D}_t)t^*$$
$$+ \sum_{i=1}^{r}(\boldsymbol{\phi}_{4,i}^{*\prime}\mathbf{x}_t + \boldsymbol{\delta}_{4,i}^{*\prime}\mathbf{D}_t)t^*\Delta_4 y_{t-i} + R(\gamma_1, \gamma_2) + \varepsilon_t, \tag{5}$$

where $R(\gamma_1, \gamma_2)$ is a remainder from the two Taylor expansions. Under the null hypothesis of linearity and parameter constancy, $R(\gamma_1, \gamma_2) \equiv 0$, such that this remainder does not affect the distribution theory.

Equation (5) is linear in parameters. Furthermore, and this is crucial, the parameter vectors $\boldsymbol{\phi}_2^* = (\boldsymbol{\phi}_{2,1}^{*\prime}, \ldots, \boldsymbol{\phi}_{2,r}^{*\prime})' = \gamma_1\widetilde{\boldsymbol{\phi}}_2^*(\boldsymbol{\theta})$ and $\boldsymbol{\delta}_2^* = (\boldsymbol{\delta}_{2,1}^{*\prime}, \ldots, \boldsymbol{\delta}_{2,r}^{*\prime})' = \gamma_1\widetilde{\boldsymbol{\delta}}_2^*(\boldsymbol{\theta})$, $\boldsymbol{\phi}_3^* = \gamma_2\widetilde{\boldsymbol{\phi}}_3^*(\boldsymbol{\theta})$ and $\boldsymbol{\delta}_3^* = \gamma_2\widetilde{\boldsymbol{\delta}}_3^*(\boldsymbol{\theta})$, and $\boldsymbol{\phi}_4^* = (\boldsymbol{\phi}_{4,1}^{*\prime}, \ldots, \boldsymbol{\phi}_{4,r}^{*\prime})' = \gamma_1\gamma_2\widetilde{\boldsymbol{\phi}}_4^*(\boldsymbol{\theta})$ and $\boldsymbol{\delta}_4^* = (\boldsymbol{\delta}_{4,1}^{*\prime}, \ldots, \boldsymbol{\delta}_{4,r}^{*\prime})' = \gamma_1\gamma_2\widetilde{\boldsymbol{\delta}}_4^*(\boldsymbol{\theta})$ where $\widetilde{\boldsymbol{\phi}}_j^*(\boldsymbol{\theta})$, $\widetilde{\boldsymbol{\delta}}_j^*(\boldsymbol{\theta})$, $j = 2, 3, 4$, are non-zero functions of the parameters $\boldsymbol{\theta} = (\boldsymbol{\phi}_1', \ldots, \boldsymbol{\phi}_4', \boldsymbol{\delta}_1', \ldots, \boldsymbol{\delta}_4')'$. In view of this, the original null hypothesis becomes

$$\mathsf{H}_0' : \boldsymbol{\phi}_{2,i}^* = \boldsymbol{\phi}_3^* = \boldsymbol{\phi}_{4,i}^* = \mathbf{0}, \qquad \boldsymbol{\delta}_{2,i}^* = \boldsymbol{\delta}_3^* = \boldsymbol{\delta}_{4,i}^* = \mathbf{0}, \qquad i = 1, \ldots, r$$

in the transformed equation (5). The standard LM statistic for testing $\mathsf{H}_0'$ has an asymptotic $\chi^2$ distribution with $(p+4)(1+2r)$ degrees of freedom under the null hypothesis. In practice, an $F$-version of the test is recommended because its size properties in small and moderate samples are much better than those of the $\chi^2$-based test statistic, especially when the number of parameters tested becomes large relative to the sample size. It should be noted that, depending on the values of $p$ and $r$, certain terms $\phi^*_{2,i,0}\Delta_4 y_{t-i}$ and $\phi^*_{2,i,j}\Delta y_{t-j}\Delta_4 y_{t-i}$ should be excluded from (5) to avoid perfect multicollinearity.

In order to keep the notation simple, we have so far discussed the case where the standard logistic function (2) is the transition function. It is useful to generalize this slightly as follows. Let

$$G_j(s_t;\gamma_j,\mathbf{c}_j) = \left(1+\exp\left\{-\frac{\gamma_j}{\sigma^k_{s_t}}\prod_{i=1}^{k}(s_t-c_{ji})\right\}\right)^{-1}, \qquad \gamma>0,\ c_{j1}\le\cdots\le c_{jk}. \tag{6}$$

This function allows more flexibility in the transition. When we test linearity against the TV-STAR model (1) with (6), a first-order Taylor expansion of (6) leads to terms with higher powers of $\Delta_4 y_{t-j}$ and $t^*$ in equation (5); see, for example, Luukkonen *et al.* (1988), Granger and Teräsvirta (1993, Ch. 6) or Lundbergh *et al.* (2003). The dimension of the null hypothesis increases linearly in $k$, which implies that for small sample sizes such as the one available here, the tests for $k>1$ can only be computed for fairly small values of $p$ and $r$. In the following we report results for $k=1$ and, whenever possible, for $k=3$. Test results for $k=2$ are available upon request. The corresponding statistics are denoted as $\text{LM}_k$.

Finally, it should be pointed out that the lag length $p$ in (1) is unknown. It is selected from the linear seasonality-augmented autoregressive model using BIC with the maximum order set equal to $p_{\max}=12$. As remaining residual autocorrelation may be mistaken for nonlinearity, we apply the Breusch–Godfrey LM test to examine the joint significance of the first 12 residual autocorrelations in the model that is preferred by the BIC. If necessary, the lag length $p$ is increased until the null hypothesis of no error autocorrelation can no longer be rejected at the 5% significance level. Testing is carried out conditionally on the selected lag length $\widehat{p}$.

### *4.2. Testing hypotheses of interest*

The test just described is a general linearity test within our maintained TV-STAR model (1). In this paper, however, the main interest lies in testing subhypotheses that place restrictions on the seasonal dummy variables. We may also set certain parameter vectors to zero (null vectors) *a priori*. This leads to a maintained model that is a submodel of (1). In particular, we are interested in testing constant seasonality against the alternative that the seasonal pattern changes smoothly over time, conditional on the assumption that seasonality is not affected by the business cycle and that the autoregressive structure does not change. In terms of the parameters in (5), the corresponding null hypothesis is

$$\mathsf{H}_0^{\text{TV}-\text{AR},D_{s,t}}:\boldsymbol{\delta}^*_3=\mathbf{0}\ \text{assuming}\ \boldsymbol{\phi}^*_{2,i}=\boldsymbol{\phi}^*_3=\boldsymbol{\phi}^*_{4,i}=\mathbf{0}, \qquad \boldsymbol{\delta}^*_{2,i}=\boldsymbol{\delta}^*_{4,i}=\mathbf{0}, \qquad i=1,\ldots,r.$$

Another hypothesis of interest is testing constant seasonality against the alternative that the seasonal pattern is affected by the business cycle only:

$$\mathsf{H}_0^{\text{STAR},D_{s,t}}:\boldsymbol{\delta}^*_{2,i}=\mathbf{0}\ \text{assuming}\ \boldsymbol{\phi}^*_{2,i}=\boldsymbol{\phi}^*_3=\boldsymbol{\phi}^*_{4,i}=\mathbf{0}, \qquad \boldsymbol{\delta}^*_3=\boldsymbol{\delta}^*_{4,i}=\mathbf{0}, \qquad i=1,\ldots,r.$$

A test against the joint alternative of smooth change and fluctuations ascribed to the business cycle may be formed accordingly. The corresponding null hypothesis is denoted as $\mathsf{H}_0^{\text{TV}-\text{STAR},D_{s,t}}$.

These tests are based on the assumption of linearity of the dynamic structure of the time series $\Delta y_t$. But then, the first difference of the volume of industrial production may be a nonlinear or time-varying process. One way of accounting for this possibility is to relax the zero restrictions on $\boldsymbol{\phi}^*_{2,i}$, $\boldsymbol{\phi}^*_3$ and $\boldsymbol{\phi}^*_{4,i}$ in the above tests. While testing the resulting null hypotheses is not difficult in practice, this may not be an optimal way to proceed. Instead it may be better to test our two competing hypotheses concerning seasonality within a model which explicitly models the changes in the autoregressive structure, either as a function of time (TV-AR) or as a function of the business cycle (STAR). In that case, we may begin by testing linearity against STAR and TV-AR. The relevant null hypotheses (assuming constant seasonality and unknown delay $d$) are

$$\mathsf{H}_0^{\mathrm{STAR},\Delta y_{t-j}} : \boldsymbol{\phi}^*_{2,i} = \mathbf{0} \text{ assuming } \boldsymbol{\phi}^*_3 = \boldsymbol{\phi}^*_{4,i} = \mathbf{0}, \qquad \boldsymbol{\delta}^*_{2,i} = \boldsymbol{\delta}^*_3 = \boldsymbol{\delta}^*_{4,i} = \mathbf{0}, \qquad i = 1, \ldots, r,$$

and

$$\mathsf{H}_0^{\mathrm{TV-AR},\Delta y_{t-j}} : \boldsymbol{\phi}^*_3 = \mathbf{0} \text{ assuming } \boldsymbol{\phi}^*_{2,i} = \boldsymbol{\phi}^*_{4,i} = \mathbf{0}, \qquad \boldsymbol{\delta}^*_{2,i} = \boldsymbol{\delta}^*_3 = \boldsymbol{\delta}^*_{4,i} = \mathbf{0}, \qquad i = 1, \ldots, r,$$

respectively. Assume for a moment that $\mathsf{H}_0^{\mathrm{STAR},\Delta y_{t-j}}$ is rejected and $\mathsf{H}_0^{\mathrm{TV-AR},\Delta y_{t-j}}$ is not. This implies that the dynamic behaviour of the process, excluding seasonality, may be adequately characterized by a STAR model. We subsequently specify, estimate and evaluate a STAR model for $\Delta y_t$. The issue is now the constancy of the coefficients of the seasonal dummy variables in the STAR model. The maintained model may be written as follows:

$$\begin{aligned}\Delta y_t = \boldsymbol{\phi}_1'\mathbf{x}_t + \boldsymbol{\phi}_2'\mathbf{x}_t G_1(s_t) + \{&\boldsymbol{\delta}_1 + \boldsymbol{\delta}_2 G_2(\Delta_4 y_{t-l}) + \boldsymbol{\delta}_3 G_3(t^*) \\ &+ \boldsymbol{\delta}_4 G_2(\Delta_4 y_{t-l}) G_3(t^*)\}'\mathbf{D}_t + \varepsilon_t,\end{aligned} \qquad (7)$$

where the transition functions $G_2(\Delta_4 y_{t-l})$, $l > 0$, and $G_3(t^*)$ are logistic functions as in (6). Note that we can choose either $s_t = \Delta_4 y_{t-d}$ or $s_t = t^*$ in (7). The relevant parameter constancy hypotheses can now be formulated within equation (7) in terms of the slope parameters in the transition functions $G_2(\Delta_4 y_{t-l})$, $l > 0$ and $G_3(t^*)$ or in terms of the coefficient vectors $\boldsymbol{\delta}_2$, $\boldsymbol{\delta}_3$ and $\boldsymbol{\delta}_4$. Asymptotic theory for inference requires the assumption that the null model, (7) with $\boldsymbol{\delta}_2 = \boldsymbol{\delta}_3 = \boldsymbol{\delta}_4 = \mathbf{0}$, is stationary and ergodic. Testing is based on the first-order Taylor approximation of $G_2(\Delta_4 y_{t-l})$ and $G_3(t^*)$ as described in Section 4.1; for a general account of STAR model misspecification tests, see, for example, Teräsvirta (1998) or van Dijk *et al.* (2002).

### *4.3. Results*

Table 1 reports $P$-values of the $F$-statistics for testing $\mathsf{H}_0^{\mathrm{TV-AR},\cdot}$, $\mathsf{H}_0^{\mathrm{STAR},\cdot}$ and $\mathsf{H}_0^{\mathrm{TV-STAR},\cdot}$ based on a linear null model. The column headings $\mathrm{LM}_1$ and $\mathrm{LM}_3$ correspond to tests based on the first-order Taylor expansion of the transition function (6) with $k = 1$ and 3, respectively. The row headings $D_{s,t}$ and $\Delta y_{t-j}$ correspond to tests involving the seasonal pattern only and the autoregressive coefficients only, respectively.[2] All tests are computed with the maximum value of the unknown delay $r$ set equal to 4.

Plenty of evidence is found to support the argument that seasonality is changing for unspecified reasons, including institutional and technological change and actions by the statistics

[2] To save space, results for tests on the seasonal pattern and the autoregressive structure simultaneously are omitted but are available at the website.

**Table 1.** Testing linearity and parameter constancy of quarterly growth rates in industrial production.

| Parameters tested | STAR LM$_1$ | STAR LM$_3$ | TV-AR LM$_1$ | TV-AR LM$_3$ | TV-STAR LM$_1$ | TV-STAR LM$_3$ |
|---|---|---|---|---|---|---|
| Canada ($\widehat{p} = 8$) | | | | | | |
| $D_{s,t}$ | 0.21 | 0.72 | 0.28 | 5.9E−5 | 0.20 | 0.049 |
| $\Delta y_{t-j}$ | 0.068 | 0.35 | 0.37 | 0.11 | 0.13 | — |
| France ($\widehat{p} = 8$) | | | | | | |
| $D_{s,t}$ | 0.34 | 0.035 | 1.0E−5 | 3.6E−8 | 3.8E−3 | 0.012 |
| $\Delta y_{t-j}$ | 0.062 | 0.12 | 4.9E−5 | 5.7E−5 | 0.033 | — |
| Germany ($\widehat{p} = 5$) | | | | | | |
| $D_{s,t}$ | 0.11 | 0.51 | 0.012 | 2.4E−4 | 0.16 | 0.10 |
| $\Delta y_{t-j}$ | 3.8E−3 | 8.3E−3 | 0.015 | 0.086 | 0.028 | 0.070 |
| Italy ($\widehat{p} = 6$) | | | | | | |
| $D_{s,t}$ | 0.17 | 0.21 | 0.061 | 9.7E−6 | 0.29 | 0.11 |
| $\Delta y_{t-j}$ | 0.094 | 0.12 | 0.11 | 8.9E−5 | 0.24 | 0.26 |
| Japan ($\widehat{p} = 5$) | | | | | | |
| $D_{s,t}$ | 0.066 | 8.2E−4 | 0.019 | 2.5E−5 | 2.2E−4 | 5.1E−3 |
| $\Delta y_{t-j}$ | 0.024 | 8.1E−3 | 3.7E−3 | 1.2E−3 | 1.1E−3 | 0.039 |
| United Kingdom ($\widehat{p} = 9$) | | | | | | |
| $D_{s,t}$ | 0.030 | 0.071 | 2.1E−3 | 2.1E−3 | 0.016 | 2.1E−4 |
| $\Delta y_{t-j}$ | 0.039 | 0.075 | 5.1E−3 | 0.016 | 0.058 | — |
| United States ($\widehat{p} = 7$) | | | | | | |
| $D_{s,t}$ | 0.034 | 0.11 | 0.020 | 0.016 | 0.089 | 0.38 |
| $\Delta y_{t-j}$ | 6.4E−3 | 0.014 | 0.49 | 0.73 | 0.33 | — |

*Notes*: The table contains $P$-values of $F$-variants of the LM$_k$, $k = 1, 3$, tests of linearity and parameter constancy within the TV-STAR model (1) for quarterly industrial production growth rates. The delay parameter $d$ is assumed unknown, that is $w_t = \sum_{i=1}^{r} a_i \Delta_4 y_{t-i}$ with $a_d = 1$ and $a_i = 0$ for all $i \neq d$, where $r$ is set equal to 4. The null hypotheses of the different tests are linearity conditional on parameter constancy (STAR), constancy conditional on linearity (TV-AR) and linearity and constancy (TV-STAR). Rows labelled $D_{s,t}$ and $\Delta y_{t-j}$ contain results for testing the seasonal dummies and the lagged growth rates, respectively. All tests are performed conditional on assuming that the remaining parameters enter linearly and with constant parameters. A dash indicates that the test could not be computed due to a shortage in degrees of freedom.

producer, proxied by the time variable. The results for the LM$_1$ statistic are mixed, but LM$_3$ rejects the null hypothesis $\mathsf{H}_0^{\text{TV}-\text{AR},D_{s,t}}$ at the 0.01 level for all series except the US. On the other hand, there is much less evidence to support the notion that seasonality varies with the business cycle, as the $P$-values for the tests corresponding to $\mathsf{H}_0^{\text{STAR},D_{s,t}}$ are considerably larger for all seven countries. The only occasion in which a $P$-value lies below 0.01 is LM$_3$ for Japan. For Japan, there is in fact substantial evidence of both nonlinearity and parameter nonconstancy in the series. For the other six countries, it seems that business cycle fluctuations are not a major cause of changes in the seasonal pattern. Finally, another fact obvious from Table 1 worth mentioning is that testing against both types of changes in seasonality jointly has an adverse effect on power. More information is gained by looking at the two alternatives separately.

Two objections may be made at this point. First, seasonality may not be fully explained by the seasonal dummy variables, but part of the seasonal variation may be absorbed in (or explained through) the autoregressive dynamic structure of model (1). Pierce (1978) discussed this possibility in connection with seasonal adjustment of economic time series. This variation may be related to the business cycle. Second, results on testing linearity against STAR in Table 1 (cells ($\Delta y_{t-j}$, STAR)), suggest that the dynamic behaviour of some of the industrial production series may be nonlinear. For other series a case can be made for a TV-AR process, that is, the dynamic behaviour may be time-varying because of phenomena proxied by time. It may therefore be argued that the results just presented are affected by misspecification of the null model and that in order to avoid this, it should already accommodate non-seasonal nonlinearity.[3]

This possibility can be considered by first modelling nonseasonal nonlinearity and carrying out the tests of constancy of the seasonal parameters within the nonlinear model, as discussed in Section 4.2. Detailed results of this approach are omitted and can be found at the website. They can be summed up by saying that by and large, the previous pattern is repeated. Admittedly, the $P$-values are somewhat higher because the autoregressive structure now explains more variation in these series than before. In fact, allowing for time-varying or STAR-type dynamic structures only eliminates the 'Kuznets-type' change in the seasonal pattern in the UK and the US. The seasonal component in the US industrial production is very small anyway. There is weak evidence that it may have been changing with the business cycle: the $P$-value for $LM_1$ when testing against STAR equals 0.064 (see the website).

A general conclusion arising from the complete set of test results is that the institutional, technological and other (due to statistics producers) changes proxied by time are the main cause of changes in the seasonal pattern in the output series of G7 countries. As we have just pointed out, however, our conclusions are not completely unaffected by the choice of the model used for carrying out the relevant tests. This may not be surprising, and mentioning it may even sound trivial. Nevertheless, we wish to argue that our general conclusion seems remarkably robust to the choice of the null model.

## 5. MODELLING CHANGING SEASONAL PATTERNS BY TV-STAR MODELS

Our test results in the previous section clearly show that seasonal patterns in the G7 output series are not constant over time. In this section, our aim is to characterize this change with a parametric model, instead of just demonstrating its existence through a number of hypothesis tests. We will attempt to build an adequate TV-STAR model for each of the series and focus on the components related to seasonal variation.

As the TV-STAR model is a rather flexible nonlinear model, we need a coherent modelling strategy or modelling cycle in order to arrive at an acceptable parameterization. We choose the 'specific-to-general' strategy of Lundbergh *et al.* (2003). The main features of this modelling cycle are the following. First, starting with a seasonality-augmented linear autoregressive model, test linearity against STAR ($\Delta_4 y_{t-d}$ being the transition variable, where the value of $d$ is varied

[3] An alternative modification of the tests presented in Table 1 would be to allow the overall intercept to be affected by the business cycle when testing for 'Gjermoe'-type changes in seasonality, and to allow for the intercept to be time-varying when testing for 'Kuznets'-type changes in seasonality, cf. Franses (1996, pp. 86–87). Results from these tests are very similar to the ones shown in Table 1 and are therefore omitted.

to determine the appropriate value of the delay parameter) and TV-AR ($t^*$ being the transition variable). Choose the submodel against which the rejection is strongest (if it is strong enough, otherwise accept the linear model). Estimate the chosen model; this involves repeated estimation while reducing the size of the model through imposing exclusion and equality restrictions on parameters. Evaluate the estimated model by subjecting it to a number of misspecification tests. The results may either indicate that the estimated model is adequate or they may point at the necessity of extending the model further, for example towards a full TV-STAR model. A detailed account of the modelling strategy can be found in Lundbergh *et al.* (2003). Below, we report the TV-STAR models obtained for Germany, Japan and the UK in detail. This is followed by a brief summary of the results obtained for the remaining countries.

### *5.1. Germany*

For Germany, the results from the LM-type misspecification tests in the linear model indicate that the seasonal dummy coefficients may be varying for unspecified reasons and the autoregressive dynamics may be varying with the business cycle. The evidence for the latter disappears, however, once we allow the seasonal dummies to vary over time. To capture the variation in the seasonal pattern, we find that three TV components with standard logistic functions are required. The final specification is:

$$\begin{aligned}\Delta y_t = {} & \underset{(0.40)}{1.67} - \underset{(1.13)}{8.95}\, D^*_{1,t} + \underset{(1.04)}{7.02}\, D^*_{2,t} - \underset{(1.11)}{8.25}\, D^*_{3,t} + \underset{(0.063)}{0.16}\, \Delta y_{t-1} + \underset{(0.055)}{0.12}\, \Delta y_{t-2} - \underset{(0.062)}{0.13}\, \Delta y_{t-7} \\ & - \underset{(0.064)}{0.18}\, \Delta y_{t-8} + (-\underset{(0.43)}{1.32} + \underset{(0.87)}{1.97}\, D^*_{1,t} - \underset{(1.14)}{2.56}\, D^*_{2,t} - \underset{(1.69)}{6.26}\, D^*_{3,t}) \times G_1(t^*; \gamma_1, c_1) \\ & + (-\underset{(0.94)}{6.24}\, D^*_{2,t} + \underset{(1.24)}{12.0}\, D^*_{3,t}) \times G_2(t^*; \gamma_2, c_2) + (\underset{(1.28)}{4.52}\, D^*_{2,t} + \underset{(0.94)}{1.98}\, D^*_{3,t}) \times G_3(t^*; \gamma_3, c_3) + \widehat{\varepsilon}_t,\end{aligned} \quad (8)$$

$$G_1(t^*; \gamma_1, c_1) = (1 + \exp\{-\underset{(2.94)}{5.89}\,(t^* - \underset{(0.025)}{0.20})/\sigma_{t^*}\})^{-1}, \quad (9)$$

$$G_2(t^*; \gamma_2, c_2) = (1 + \exp\{-\underset{(-)}{500}\,(t^* - \underset{(-)}{0.40})/\sigma_{t^*}\})^{-1}, \quad (10)$$

$$G_3(t^*; \gamma_3, c_3) = (1 + \exp\{-\underset{(-)}{5.58}\,(t^* - \underset{(0.035)}{0.83})/\sigma_{t^*}\})^{-1}, \quad (11)$$

$\widehat{\sigma}_\varepsilon = 1.60$, $\widehat{\sigma}_{\text{TV-STAR/AR}} = 0.70$, SK $= -0.43(0.015)$, EK $= 0.77(0.026)$, JB $= 8.55(0.014)$, $\text{LM}_{\text{SC}}(1) = 0.38(0.54)$, $\text{LM}_{\text{SC}}(4) = 0.37(0.83)$, $\text{LM}_{\text{SC}}(12) = 1.17(0.31)$, $\text{ARCH}(1) = 8.04(4.5\text{E}-3)$, $\text{ARCH}(4) = 8.66(0.070)$, $\text{AIC}_{\text{TV-STAR/AR}} = -0.51$, $\text{BIC}_{\text{TV-STAR/AR}} = -0.22$,

where OLS standard errors are given in parentheses below the parameter estimates, $\widehat{\varepsilon}_t$ denotes the regression residual at time $t$, $\widehat{\sigma}_\varepsilon$ is the residual standard deviation, $\widehat{\sigma}_{\text{TV-STAR/AR}}$ is the ratio of the residual standard deviations in the estimated TV-STAR model (8) and the best fitting subset AR model, SK is skewness, EK excess kurtosis, JB the Jarque–Bera test of normality of the residuals, $\text{LM}_{\text{SC}}(j)$ is the LM test for no residual autocorrelation up to and including lag $j$, $\text{ARCH}(q)$ is the LM test of no ARCH effects up to order $q$, and $\text{AIC}_{\text{TV-STAR/AR}}$ and $\text{BIC}_{\text{TV-STAR/AR}}$ are differences between the Akaike and Schwarz Information Criteria, respectively, of the estimated TV-STAR and the AR models. The numbers in parentheses following the test statistics are $P$-values. Further misspecification tests are reported in the top panel of Table 2. These indicate that the model is

**Table 2.** Diagnostic tests of parameter constancy and no remaining nonlinearity in TV-STAR models.

| Transition | $D_{s,t}$ | | $\Delta y_{t-j}$ | | $\sigma_\varepsilon^2$ | |
|---|---|---|---|---|---|---|
| variable | $LM_1$ | $LM_3$ | $LM_1$ | $LM_3$ | $LM_1$ | $LM_3$ |
| Germany | | | | | | |
| $t$ | 0.91 | 0.83 | 0.61 | 0.49 | 0.61 | 0.52 |
| $\Delta_4 y_{t-1}$ | 0.54 | 0.24 | 0.22 | 0.16 | 0.091 | 0.40 |
| $\Delta_4 y_{t-2}$ | 0.29 | 0.11 | 0.89 | 0.63 | 0.28 | 0.75 |
| $\Delta_4 y_{t-3}$ | 0.70 | 0.90 | 0.83 | 0.62 | 0.37 | 0.62 |
| $\Delta_4 y_{t-4}$ | 0.41 | 0.60 | 0.40 | 0.51 | 0.14 | 0.44 |
| Japan | | | | | | |
| $t$ | 0.34 | 0.047 | 0.87 | 0.35 | 0.68 | 0.65 |
| $\Delta_4 y_{t-1}$ | 0.21 | 0.085 | 0.49 | 0.21 | 0.28 | 0.41 |
| $\Delta_4 y_{t-2}$ | 0.35 | 0.58 | 0.73 | 0.31 | 0.89 | 0.99 |
| $\Delta_4 y_{t-3}$ | 0.59 | 0.44 | 0.87 | 0.95 | 0.41 | 0.83 |
| $\Delta_4 y_{t-4}$ | 0.56 | 0.78 | 0.70 | 0.95 | 0.14 | 0.52 |
| United Kingdom | | | | | | |
| $t$ | 0.21 | 0.087 | 0.65 | 0.36 | 0.47 | 0.13 |
| $\Delta_4 y_{t-1}$ | 0.46 | 0.54 | 0.89 | 0.22 | 0.57 | 0.51 |
| $\Delta_4 y_{t-2}$ | 0.92 | 0.35 | 0.50 | 0.89 | 0.81 | 0.96 |
| $\Delta_4 y_{t-3}$ | 0.69 | 0.44 | 0.21 | 0.26 | 0.40 | 0.87 |
| $\Delta_4 y_{t-4}$ | 0.62 | 0.29 | 0.45 | 0.61 | 0.58 | 0.34 |

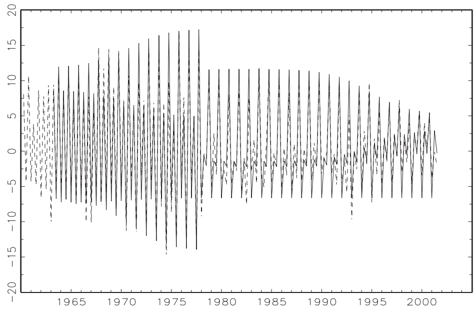
*Notes*: The table contains $P$-values of $F$-variants of LM diagnostic tests of parameter constancy (rows labelled $t$) and no remaining nonlinearity (rows labelled $\Delta_4 y_{t-l}$, with $l = 1, \ldots, 4$) of seasonal dummy coefficients (columns headed $D_{s,t}$), autoregressive parameters (columns headed $\Delta y_{t-j}$), and residual variance (columns headed $\sigma_\varepsilon^2$) in estimated TV-STAR models for quarterly industrial production growth rates for Germany, Japan and the UK.

adequate, at least in the sense that parameter constancy and no remaining nonlinearity are not rejected.

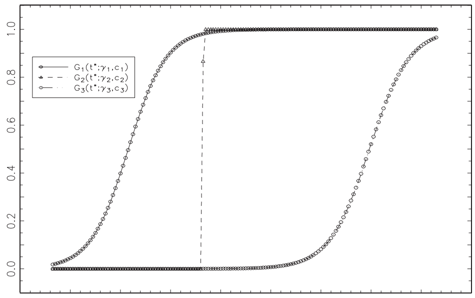
Panels (a) and (b) of Figure 2 show the value of the deterministic seasonal component in the TV-STAR model and the transition functions, respectively. The first change in the seasonal pattern, which is centred around 1970, implies a substantial decline in the overall mean growth rate equal to 1.3%. In addition, the seasonal effects for the third and fourth quarters are amplified. This is partially reversed by the instantaneous change in the seasonal pattern that occurred in 1978, which also captures a change in the seasonal effect in the second quarter from positive $(7.02 - 2.56 = 4.46)$ to negative $(4.46 - 6.24 = -1.78)$. The latter is reversed again by the last change, starting around the unification in 1989, which also further dampens the seasonal effects for the third and fourth quarters.

### *5.2. Japan*

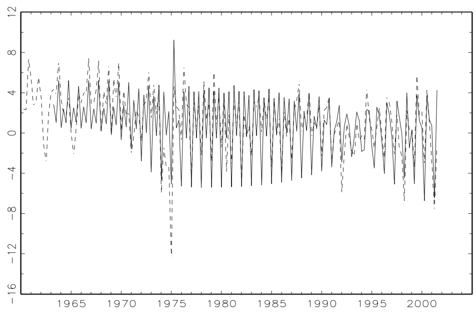
In the linear model for the Japanese industrial production series, both parameter constancy and linearity are forcefully rejected for both the lagged autoregressive parameters and the seasonal



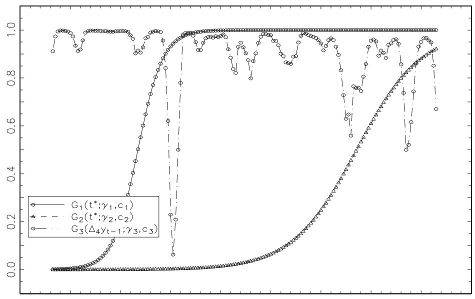

(a) Germany - First difference (dashed line) and deterministic seasonal component in TV-STAR model (solid line)



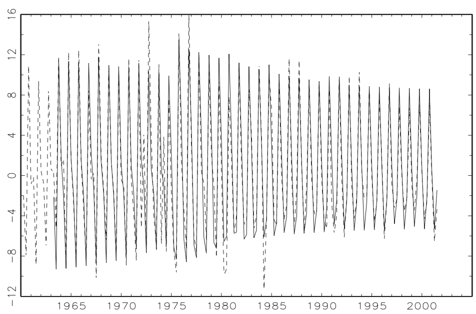

(b) Germany - Transition functions in TV-STAR model



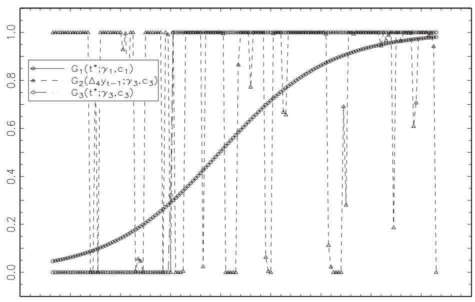

(c) Japan - First difference (dashed line) and deterministic seasonal component in TV-STAR model (solid line)




(d) Japan - Transition functions in TV-STAR model




(e) UK - First difference (dashed line) and deterministic seasonal component in TV-STAR model (solid line)




(f) UK - Transition functions in TV-STAR model

**Figure 2.** Characteristics of TV-STAR models for quarterly industrial production growth rates in Germany, Japan and the UK.

dummy coefficients. As parameter constancy of the seasonal dummy coefficients is rejected most convincingly, we start with a TV-AR model with time-varying seasonal dummy coefficients only. In the resulting TV-AR model, linearity and parameter constancy of the seasonal dummies are still strongly rejected by the diagnostic tests. Accounting for this by sequentially including a nonlinear component with $\Delta_4 y_{t-1}$ as transition variable and a second TV-AR component and recursively deleting insignificant coefficients, we finally obtain the specification:

$$\begin{aligned}\Delta y_t = {} & \underset{(0.51)}{2.29} - \underset{(0.54)}{1.77}\, D^*_{1,t} + \underset{(2.11)}{5.72}\, D^*_{2,t} + \underset{(0.063)}{0.51}\, \Delta y_{t-1} + \underset{(0.054)}{0.17}\, \Delta y_{t-2} - \underset{(0.059)}{0.36}\, \Delta y_{t-5} - \underset{(0.062)}{0.17}\, \Delta y_{t-10} \\ & + \underset{(0.070)}{0.29}\, \Delta y_{t-11} - \underset{(0.066)}{0.18}\, \Delta y_{t-12} + (-\underset{(0.44)}{1.61} - \underset{(0.91)}{4.41}\, D^*_{1,t} + \underset{(0.82)}{3.34}\, D^*_{2,t}) \times G_1(t^*; \gamma_1, c_1) \\ & + (-\underset{(0.45)}{1.04} + \underset{(1.55)}{7.91}\, D^*_{1,t} - \underset{(1.86)}{11.3}\, D^*_{2,t} + \underset{(1.12)}{5.85}\, D^*_{3,t}) \times G_2(t^*; \gamma_2, c_2) \\ & + (-\underset{(2.08)}{5.66}\, D^*_{2,t} - \underset{(0.41)}{1.27}\, D^*_{3,t}) \times G_3(\Delta_4 y_{t-1}; \gamma_3, c_3) + \widehat{\varepsilon}_t, \end{aligned} \tag{12}$$

$$G_1(t^*; \gamma_1, c_1) = (1 + \exp\{-\underset{(1.82)}{8.92}\, (t^* - \underset{(0.019)}{0.23})/\sigma_{t^*}\})^{-1}, \tag{13}$$

$$G_2(t^*; \gamma_2, c_2) = (1 + \exp\{-\underset{(0.86)}{3.47}\, (t^* - \underset{(0.027)}{0.79})/\sigma_{t^*}\})^{-1}, \tag{14}$$

$$G_3(\Delta_4 y_{t-1}; \gamma_3, c_3) = (1 + \exp\{-\underset{(0.79)}{1.60}\, (\Delta_4 y_{t-1} + \underset{(3.31)}{8.56})/\sigma_{\Delta_4 y_{t-1}}\})^{-1}, \tag{15}$$

$\widehat{\sigma}_\varepsilon = 1.30$, $\widehat{\sigma}_{\text{TV-STAR/AR}} = 0.72$, SK $= -0.41(0.020)$, EK $= 0.48(0.11)$, JB $= 5.70(0.058)$, $\text{LM}_{\text{SC}}(1) = 0.32(0.57)$, $\text{LM}_{\text{SC}}(4) = 0.46(0.76)$, $\text{LM}_{\text{SC}}(12) = 1.13(0.34)$, ARCH(1) $= 1.48(0.22)$, ARCH(4) $= 5.30(0.26)$, $\text{AIC}_{\text{TV-STAR/AR}} = -0.46$, $\text{BIC}_{\text{TV-STAR/AR}} = -0.17$.

The model contains two relatively smooth changes in the seasonal pattern, see also panels (c) and (d) in Figure 2. The first, which occurred during the first half of the 1970s, considerably amplified the seasonal pattern, especially for the first and second quarters. The seasonal pattern is changed completely by the second transition, which started around 1985 and was almost completed at the end of the sample period: the deviations of the mean for the first, second and third quarters change from −6.18, 3.40 and −1.27, respectively, when $G_1 = G_3 = 1$ and $G_2 = 0$–1.73, −7.94, and 4.58 when $G_1 = G_2 = G_3 = 1$. Note that the structural changes also involve a substantial reduction of the average growth rate, from 2.29% via 0.68 to −0.37%.

### *5.3. United Kingdom*

The test results for the UK in Table 1 indicate that both linearity and constancy can be rejected for both the seasonal dummy parameters and the lagged autoregressive terms at conventional significance levels. As the $P$-value of the parameter constancy test applied to the seasonal dummies is the smallest, we start by specifying a TV-AR model where only the seasonal pattern is allowed to change over time. Misspecification tests of parameter constancy and no remaining nonlinearity in this model indicate that linearity of the autoregressive parameters is rejected, where the tests select $\Delta_4 y_{t-1}$ as the appropriate transition variable. In the resulting model, we find evidence for additional time-variation in the seasonal pattern. Hence, we specify a model which includes two TV-components operating on the seasonal dummy coefficients and a single STAR-component (with $\Delta_4 y_{t-1}$ as transition variable) operating on the coefficients of the lagged first differences. After deleting insignificant lagged first differences and intercepts, the final specification is:

$$\begin{aligned}\Delta y_t = \; & \underset{(0.35)}{1.12} + \underset{(0.95)}{1.65} D^*_{1,t} - \underset{(0.84)}{2.68} D^*_{2,t} - \underset{(1.37)}{10.2} D^*_{3,t} + \underset{(0.080)}{0.37} \Delta y_{t-2} + \underset{(0.10)}{0.20} \Delta y_{t-4} \\ & + (-\underset{(1.38)}{6.57} D^*_{1,t} + \underset{(0.84)}{2.68} D^*_{2,t} + \underset{(1.37)}{10.2} D^*_{3,t}) \times G_1(t^*; \gamma_1, c_1) + (-\underset{(0.40)}{0.69} - \underset{(0.080)}{0.37} \Delta y_{t-2} \\ & + \underset{(0.069)}{0.13} \Delta y_{t-3} - \underset{(0.087)}{0.27} \Delta y_{t-4} - \underset{(0.063)}{0.13} \Delta y_{t-5} - \underset{(0.061)}{0.15} \Delta y_{t-7}) \times G_2(\Delta_4 y_{t-1}; \gamma_2, c_2) \\ & + (\underset{(0.94)}{4.95} D^*_{1,t} - \underset{(0.55)}{5.68} D^*_{2,t} - \underset{(0.70)}{2.37} D^*_{3,t}) \times G_3(t^*; \gamma_3, c_3) + \widehat{\varepsilon}_t, \end{aligned} \quad (16)$$

$$G_1(t^*; \gamma_1, c_1) = (1 + \exp\{-\underset{(-)}{2.02}(t^* - \underset{(0.048)}{0.44})/\sigma_{t^*}\})^{-1}, \quad (17)$$

$$G_2(\Delta_4 y_{t-1}; \gamma_2, c_2) = (1 + \exp\{-\underset{(-)}{19.5}(\Delta_4 y_{t-1} + \underset{(0.33)}{0.37})/\sigma_{\Delta_4 y_{t-1}}\})^{-1}, \quad (18)$$

$$G_3(t^*; \gamma_3, c_3) = (1 + \exp\{-\underset{(-)}{500}(t^* - \underset{(0.44)}{0.31})/\sigma_{t^*}\})^{-1}, \quad (19)$$

$\widehat{\sigma}_\varepsilon = 1.65$, $\widehat{\sigma}_{\text{TV-STAR/AR}} = 0.76$, SK $= 0.34(0.042)$, EK $= 1.29(5.5\text{E} - 4)$, JB $= 13.7(1.0\text{E} - 3)$, $\text{LM}_{\text{SC}}(1) = 0.24(0.62)$, $\text{LM}_{\text{SC}}(4) = 0.59(0.67)$, $\text{LM}_{\text{SC}}(12) = 0.69(0.76)$, ARCH(1) $= 0.19(0.66)$, ARCH(4) $= 16.4(2.5\text{E} - 3)$, $\text{AIC}_{\text{TV-STAR/AR}} = -0.39$, $\text{BIC}_{\text{TV-STAR/AR}} = -0.15$.

The two structural changes in the seasonal pattern have quite different characteristics. On the one hand, an almost instantaneous change has occurred in 1975, which involves a strengthening of the seasonal pattern mainly in the first and second quarters: whereas initially the average growth rate for the first (second) quarter was larger (smaller) than the overall mean by only 1.65% (2.68%), after the change in 1975 this equals 6.59% (8.36%). On the other hand, the model indicates the presence of a very smooth structural change, which takes the entire 40 year sample period to be completed. This change effectively eliminates the seasonal effect in the first quarter in the sense that when $G_1 = G_3 = 1$ the coefficient for $D^*_{1,t}$ is very close to zero. It also involves a strong reduction in the amplitude of the seasonal pattern for the third and fourth quarters. The (implied) deviation of the mean for the third (fourth) quarter changes from −10.23 (11.27) when $G_1 = G_3 = 0$ via −12.60 (14.38) when $G_1 = 0$ and $G_3 = 1$ to −2.37 (8.02) when $G_1 = G_3 = 1$. Finally, the STAR component in the model effectively captures the business cycle nonlinearity in the series. From panels (e) and (f) in Figure 2, it can be seen that periods when $G_2 = 0$ roughly coincide with recessionary periods in the UK. Apart from a lower mean growth rate, the dynamic properties of the series also are different during recessions. Note that a ± restriction is imposed on the coefficients of $\Delta y_{t-2}$ such that it equals zero when $G_2 = 1$, while the effective coefficient on $\Delta y_{t-4}$ is close to zero in this case as well.

## *5.4. Other countries*

The estimated models for the remaining countries are discussed in full detail in the document available at `http://swopec.hhs.se/hastef/abs/hastef/hastef429.htm`, together with a brief account of the most important modelling events or decisions made during the modelling cycle. To illustrate the main implications of the models for the seasonal patterns in industrial production in these countries, Figure 3 shows the seasonal component in the estimated TV-STAR models for Canada, France and Italy.

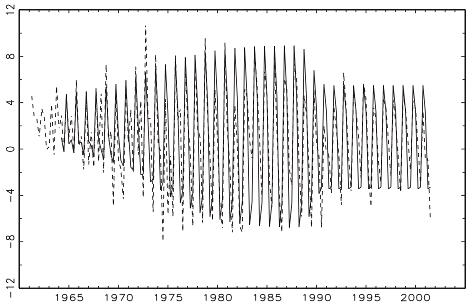
The TV-STAR model for France shows a slowly changing seasonal pattern with decreasing amplitude. The deterministic component obtained from the model for Canadian output is such that the amplitude of the seasonal pattern first slowly increases until a rapid decrease takes place in the late 1980s. For Italy we find a similar pattern, with seasonality becoming more pronounced during the second half of the 1970s, followed by a swift (but relatively small) decline in the amplitude in 1994. Finally, for the US we find that allowing for nonlinearity in the autoregressive structure eliminates all evidence suggesting that the seasonal pattern varies over time due to unspecified reasons or over the business cycle.

## 6. FINAL REMARKS

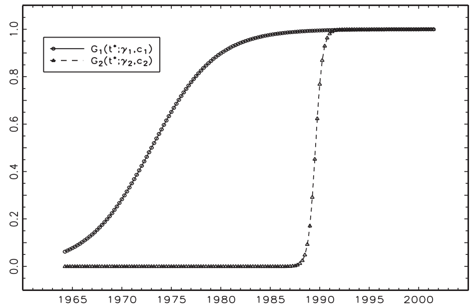
The results of this paper suggest that seasonal patterns in quarterly industrial production series for the G7 countries have been changing over time. On the other hand, business cycle fluctuations do not seem to be the main cause for this change. Our findings are in contrast with Canova and Ghysels (1994) and Franses (1996), who considered US output and concluded that the business cycle influences the seasonal cycle. Similarly, Cecchetti *et al.* (1997) found that in the US seasonal fluctuations in production and inventories vary with the state of the business cycle. There are at least two reasons for differences between our results and those of the above authors. First, they only considered US series and included the GNP and inventories. The second, and perhaps the most important, reason is that those authors did not consider causes other than business cycle fluctuations. Less restrictive considerations appear to lead to rather different conclusions.

It seems possible to reconcile our results with the findings of Matas-Mir and Osborn (2001). An important detail is that they used monthly series, whereas ours are quarterly. As the authors explain, a business-cycle induced change in summer months, visible in monthly series, can be substantially masked at a quarterly frequency. Another reason for the differences in results is that Matas-Mir and Osborn (2001) implicitly give a preference to business-cycle induced pattern shifts, because other types of change are only described by linear trends in seasonal dummy coefficients. This may be too rigid a solution and a more flexible parameterization, offered by the TV-STAR model, is needed to fully assess the role and significance of institutional and technological change in seasonal patterns of the series considered here. Thus the differences in results between Matas-Mir and Osborn (2001) and our work may to a large extent be ascribed to differences in the emphasis, reflected both in the frequency of the series and the choice of model.

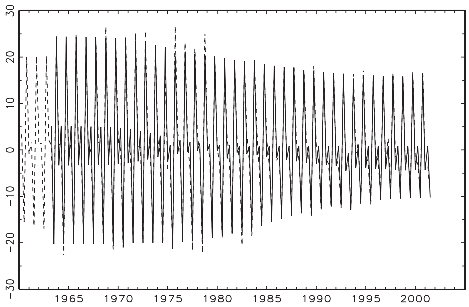
As the ‘Kuznets-type’ unspecified change in seasonal patterns is in our work proxied by time, we cannot give a definite answer to the question of what kind of change, technological, institutional, or ‘other’, has been important in the industrial output series we have investigated. The importance of our results lies in the fact that they make us aware of changes such as the gradual decrease in amplitude many series are showing. Some speculation about the reasons for this may be allowed. There is evidence of changes in inventory management affecting the seasonal pattern of industrial output. Carpenter and Levy (1998) showed that inventory investment and output are highly correlated not only at business cycle frequencies but also at seasonal frequencies. Given the importance of inventories for (changes in) fluctuations in output



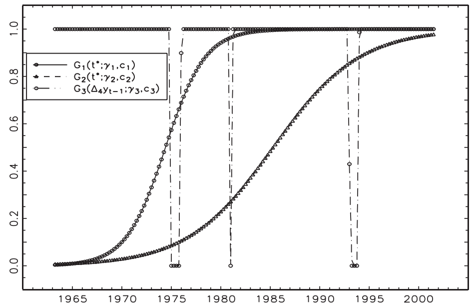
(a) Canada - First difference (dashed line) and deterministic seasonal component in TV-STAR model (solid line)



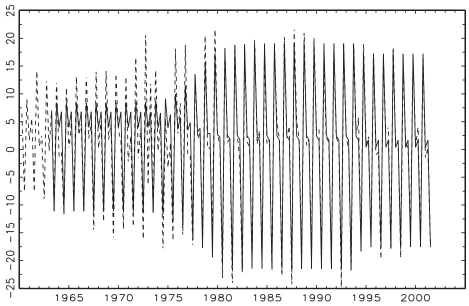

(b) Canada - Transition functions in TV-STAR model



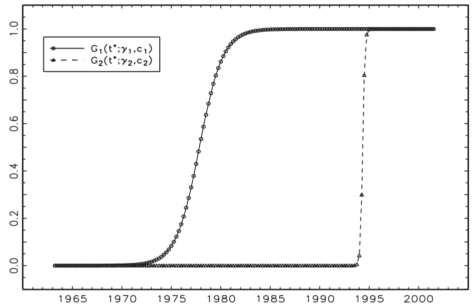
(c) France - First difference (dashed line) and deterministic seasonal component in TV-STAR model (solid line)




(d) France - Transition functions in TV-STAR model



(e) Italy - First difference (dashed line) and deterministic seasonal component in TV-STAR model (solid line)




(f) Italy - Transition functions in TV-STAR model

**Figure 3.** Characteristics of TV-STAR model for quarterly industrial production growth rates in Canada, France and Italy.

(see Sichel (1994) and McConnell and Perez Quiros (2000), among others), it may well be that changes in inventory management such as the use of 'just-in-time' techniques have dampened the seasonal cycle in inventory investment and thereby affected the seasonal cycle in production.

On the other hand, very abrupt changes, such as the one in the German industrial output series in 1978, may most naturally be ascribed to the agency producing the data, unless other information about the nature of the change is available. In general, it may sometimes be relatively easy to suggest individual causes for shifts in the seasonal pattern at the industry level. Because of aggregation this becomes more difficult where the volume of the total industrial output is concerned.

The results also give rise to the question of how the current seasonal adjustment methods cope with series with time-varying seasonality. One may also ask what the consequences of such variation are on using seasonally adjusted series in macroeconomic modelling. Investigating this question in the present context, however, must be left for future work. On the other hand, the models estimated for seasonally unadjusted first differences in this work cannot be expected to be useful in forecasting the volume of industrial production. Models that enhance and explain the low-frequency fluctuations in the series are better suited for that purpose.

## ACKNOWLEDGEMENTS

Financial support from the Jan Wallander's and Tom Hedelius' Foundation for Social Research, Contract No. J99/37, is gratefully acknowledged. The first author acknowledges financial support from the Netherlands Organization for Scientific Research (N. W. O.). The third author acknowledges financial support from the Swedish Council for Research in the Humanities and Social Sciences. We thank Jan Tore Klovland for bringing Gjermoe (1926) to our attention. We have also benefited from helpful comments and suggestions by the editor, an anonymous referee, Eilev Jansen and participants at the conferences 'Growth and Business Cycles in Theory and Practice', Manchester, June 2000, 'Seasonality in Economic and Financial Variables', Faro, October 2000, the 'Third Workshop on New Approaches to the Study of Economic Fluctuations', Hydra, May 2001, the Annual Conference of the European Economic Association, Lausanne, August 2001, and a seminar at Bilkent University, Ankara. Any remaining errors and shortcomings in the paper are ours.

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