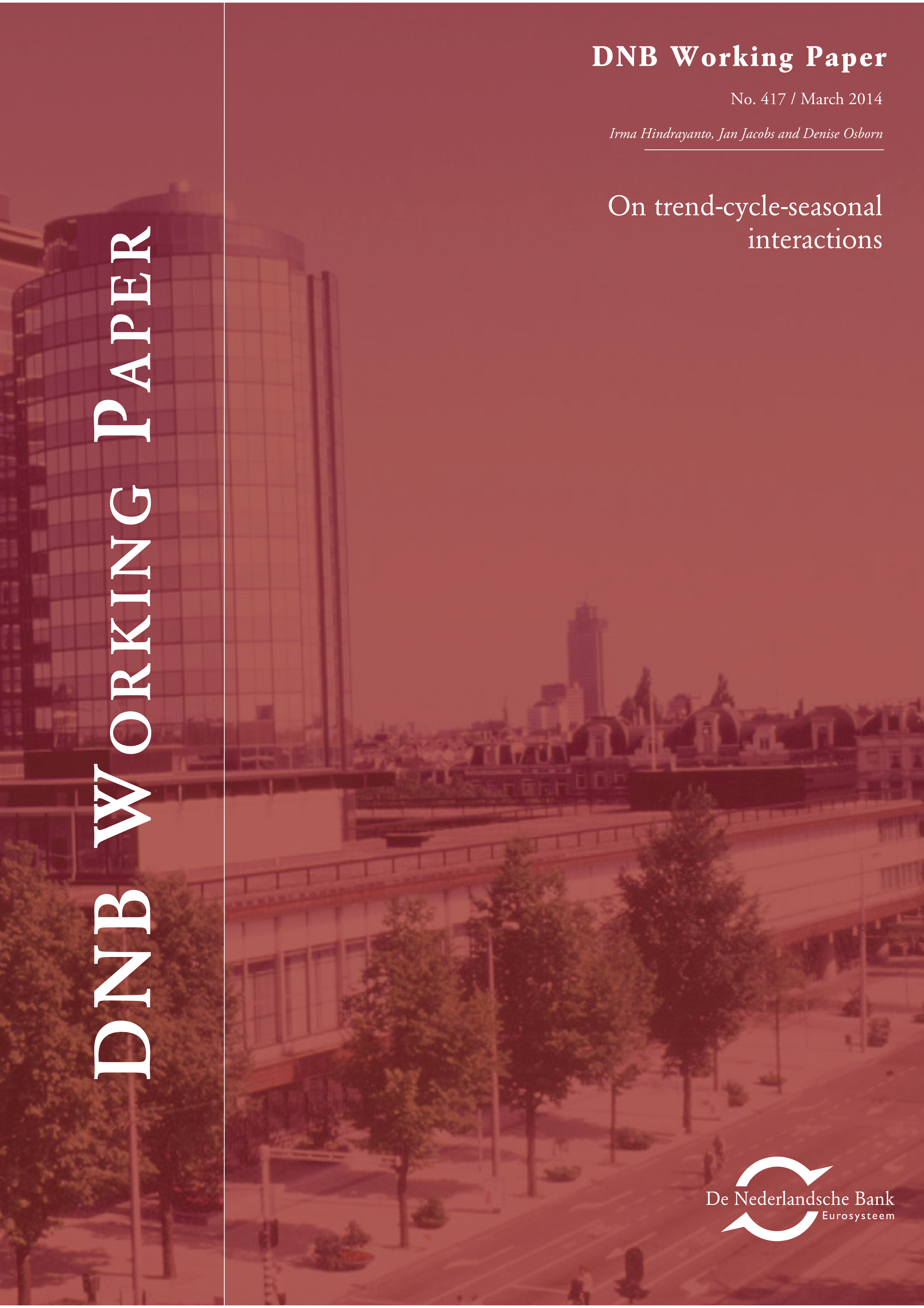

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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

On Trend-Cycle-Seasonal Interactions*

Irma Hindrayanto
De Nederlandsche Bank

Jan P.A.M. Jacobs
University of Groningen, UTAS, CAMA and CIRANO

Denise R. Osborn
University of Manchester and UTAS

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Abstract

Traditional unobserved component models assume that the trend, cycle and seasonal components of an individual time series evolve separately over time. Although this assumption has been relaxed in recent papers that focus on trend-cycle interactions, it remains at the core of all seasonal adjustment methods applied by official statistical agencies around the world. The present paper develops an unobserved components model that permits non-zero correlations between seasonal and non-seasonal shocks, hence allowing testing of the uncorrelated assumption that is traditionally imposed. Identification conditions for estimation of the parameters are discussed, while applications to observed time series illustrate the model and its implications for seasonal adjustment.

JEL classification: C22; E24; E32; E37; F01
Keywords: trend-cycle-seasonal decomposition, unobserved components, state-space models, seasonal adjustment, global real economic activity, unemployment

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1 Introduction

Nowadays, economic time series are typically analysed in *seasonally adjusted* form. That is, (estimated) seasonality is removed prior to undertaking substantive analysis of economic questions. Seasonal adjustment is usually based on the unobserved component approach, of which the key assumption is that trend, cycle and seasonal components are uncorrelated. This assumption is almost invariably untested, although a growing recent literature strongly suggests that trend and cycle can be correlated (Morley, Nelson and Zivot 2003; Dungey et al. 2013). While this has important implications for economic analyses that employ detrended data, the use of seasonally adjusted data in economics is much more pervasive. This paper extends the trend-cycle decomposition literature to examine the seasonal components and, more specifically, the existence and implications of correlation between cyclical and seasonal components. Our analysis, therefore, may deepen our understanding of the propagation of shocks and challenge the basis of conventional seasonal adjustment.

At its simplest level, the decomposition of an observed time series into trend-cycle component and a seasonal component can be considered as

$$\text{observed}_t = \text{trend-cycle}_t + \text{seasonal}_t \tag{1}$$

with uncorrelated components. The simple idea behind (1) underlies all commonly applied seasonal adjustment procedure, including the well-known *X-12-ARIMA* method of the US Bureau of the Census and *TRAMO-SEATS* widely used within EuroStat (these methods recently merged to form *X-13ARIMA-SEATS*), and Harvey (1990)'s so called 'structural' econometric analysis of time series. The zero correlation assumption is fundamental to seasonal adjustment because it ensures a unique decomposition, given sufficient other assumptions. The thought-provoking discussion of Bell and Hillmer (1984) refers to the assumptions embodied in (1) and independence of the trend-cycle and seasonal components as the two basic assumptions of seasonal adjustment that 'define the problem'. There are two important implications. Firstly, the identification of seasonal and nonseasonal components is model-dependent and, secondly, this decomposition is a mechanical one. Apparently successful seasonal adjustment is not evidence that the observed data are generated by separate seasonal and nonseasonal forces, as in (1).

Viewing seasonal adjustment as a signal extraction problem, a number of studies have considered the nature of the unobserved components model implied by conventional adjustment methods; Cleveland and Tiao (1976) and Burridge and Wallis (1984) discuss the *X-11* filter, which is also embedded in *X-12* and *X-13*, while Planas and Depoutot (2002) examine *TRAMO-SEATS* in the context of the so-called 'airline model'. However, these decompositions are purely statistical in nature and imply a trend-cycle component with a specific form that differs from the characteristics typically employed in empirical analyses of seasonally adjusted macroeconomic data; see section 2.

Following the tradition that dates back to at least Grether and Nerlove (1970) and Engle (1978), which also underlines the *structural time series* approach used by Harvey (1990) and Commandeur and Koopman (2007), our approach is to specify individual time series components that are both economically meaningful and often employed in empirical analyses. However, rather than maintaining the uncorrelated components assumption, as in previous studies, this paper asks whether the zero correlation assumption is justified and investigates implications if it is not. In order to do so, we postulate processes for the components in an unobserved component set-up, investigate whether the underlying parameters are identified when the zero correlation assumption is relaxed, and consider the nature of seasonal adjustment in this context.

Stylized facts on economic interactions point in the direction of correlation (Burns and Mitchell 1946). Cecchetti and Kashyap (1996), for example, observe that seasonal cycles in production are less marked in business cycle booms. Since holidays in summer imply the existence of spare capacity, this summer slack can be used during a boom for additional production. This line of arguments implies negative correlation between business cycle and seasonal component in production. As noted by Proietti (2006) negative correlations lead to higher weights on future observations in the Kalman smoother, resulting in relatively large revisions to filtered estimates, see Dungey et al. (2013).

Although there is not a large existing literature, nevertheless a number of previous studies have indicated links between business cycles and seasonality. Barsky and Miron (1989) and Beaulieu, MacKie-Mason and Miron (1992) observe that seasonal and business cycles have common characteristics. Other studies noted that seasonal patterns change with the stage of the business cycle (Canova and Ghysels 1994; Cecchetti and Kashyap 1996; Krane and Wascher 1999; Matas-Mir and Osborn 2004). Recently, Koopman and Lee (2009) model interactions between trend-cycle and seasonal components within a non-linear framework; see Section 2 below.

An extreme form of correlated components is the *Single Source of Error* (SSE) model, where a common shock drives all components (Ord, Koehler and Snyder 1997; De Livera, Hyndman and Snyder 2011). It is clear that the SSE model raises questions for seasonal adjustment, and the same holds if any imperfect correlation exists between components.

The remainder of this paper is structured as follows. Section 2 discusses unobserved component models without correlation and with (imperfect or perfect) correlation, identification and implications for seasonal adjustment. Section 3 presents some empirical results. Section 4 offers some concluding remarks.

2 Methodology

Unobserved components models

The basic model of this paper consists of a *measurement equation* in which an observed series is decomposed into a trend τ_t, a cycle c_t and a seasonal s_t component through

$$y_t = \tau_t + c_t + s_t, \tag{2}$$

and *state equations* describing the dynamics of these unobserved components in terms of the state vector $\boldsymbol{\alpha}$

$$\begin{bmatrix} \tau_t \\ c_t \\ s_t \end{bmatrix} = \mathbf{T} \begin{bmatrix} \tau_{t-1} \\ c_{t-1} \\ s_{t-1} \end{bmatrix} + \mathbf{R}\, \eta_t. \tag{3}$$

Here, the matrix $\boldsymbol{T}$ captures the dynamics of the unobserved components and can take various forms, but perhaps most common consists of a unit root process as trend, stationary AR(2) or a stochastic cycle for c_t, and a nonstationary seasonal cycle. The shocks $\boldsymbol{\eta}_t$ are assumed i.i.d. with zero means and unit variances, $\eta_t \sim i.i.d.(\mathbf{0}, \mathbf{I}_3)$. Finally, and crucially for our investigation, $\mathbf{R}$ embodies correlation assumptions between the innovations of the state equations.

The state-space representation form of this system of equations is

$$\begin{aligned} y_t &= \mathbf{Z}_t \alpha_t \\ \alpha_t &= \mathbf{T}\, \alpha_{t-1} + \mathbf{R}\, \eta_t \end{aligned}$$

The standard assumption in the unobserved components approach is uncorrelated innovations, namely

$$\mathbf{R}\, \eta_t = \begin{bmatrix} \sigma_\tau & 0 & 0 \\ 0 & \sigma_c & 0 \\ 0 & 0 & \sigma_s \end{bmatrix} \begin{bmatrix} \eta_{\tau,t} \\ \eta_{c,t} \\ \eta_{s,t} \end{bmatrix}$$

However, if correlation exists it can be modelled in different ways.

One option is to adapt the measurement equation (2)

$$y_t = \tau_t + c_t + s_t + b \exp(c_t s_t),$$

as in Koopman and Lee (2009), while Krane and Wascher (1999) adopt a similar specification. This specification implies that the underlying seasonal and cyclical components are determined by separate uncorrelated forces, but then interact in a nonlinear way. Such a model may be interpreted as the cyclical forces altering the impact that the seasonal would otherwise have on the observed data. An alternative is to allow the cyclical and seasonal innovations themselves to be correlated, as discussed next.[1]

Correlated cycle-seasonal innovations can be modelled in the following way:

$$\mathbf{v}_t = \begin{bmatrix} v_{\tau,t} \\ v_{c,t} \\ v_{s,t} \end{bmatrix} \equiv \mathbf{R}\,\eta_t = \begin{bmatrix} \sigma_\tau & 0 & 0 \\ 0 & r_{cc} & r_{cs} \\ 0 & r_{sc} & r_{ss} \end{bmatrix} \begin{bmatrix} \eta_{\tau,t} \\ \eta_{c,t} \\ \eta_{s,t} \end{bmatrix},$$

with

$$\begin{aligned} \mathbf{Q} \equiv= E[\mathbf{v}_t \mathbf{v}_t'] &= \begin{bmatrix} \sigma_\tau^2 & 0 & 0 \\ 0 & r_{cc}^2 + r_{cs}^2 & r_{cc}r_{sc} + r_{cs}r_{ss} \\ 0 & r_{cc}r_{sc} + r_{cs}r_{ss} & r_{sc}^2 + r_{ss}^2 \end{bmatrix} \\ &= \begin{bmatrix} \sigma_\tau^2 & 0 & 0 \\ 0 & \sigma_c^2 & \sigma_{cs} \\ 0 & \sigma_{cs} & \sigma_s^2 \end{bmatrix}. \end{aligned}$$

A distinct advantage of this second approach is that nonlinear estimation is avoided.

The Single Source of Error[2] (SSE) model gives the extreme case of perfectly correlated errors:

$$\mathbf{R}\,\eta_t = \begin{bmatrix} k_\tau \\ k_c \\ k_s \end{bmatrix} u_t, \tag{4}$$

[1]A third possibility is to allow for correlation between elements of the state vector and innovations. This requires the use of non-linear Kalman filters, a complication considered beyond the scope of the present paper.

[2]The usual formulation of the SSE model also adds an idiosyncratic error to the measurement equation (2) and assumes this is also driven by u_t; see Ord, Koehler and Snyder (1997). However, our applications do not find a role for this idiosyncratic error and hence we use the modified form given by (4) in conjunction with (2).

with $u_t \sim i.i.d.(0,1)$ and

$$\boldsymbol{\Sigma} = E[\mathbf{v}_t\mathbf{v}_t'] = \begin{bmatrix} k_\tau^2 & k_\tau k_c & k_\tau k_s \\ k_\tau k_c & k_c^2 & k_c k_s \\ k_\tau k_s & k_c k_s & k_s^2 \end{bmatrix} = \begin{bmatrix} \sigma_\tau^2 & \sigma_{\tau c} & \sigma_{\tau s} \\ \sigma_{\tau c} & \sigma_c^2 & \sigma_{cs} \\ \sigma_{\tau s} & \sigma_{cs} & \sigma_s^2 \end{bmatrix}.$$

The assumption of a single source of error driving trend, cycle and seasonal might be overly restrictive. Two sources of error, e.g. one driving the trend, another driving the cycle and the seasonal or one driving the trend and the cycle, another the seasonal , could be more realistic and in line with the Barsky-Miron view that the cycle and seasonal have common characteristics. This is, however, an empirical issue.

In the application below, we estimate all three forms and test the in-between case of correlated innovations against the polar cases of uncorrelated innovations and perfectly correlated innovations (SSE model).

Identification

The workhorse of unobserved component modelling over the last two decades has been the *Basic Structural Model* (BSM) of Harvey (1989), where

$$y_t = \tau_t + \gamma_t + \varepsilon_t \tag{5}$$

with 'local linear trend'

$$\tau_{t+1} = \tau_t + \beta_t + \eta_t \tag{6}$$

$$\beta_{t+1} = \beta_t + \zeta_t \tag{7}$$

and 'dummy variable' seasonality

$$S(L)\gamma_{t+1} = \omega_t. \tag{8}$$

The usual assumption is that the innovations ε_t, η_t, ζ_t and ω_t are uncorrelated, with one or more of these often set to zero in practice. Although the model contains no explicit cyclical component, the evolution of the slope parameter β_t through (7) gives rise to long run behaviour which can appear cyclical. Hence, to allow for correlation across cyclical and seasonal innovations, we generalise the model with

$$E[\zeta_t \omega_t] = \sigma_{\zeta\omega} \neq 0 \tag{9}$$

while maintaining the uncorrelated assumption for other innovation pairs. The first question is what conditions are required in order that the parameters of the expanded model of (5) to (9) are identified.

Assuming (for expositional simplicity) that the data under analysis are observed at the quarterly frequency, the reduced form of this model is

$$\Delta\Delta_4 y_t = S(L)\zeta_{t-2} + \Delta_4 \eta_{t-1} + \Delta^2 \omega_{t-1} + \Delta\Delta_4 \varepsilon_t \tag{10}$$

where L is the usual lag operator, $\Delta_r = 1 - L^r$ and $S(L) = 1 + L + L^2 + L^3$. Standard techniques reveal that the autocovariances Γ_i $(i = 0, 1, ...)$ for $\Delta\Delta_4 y_t$ are given by

$$\begin{aligned}
\Gamma_0 &= 4\sigma_\zeta^2 + 2\sigma_\eta^2 + 6\sigma_\omega^2 + 4\sigma_\varepsilon^2 - \sigma_{\zeta\omega} \\
\Gamma_1 &= 3\sigma_\zeta^2 - 4\sigma_\omega^2 - \sigma_\varepsilon^2 + \sigma_{\zeta\omega} \\
\Gamma_2 &= 2\sigma_\zeta^2 + \sigma_\omega^2 \\
\Gamma_3 &= \sigma_\zeta^2 + \sigma_\omega^2 - \sigma_{\zeta\omega} \\
\Gamma_4 &= -\sigma_\eta^2 - 2\sigma_\varepsilon^2 - \sigma_{\zeta\omega} \\
\Gamma_5 &= \sigma_\varepsilon^2 \\
\Gamma_k &= 0,\ k > 5
\end{aligned}$$

This reduced form has five parameters, namely the innovation variances σ_ε^2, σ_η^2, σ_ζ^2 and σ_ω^2, together with the covariance $\sigma_{\zeta\omega}$. Since there are six $\Gamma_k \neq 0$ $(k = 0, \ldots, 5)$, in principle,

$\sigma_{\zeta\omega}$ is therefore identified. The reduced forms of some alternative models are analysed in the appendix.

To investigate identification further, we simulated the BSM with an added cycle component, using a model of the form implemented below for the 300 quarterly observations of the US non-farm payroll unemployment and with parameter values similar to those estimated. To be specific, the data generating process has $\sigma_\zeta = 0.010$, $\sigma_\kappa = 0.050$, $\sigma_\omega = 0.006$, $\rho = 0.950$, period $= 4.5$ years, and $\text{corr}(\omega, \kappa) = -0.750$, with 5000 replications used. Figure 1 provides the distributions of the resulting estimates. For reference purposes, a normal distribution is fitted to each empirical distribution using its mean and standard deviation and this is also shown in the figure. Also note that $\text{corr}(\omega, \kappa)$ is not estimated directly, but rather the covariance is estimated and the correlation is deduced from this and the corresponding standard deviations.

It is evident that the model parameters are quite well estimated in the simulation study, with each empirical distribution being centered close to its respective true value and the normal distribution being a reasonable approximation. Nevertheless, the empirical distribution of the cyclical/seasonal correlation is truncated in the left-hand tail, which arises because the covariance and variance estimates can imply an estimated correlation outside the admissable range $-1 \leq \text{corr}(\omega, \kappa) \leq 1$. This occurred in approximately 40% of the replications; the results shown for all parameters exclude these cases.

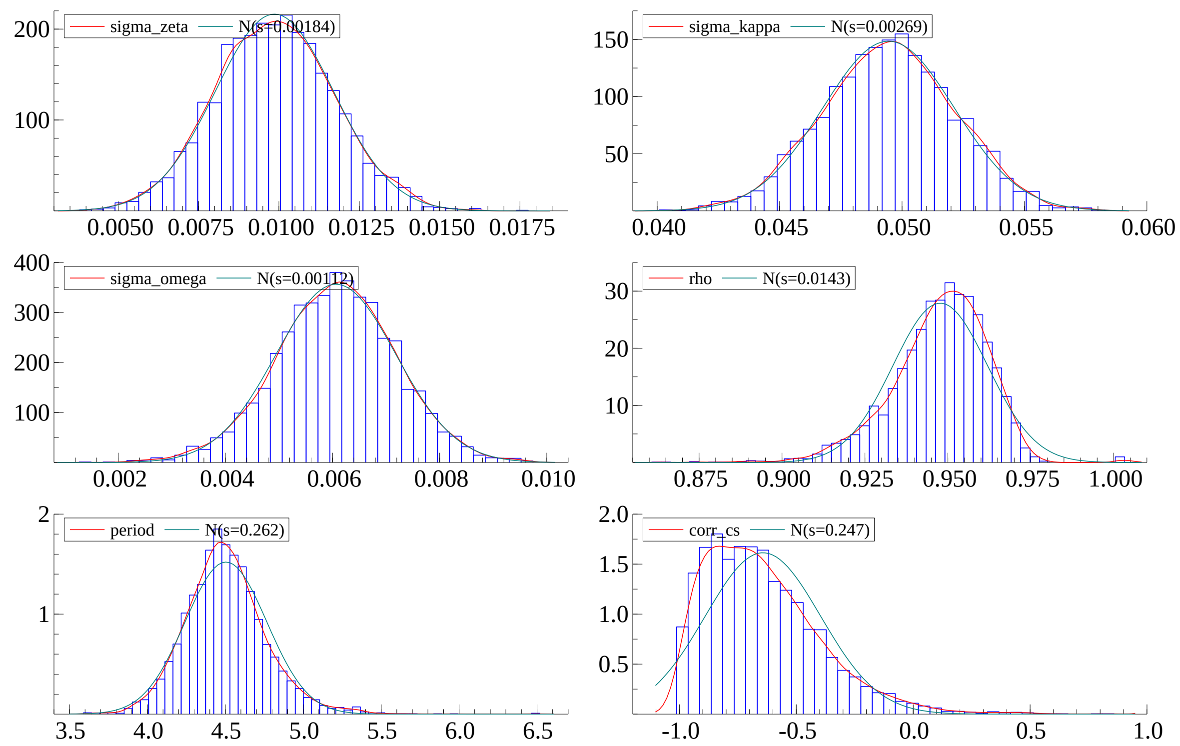
Seasonal adjustment

Correlated innovations can raise questions about the nature of seasonal adjustment. In the measurement equation (2), seasonally adjusted values can be computed as

$$y_t^{sa} = \tau_t + c_t = y_t - s_t. \tag{11}$$

However, when the innovations driving c_t and s_t are no longer uncorrelated, then y_t^{sa} and s_t in (11) are correlated. Analogous issues arise in Beveridge-Nelson vs unobserved

Figure 1: BSM and cycle plus correlated innovations: simulation results



component detrending (Morley, Nelson and Zivot, 2003), where relaxation of the zero correlation assumption results in the trend and detrended components being correlated.

Conventional seasonal adjustment is based on uncorrelated components. However, as shown by Burridge and Wallis (1984) for the *X-11* filters and Planas and Depoutot (2002) for the 'airline' model analysed through *TRAMO-SEATS*, the implied nonseasonal component underlying seasonal adjustment is $ARIMA(0,2,2)$. This differs from the univariate models typically employed for real (seasonally adjusted) macroeconomic time series both in the presence of two zero frequency unit roots and in the lack of any stationary AR component; see, for example, the models discussed by Morley, Nelson and Zivot (2003). This raises the possibility that the seasonal adjustment filters embedded in official procedures (including the uncorrelated component assumption) may be inappropriate from an economic perspective. If so, then adjustment will distort the properties of interest to economists, namely the trend and cyclical characteristics.

3 Applications

Global Activity

In a widely referenced paper, Kilian (2009) analyses a monthly real global activity measure of the business cycle. His series is detrended, but not seasonally adjusted. Our sample uses monthly data over 1968:01–2013:03.[3]

Since the data are detrended, we estimate the local level plus seasonal model version of the BSM, with

$$\begin{aligned} y_t &= \mu_t + \gamma_t + \varepsilon_t, & \varepsilon_t &\sim \mathrm{NID}(0, \sigma_\varepsilon^2) \\ \mu_{t+1} &= \mu_t + \eta_t, & \eta_t &\sim \mathrm{NID}(0, \sigma_\eta^2) \\ S(L)\gamma_{t+1} &= \omega_t, & \omega_t &\sim \mathrm{NID}(0, \sigma_\omega^2) \end{aligned}$$

with and without imposing $E[\eta_t \omega_t] = 0$. Note that, with monthly data, $S(L) = 1 + L + ... + L^{11}$. In addition we estimate a perfectly correlated SSE specification with

$$\varepsilon_t = k_\varepsilon u_t, \quad \eta_t = k_\eta u_t, \quad \omega_t = k_\omega u_t, \quad u_t \sim \mathrm{NID}(0, 1).$$

Table 1: Global Activity: estimation results

	Zero correlation		With correlation		SSE specification	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
σ_ε	0.0003	0.4778	0.0003	0.4878	4.0744×10^{-6}	0.5062
σ_η	7.2107	0.2242	7.2490	0.2267	7.2785	0.2234
σ_ω	0.1353	0.0601	0.2319	0.0823	0.2163	0.0765
Correlation (η,ω)			-0.8778	0.2035	-1^*	restricted
Log Lik.	-1830.67		-1828.47		-1828.69	

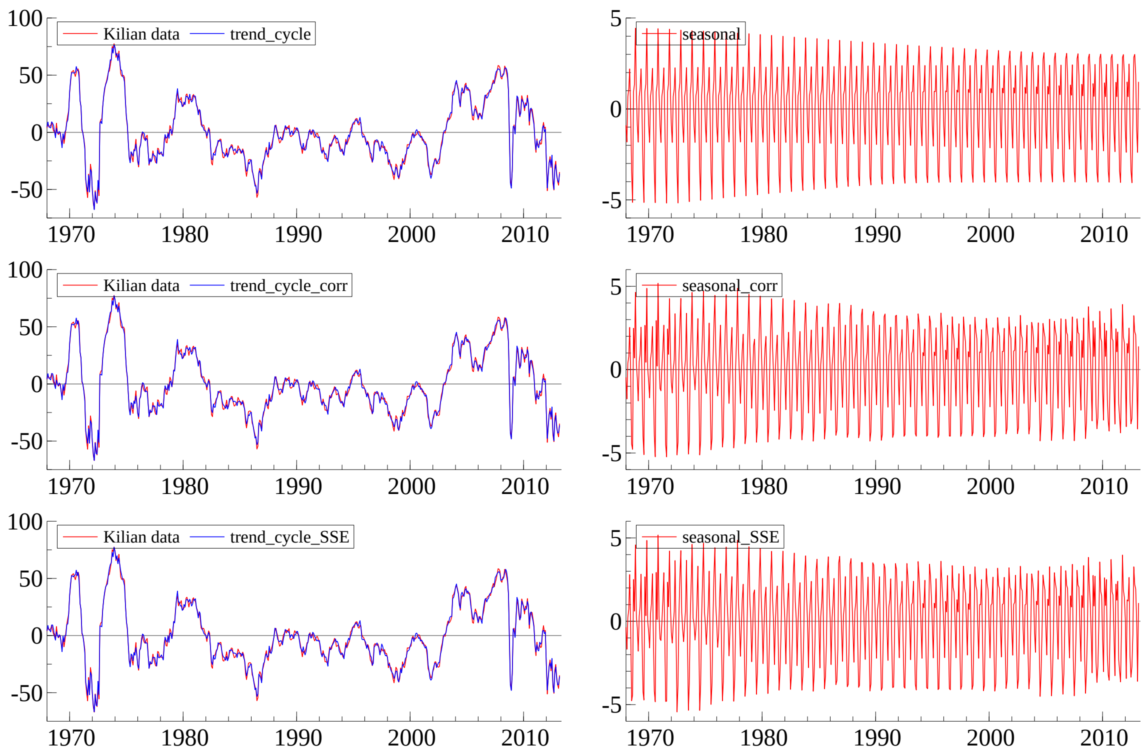
Note: * indicates that correlation in SSE specification is set (or restricted), and is not estimated.

[3] Lutz Kilian makes an updated series available on his website, at http://www-personal.umich.edu/~lkilian. The series is available as percent deviations from trend. Our sample period is that available from Kilian when the analysis was undertaken.

Table 1 presents our estimation results. To facilitate interpretation, Table 1 presents the estimated correlation between η_t and ω_t, rather than the covariance. It is seen that this estimated cyclical/seasona correlation is negative, as anticipated, implying that positive (negative) business cycle innovations are associated with negative (positive) seasonal innovations. This correlation is not only highly significant, but it is also not significantly different from -1. Consequently, the SSE parameter estimates are very close to those delivered by the model with unrestricted correlation and the log likelihood values are also very close.

On the other hand, the zero correlation model yields a significantly lower log likelihood value, according to a likelihood ratio test at a conventional 5% significance level. Notice that while the estimate of the standard deviation of the cycical innovation (σ_η) is relatively constant across specifications, the estimate corresponding to the seasonal innovation (σ_ω) is substantially larger when correlation is permitted.

Figure 2: Monthly index of global real activity (1968:1–2013:3): filtered outcomes without and with correlation between trend-cycle and seasonal innovations, and single source of error



These features are seen in Figure 2, which presents the smoothed estimates of the trend-cyle and the seasonal components over time for each of the three specifications. The graphs of the estimated components in the left-hand panels are visually very similar across models and, indeed, very close to the observed data, implying that the (estimated) extent of seasonality is relatively small. However, whereas the seasonal component of the uncorrelated model (uppermost in the figure) evidences no cyclical movement, this is not the case in the other two models (with the uncorrelated case shown in the middle panel and SSE in the bottom panel).

US Non-Farm Payroll Unemployment

The monthly series of US non-farm payroll unemployment has been previously studied in the cycle-seasonal context by Koopman and Lee (2009) and Koopman, Ooms and Hindrayanto (2009). In this paper we use the same data, but quarterly instead of monthly by taking 3-months averages of the monthly series. Sample period is 1948.M1 up to 2012.M12, in logarithms. To take account of the properties of the data, the model we estimate for this series adds a stochastic cycle to the BSM of (5). To be specific, our model consists of a measurement equation

$$y_t = \mu_t + \psi_t + \gamma_t + \varepsilon_t, \quad \varepsilon_t \sim \text{NID}(0, \sigma_\varepsilon^2),$$

a smooth trend

$$\mu_{t+1} = \mu_t + \beta_t, \quad \beta_{t+1} = \beta_t + \varsigma_t, \quad \varsigma_t \sim \text{NID}(0, \sigma_\varsigma^2),$$

a stochastic cycle

$$\begin{bmatrix} \psi_{t+1} \\ \psi_{t+1}^* \end{bmatrix} = \rho \begin{bmatrix} \cos\lambda & \sin\lambda \\ -\sin\lambda & \cos\lambda \end{bmatrix} \begin{bmatrix} \psi_t \\ \psi_t^* \end{bmatrix} + \begin{bmatrix} \kappa_t \\ \kappa_t^* \end{bmatrix} \qquad \text{with } \kappa_t, \kappa_t^* \sim \text{NID}(0, \sigma_\kappa^2)$$

and the seasonal process

$$S(L)\gamma_{t+1} = \omega_t, \quad \omega_t \sim \text{NID}(0, \sigma^2_\omega).$$

To capture seasonal-cyclical interactions, we estimate a specification allowing nonzero correations between the respective shocks, namely κ_t/κ^*_t and ω_t, in addition to the usual uncorrelated model. For the purposes of comparison, the SSE specification is also implemented, with this assuming

$$\varepsilon_t = k_\varepsilon u_t, \quad \varsigma_t = k_\varsigma u_t, \quad \omega_t = k_\omega u_t, \quad u_t \sim \text{NID}(0, 1).$$

Results are shown in Table 2 and Figure 3.

Table 2: US non-farm payroll unemployment: estimation results

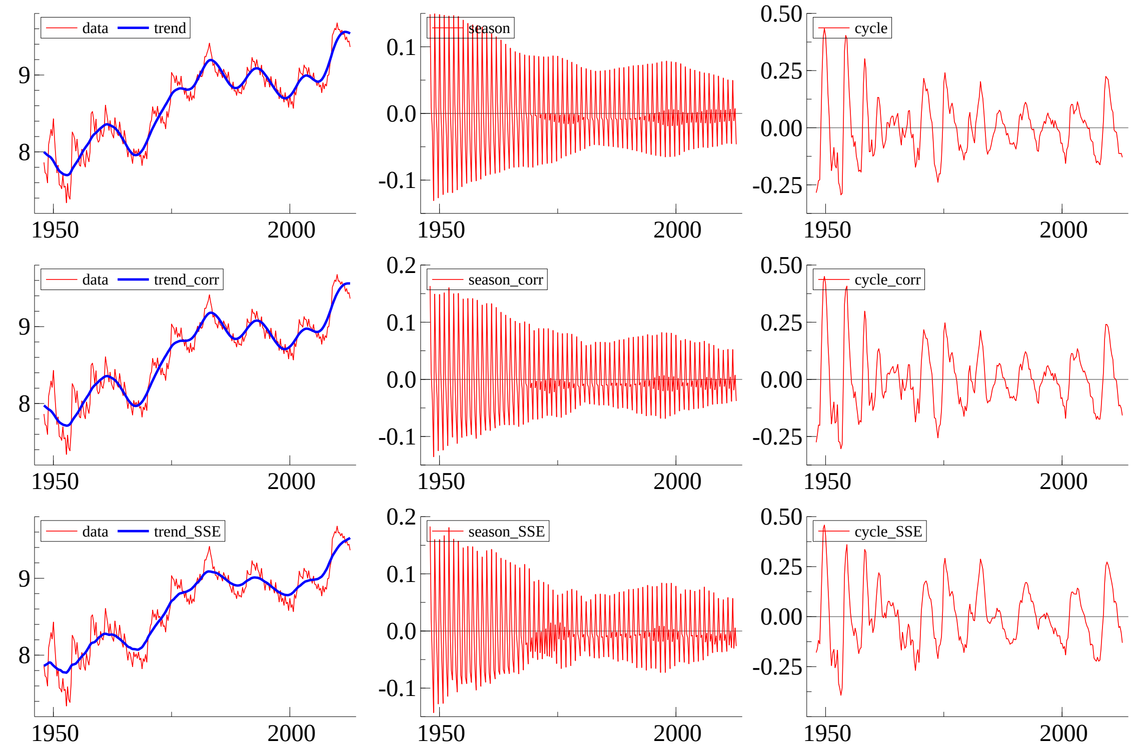
	Zero correlation		With correlation		SSE specification	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
σ_ε	1.75×10^{-6}	0.0045	1.13×10^{-6}	0.0049	0.0135	0.0039
σ_ς	0.0112	0.0039	0.0101	0.0034	0.0043	0.0020
σ_κ	0.0475	0.0036	0.0491	0.0035	0.0556	0.0052
σ_ω	0.0049	0.0009	0.0058	0.0011	0.0063	0.0009
ρ	0.9400	0.0180	0.9407	0.0174	0.9027	0.0252
Period (years)	4.2564	0.4559	4.4690	0.4650	4.2454	0.6043
Correlation (κ/κ^*,ω)			-0.7326	0.2438	-1^*	restricted
Log Lik.	305.66		308.16		306.64	

Note: * correlation in SSE specification is set (or restricted), and is not estimated.

Once again, the estimated correlation between the cyclical and seasonal innovations is negative and highly significant in Table 2. Comparing the remaining parameter estimates for these two models again indicates that these are relatively unaffected by permitting correlation between the seasonal and cyclical innovations, except for an increase in the seasonal variance.

The imposition of perfect correlation has more impact on estimates obtained from the SSE specification (especialy the estimates of σ_ε and σ_ς), although it is important to note that the model implies perfect correlation across all innovations and not just the cyclical and seasonal ones. Interestingly, viewing the zero and perfect correlation models as two extremes, the value of the log likelihood points to the perfect correlation one fitting the data better than the conventional uncorrelated component model.

Figure 3: Quarterly US non-farm payroll unemployment, 1948:Q1-2012:Q4



The first two horizontal panels of Figure 3 once again imply that allowing correlation between the seasonal and cyclical innovations has only a relatively small impact on the estimation of the individual components. To be specific, the estimated trend and cyclical components are particularly close in these models, with some subtle differences to be seen in the seasonal component. The final horizontal panel, on the other hand, implies that the SSE specification effectively transfers some of the apparent cyclicality otherwise seen in the estimated 'trend' component (far left graphs) to the estimated cycle (bottom right-hand graph). Consequently, the trend is substantially less variable for the SSE model than in the other specifications; this can aso be seen in the estimated standard deviations of Table 2.

4 Conclusion

This paper argues that the assumption of zero correlation between seasonal and cyclical components may be unrealistic for economic data. We show analytically and through Monte Carlo simulations that the parameters of an unobserved component model with innovations that exhibit non-zero cycle-seasonal correlation can be identified from observed autocorrelations, if such a model is the true data generating process.

The cycle-seasonal correlation is statistically significant in applications to observed data. However, the effects are not quantitatively strong in the examples considered. Nevertheless, the impact can be huge especially around business cycle turning points. In 2013Q3 the recession in the Netherlands ended for example with a mere 0.1% GDP growth rate.

Future research will develop the analytical framework further, investigate the implications of correlated innovations for estimation of unobserved component models, empirically analyse more examples and deal with implications for seasonal adjustment and forecasting.

A Identification: Uncorrelated UC

A.1 Making BSM stationary

The basic structural model (BSM) is defined in Harvey (1989) as follows,

$$
\begin{aligned}
y_t &= \mu_t + \gamma_t + \varepsilon_t, && \varepsilon_t \sim \mathrm{NID}(0, \sigma_\varepsilon^2), && (12)\\
\mu_{t+1} &= \mu_t + \beta_t + \eta_t, && \eta_t \sim \mathrm{NID}(0, \sigma_\eta^2), && (13)\\
\beta_{t+1} &= \beta_t + \zeta_t, && \zeta_t \sim \mathrm{NID}(0, \sigma_\zeta^2), && (14)\\
\gamma_{t+1} &= -\sum_{j=0}^{s-2} \gamma_{t-j} + \omega_t, && \omega_t \sim \mathrm{nid}(0, \sigma_\omega^2), && (15)
\end{aligned}
$$

where the disturbances are assumed to be uncorrelated at any lead and lag. Note that s is the number of seasonal frequency in a year.

The presence of random walk process in the trend (and slope) component shows that BSM is a stochastic trend model. We can make BSM stationary by working out each component and add them up together again. Starting with the slope, we have

$$
\beta_{t+1} = \beta_t + \zeta_t, \quad \beta_{t+1} - \beta_t = \zeta_t, \quad (1-L)\beta_{t+1} = \zeta_t, \quad \beta_{t+1} = \frac{\zeta_t}{1-L}.
$$

Substitute the latest expression of the slope (β_t) into the trend (μ_t) and we have,

$$
\begin{aligned}
\mu_{t+1} &= \mu_t + \beta_t + \eta_t,\\
(1-L)\mu_{t+1} &= \frac{\zeta_{t-1}}{1-L} + \eta_t,\\
\mu_{t+1} &= \frac{\zeta_{t-1}}{(1-L)^2} + \frac{\eta_t}{1-L}.
\end{aligned}
$$

We continue with the seasonal component (γ_t), where

$$
\begin{aligned}
\gamma_{t+1} &= -\sum_{j=0}^{s-2} \gamma_{t-j} + \omega_t, \quad (1 + L + \cdots + L^{s-1})\gamma_{t+1} = \omega_t,\\
\gamma_{t+1} &= \frac{\omega_t}{(1 + L + \cdots + L^{s-1})}.
\end{aligned}
$$

Back to the BSM, we now have the expression,

$$\begin{aligned} y_t &= \mu_t + \gamma_t + \varepsilon_t, \\ &= \frac{\zeta_{t-2}}{(1-L)^2} + \frac{\eta_{t-1}}{1-L} + \frac{\omega_{t-1}}{(1+L+\cdots+L^{s-1})} + \varepsilon_t, \end{aligned}$$

which boils down to

$$\begin{aligned} (1-L)^2(1+L+\cdots+L^{s-1})y_t = (1+L+\cdots+L^{s-1})\zeta_{t-2} \\ + (1-L)(1+L+\cdots+L^{s-1})\eta_{t-1} + (1-L)^2\omega_{t-1} \\ + (1-L)^2(1+L+\cdots+L^{s-1})\varepsilon_t, \end{aligned}$$

or after re-writing the above equation,

$$\begin{aligned} (1-L)(1-L^s)y_t = (1+L+\cdots+L^{s-1})\zeta_{t-2} + (1-L^s)\eta_{t-1} + (1-L)^2\omega_{t-1} \\ + (1-L)(1-L^s)\varepsilon_t, \end{aligned}$$

which equals to

$$\Delta\Delta_s y_t = S(L)\zeta_{t-2} + \Delta_s\eta_{t-1} + \Delta^2\omega_{t-1} + \Delta\Delta_s\varepsilon_t,$$

where the usual time series operator definition holds, $L^j y_t = y_{t-j}$, $S(L) = (1 + L + \cdots + L^{s-1})$, $\Delta^k = (1-L)^k$, and $\Delta_s = (1-L^s)$. As we can see from the right hand side, $\Delta\Delta_s y_t$ is a restricted MA$(s+1)$ process. For $s = 2$ we have a restricted MA(3) process, for $s = 4$ we have a restricted MA(5) process, and $s = 12$ we have a restricted MA(13) process.

A.2 ARMA form for the cycle component

The usual form of the cyclical component in unobserved component models is given by

$$\begin{pmatrix} \psi_{t+1} \\ \psi^*_{t+1} \end{pmatrix} = \rho \begin{pmatrix} \cos\lambda & \sin\lambda \\ -\sin\lambda & \cos\lambda \end{pmatrix} \begin{pmatrix} \psi_t \\ \psi^*_t \end{pmatrix} + \begin{pmatrix} \kappa_t \\ \kappa^*_t \end{pmatrix}.$$

In the single equation form, we have

$$\psi_{t+1} = \rho \cos \lambda \psi_t + \rho \sin \lambda \psi_t^* + \kappa_t,$$
$$\psi_{t+1}^* = -\rho \sin \lambda \psi_t + \rho \cos \lambda \psi_t^* + \kappa_t^*.$$

The second cycle equation can be written out as follows, In the single equation form, we have

$$\begin{aligned}
\psi_{t+1}^* - \rho \cos \lambda \psi_t^* &= -\rho \sin \lambda \psi_t + \kappa_t^*, \\
(1 - \rho \cos \lambda L)\psi_{t+1}^* &= -\rho \sin \lambda \psi_t + \kappa_t^*, \\
\psi_{t+1}^* &= \frac{-\rho \sin \lambda \psi_t}{(1 - \rho \cos \lambda L)} + \frac{\kappa_t^*}{(1 - \rho \cos \lambda L)}.
\end{aligned}$$

Substitute the above expression into the first cycle equation, we get

$$\begin{aligned}
\psi_{t+1} &= \rho \cos \lambda \psi_t + \rho \sin \lambda \left[\tfrac{-\rho \sin \lambda \psi_{t-1}}{(1-\rho \cos \lambda L)} + \tfrac{\kappa_{t-1}^*}{(1-\rho \cos \lambda L)} \right] + \kappa_t, \\
\psi_{t+1} - \rho \cos \lambda \psi_t &= \rho \sin \lambda \left[\tfrac{-\rho \sin \lambda \psi_{t-1}}{(1-\rho \cos \lambda L)} + \tfrac{\kappa_{t-1}^*}{(1-\rho \cos \lambda L)} \right] + \kappa_t, \\
(1 - \rho \cos \lambda L)\psi_{t+1} &= \rho \sin \lambda \left[\tfrac{-\rho \sin \lambda \psi_{t-1}}{(1-\rho \cos \lambda L)} + \tfrac{\kappa_{t-1}^*}{(1-\rho \cos \lambda L)} \right] + \kappa_t, \\
(1 - \rho \cos \lambda L)^2 \psi_{t+1} &= -\rho^2 (\sin \lambda)^2 \psi_{t-1} + \rho \sin \lambda \kappa_{t-1}^* + (1 - \rho \cos \lambda L)\kappa_t, \\
(1 - 2\rho \cos \lambda L + \rho^2 (\cos \lambda)^2 L^2)\psi_{t+1} &= -\rho^2 (\sin \lambda)^2 \psi_{t-1} + \rho \sin \lambda \kappa_{t-1}^* + (1 - \rho \cos \lambda L)\kappa_t.
\end{aligned}$$

After some re-arrangements and using the fact that $\sin^2 \lambda + \cos^2 \lambda = 1$, we get

$$\psi_{t+1} = 2\rho \cos \lambda \psi_t - \rho^2 \psi_{t-1} + \kappa_t + \rho \sin \lambda \kappa_{t-1}^* - \rho \cos \lambda \kappa_{t-1}, \tag{16}$$

which is a restricted ARMA(2,1) process. To get the explicit expression of the cycle component, we may also write

$$\begin{aligned}(1 - 2\rho\cos\lambda L + \rho^2 L^2)\psi_{t+1} &= \kappa_t + \rho\sin\lambda\kappa^*_{t-1} - \rho\cos\lambda\kappa_{t-1},\\ \psi_{t+1} &= \frac{\kappa_t + \rho\sin\lambda\kappa^*_{t-1} - \rho\cos\lambda\kappa_{t-1}}{(1 - 2\rho\cos\lambda L + \rho^2 L^2)}.\end{aligned}$$

A.3 Reduced form of BSM plus cycle

The BSM plus cycle is defined as

$$y_t = \mu_t + \gamma_t + \psi_t + \varepsilon_t. \tag{17}$$

Using the reduced form of the individual components, we get

$$y_t = \frac{\zeta_{t-2}}{(1-L)^2} + \frac{\eta_{t-1}}{1-L} + \frac{\omega_{t-1}}{(1 + L + \cdots + L^{s-1})} + \frac{\kappa_{t-1} + \rho\sin\lambda\kappa^*_{t-2} - \rho\cos\lambda\kappa_{t-2}}{(1 - 2\rho\cos\lambda L + \rho^2 L^2)} + \varepsilon_t,$$

which has become pretty complicated due to the presence of the cyclical component. Since the cycle is a restricted ARMA(2,1) process, we could simplify the above expression as follows,

$$y_t = \frac{\zeta_{t-2}}{(1-L)^2} + \frac{\eta_{t-1}}{1-L} + \frac{\omega_{t-1}}{(1 + L + \cdots + L^{s-1})} + \frac{(1+\theta L)\kappa_{t-1}}{(1 - \phi_1 L - \phi_2 L^2)} + \varepsilon_t.$$

Let us define $S(L) = 1 + L + \cdots + L^{s-1}$ and $\Phi(L) = 1 - \phi_1 L - \phi_2 L^2$. Then the reduced form of the BSM plus cycle becomes

$$\begin{aligned}(1-L)^2 S(L)\Phi(L) y_t &= S(L)\Phi(L)\zeta_{t-2} + (1-L)S(L)\Phi(L)\eta_{t-1}\\ &\quad + (1-L)^2\Phi(L)\omega_{t-1} + (1-L)^2 S(L)(1+\theta L)\kappa_{t-1}\\ &\quad + (1-L)^2 S(L)\Phi(L)\varepsilon_t.\end{aligned}$$

Since $(1-L)S(L) = 1 - L^s$, we get

$$(1-L)(1-L^s)\Phi(L)y_t = S(L)\Phi(L)\zeta_{t-2} + (1-L^s)\Phi(L)\eta_{t-1} \\ + (1-L)^2\Phi(L)\omega_{t-1} + (1-L)(1-L^s)(1+\theta L)\kappa_{t-1} \\ + (1-L)(1-L^s)\Phi(L)\varepsilon_t,$$

which is a restricted MA($s+3$) process. For $s = 2$ we have a restricted MA(5) process, for $s = 4$ we have a restricted MA(7) process and for $s = 12$ a restricted MA(15) process.

A.4 Deriving the ACVFs of BSM

Recall the reduced form of BSM, which was given by

$$\Delta\Delta_s y_t = S(L)\zeta_{t-2} + \Delta_s\eta_{t-1} + \Delta^2\omega_{t-1} + \Delta\Delta_s\varepsilon_t.$$

Let us define $x_t = \Delta\Delta_s y_t$ and for the time being, let $s = 2$. Then the reduced form in this case becomes,

$$x_t = (1-L)(1-L^2)y_t = (1+L)\zeta_{t-2} + (1-L^2)\eta_{t-1} + (1-L)^2\omega_{t-1} + (1-L)(1-L^2)\varepsilon_t.$$

Writing out the above equation, we get

$$x_t = \zeta_{t-2} + \zeta_{t-3} + \eta_{t-1} - \eta_{t-3} + \omega_{t-1} - 2\omega_{t-2} + \omega_{t-3} + \varepsilon_t - \varepsilon_{t-1} - \varepsilon_{t-2} + \varepsilon_{t-3},$$

which is a restricted MA(3) process since the highest lag variable is 3. And as we know, the usual MA(3) process has 4 non-zero autocovariance functions, say $\Gamma_0, \Gamma_1, \Gamma_2$ and Γ_3. Assuming all disturbances are i.i.d, we can derive the following autocovariance functions for reduced form BSM,

$$\begin{aligned}
\Gamma_0 &= \mathrm{E}[x_t^2] = 2\sigma_\zeta^2 + 2\sigma_\eta^2 + 4\sigma_\omega^2 + 4\sigma_\varepsilon^2, \\
\Gamma_1 &= \mathrm{E}[x_t x_{t-1}] = \sigma_\zeta^2 - 4\sigma_\omega^2 - \sigma_\varepsilon^2, \\
\Gamma_2 &= \mathrm{E}[x_t x_{t-2}] = -\sigma_\eta^2 + \sigma_\omega^2 - 2\sigma_\varepsilon^2, \\
\Gamma_3 &= \mathrm{E}[x_t x_{t-3}] = \sigma_\varepsilon^2, \\
\Gamma_k &= \mathrm{E}[x_t x_{t-k}] = 0, \qquad \text{for } k > 3.
\end{aligned}$$

We now have 4 autocovariance equations with 4 unknown paramaters, or in matrix form,

$$\begin{pmatrix} \Gamma_0 \\ \Gamma_1 \\ \Gamma_2 \\ \Gamma_3 \end{pmatrix} = \begin{pmatrix} 2 & 2 & 4 & 4 \\ 1 & 0 & -4 & -1 \\ 0 & -1 & 1 & -2 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \sigma_\zeta^2 \\ \sigma_\eta^2 \\ \sigma_\omega^2 \\ \sigma_\varepsilon^2 \end{pmatrix},$$

such that $\mathrm{rank}(A) = 4$, where A is the matrix on the right hand side of the above expression. This means all parameters are exactly identified.

For $s = 3$, we have

$$x_t = (1-L)(1-L^3)y_t = (1+L+L^2)\zeta_{t-2} + (1-L^3)\eta_{t-1} + (1-L)^2\omega_{t-1} + (1-L)(1-L^3)\varepsilon_t.$$

Writing out the above equation, we get

$$x_t = \zeta_{t-2} + \zeta_{t-3} + \zeta_{t-4} + \eta_{t-1} - \eta_{t-4} + \omega_{t-1} - 2\omega_{t-2} + \omega_{t-3} + \varepsilon_t - \varepsilon_{t-1} - \varepsilon_{t-3} + \varepsilon_{t-4},$$

which is a restricted MA(4) process since the highest lag variable is 4. The autocovariance functions are derived as follows,

$$
\begin{aligned}
\Gamma_0 &= \mathrm{E}[x_t^2] = 3\sigma_\zeta^2 + 2\sigma_\eta^2 + 4\sigma_\omega^2 + 4\sigma_\varepsilon^2, \\
\Gamma_1 &= \mathrm{E}[x_t x_{t-1}] = 2\sigma_\zeta^2 - 4\sigma_\omega^2 - 2\sigma_\varepsilon^2, \\
\Gamma_2 &= \mathrm{E}[x_t x_{t-2}] = \sigma_\zeta^2 + \sigma_\omega^2 + \sigma_\varepsilon^2, \\
\Gamma_3 &= \mathrm{E}[x_t x_{t-3}] = -\sigma_\eta^2 - 2\sigma_\varepsilon^2, \\
\Gamma_4 &= \mathrm{E}[x_t x_{t-4}] = \sigma_\varepsilon^2, \\
\Gamma_k &= \mathrm{E}[x_t x_{t-k}] = 0, \qquad \text{for } k > 4.
\end{aligned}
$$

So now we have 5 autocovariance equations with 4 unknown paramaters, or in matrix form,

$$
\begin{pmatrix} \Gamma_0 \\ \Gamma_1 \\ \Gamma_2 \\ \Gamma_3 \\ \Gamma_4 \end{pmatrix} = \begin{pmatrix} 3 & 2 & 4 & 4 \\ 2 & 0 & -4 & -2 \\ 1 & 0 & 1 & 1 \\ 0 & -1 & 0 & -2 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \sigma_\zeta^2 \\ \sigma_\eta^2 \\ \sigma_\omega^2 \\ \sigma_\varepsilon^2 \end{pmatrix},
$$

such that $\mathrm{rank}(A) = 4$, where A is the matrix on the right hand side of the above expression. This means that we have over-identification.

In the same way, we can also derive ACVF for $s = 4$ and $s = 12$ from a restricted MA(5) and a restricted MA(13) process respectively. The problem is that we still only have 4 unknown parameters, but we have more ACVF equations to solve. This leads to over-identification of the parameters. But whether this is actually a problem, remains to be seen.

A.5 Deriving the ACVFs of BSM plus cycle

Now we come to the most tedious part of all. Recall the reduced form of BSM plus cycle, which was given by

$$
\begin{aligned}
(1-L)(1-L^s)\Phi(L)y_t = S(L)\Phi(L)\zeta_{t-2} + (1-L^s)\Phi(L)\eta_{t-1} \\
+ (1-L)^2\Phi(L)\omega_{t-1} + (1-L)(1-L^s)(1+\theta L)\kappa_{t-1} \\
+ (1-L)(1-L^s)\Phi(L)\varepsilon_t,
\end{aligned}
$$

where $\Phi(L) = 1 - \phi_1 L - \phi_2 L^2$.

We start with $s = 2$ and proceed from there. Define $x_t = (1-L)(1-L^2)(1-\phi_1 L - \phi_2 L^2)y_t$. Then,

$$
\begin{aligned}
x_t &= (1+L)(1-\phi_1 L - \phi_2 L^2)\zeta_{t-2} + (1-L^2)(1-\phi_1 L - \phi_2 L^2)\eta_{t-1} \\
&+ (1-L)^2(1-\phi_1 L - \phi_2 L^2)\omega_{t-1} + (1-L)(1-L^2)(1+\theta L)\kappa_{t-1} \\
&+ (1-L)(1-L^2)(1-\phi_1 L - \phi_2 L^2)\varepsilon_t,
\end{aligned}
$$

where we can count that there are 8 unknown parameters $(\phi_1, \phi_2, \theta, \sigma^2_\eta, \sigma^2_\zeta, \sigma^2_\omega, \sigma^2_\kappa, \sigma^2_\varepsilon)$ with 6 equations (since for $s = 2$ we have an MA(5) process, which means 6 autocovariance functions). One way to solve this problem is to give restrictions to a number of parameters. Writing out the above equation, we get

$$
\begin{aligned}
x_t &= (1 + (1-\phi_1)L - (\phi_1+\phi_2)L^2 - \phi_2 L^3)\zeta_{t-2} \\
&+ (1 - \phi_1 L - (1+\phi_2)L^2 + \phi_1 L^3 + \phi_2 L^4)\eta_{t-1} \\
&+ (1 - (2+\phi_1)L + (1+2\phi_1-\phi_2)L^2 + (2\phi_2-\phi_1)L^3 - \phi_2 L^4)\omega_{t-1} \\
&+ (1 + (\theta-1)L - (\theta+1)L^2 - (\theta-1)L^3 + \theta L^4)\kappa_{t-1} \\
&+ (1 - (1+\phi_1)L + (\phi_1-\phi_2-1)L^2 + (\phi_1+\phi_2+1)L^3 - (\phi_1+\phi_2)L^4 - \phi_2 L^5)\varepsilon_t.
\end{aligned}
$$

Deriving the autocovariance functions of the above equation is nothing but simple due to the non-linear expression.

Continuing with $s = 4$ and $s = 12$, we get restricted MA(7) and restricted MA(15) processes, respectively. With 8 unknown parameters that we have, it seems that only $s = 4$ case is exactly identified.

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