Detecting changes in seasonal patterns

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Introduction

Consider a seasonal time series, denoted by y_t at time t. This can be decomposed multiplicatively as $y_t = T_t \times s_t \times i_t$. Seasonally adjusted estimates are derived by the estimation and removal of the seasonal component, $\hat{SA}_t = y_t/\hat{s}_t = T_t \times i_t$. Estimation of quality seasonal factors are important. Seasonality which evolves slowly over time can be adequately captured by the seasonal factor estimation process. Abrupt changes to the seasonal pattern can be difficult to detect. This can lead to poor quality seasonal factors and hence seasonally adjusted and trend estimates. This paper evaluates X12-SEATS for the detection of changes in seasonal patterns.

Modelling frameworks

Common seasonal adjustment approaches are X-12ARIMA (Findley et. al, 1998) and SEATS (Maravall and Gomez, 1996). The current production versions of these packages do not include automatic detection for changes in seasonal patterns. SEASABS (ABS, 2001) uses an iterative knowledge based algorithm to detect changes in seasonal patterns. Penzer (2004) describes statistics to detect seasonal breaks in a model based framework. A new version of X12-SEATS (www.census.gov) will contain a seasonal outlier detection algorithm based on Kaiser and Maravall (2001). An evaluation copy of X12-SEATS was used in this study. Kaiser and Maravall (2001) express an observed series which contains k outliers as $y_t^* = \sum_{j=1}^{k} \xi_j(B)\omega_j I_t^{(\tau_j)} + y_t$, where y_t^* is the observed series contaminated by k outliers, y_t is the true series which follows an ARIMA process, ω_j is the impact of the outlier at time $t = \tau_j$, $I_t^{(\tau_j)}$ is an indicator variable set to one where the outlier is present, and $\xi_j(B)$ describes the dynamics of the outlier at $t = \tau_j$. The seasonal outlier used in this study has the following form for monthly time series, $\xi(B) = 1/(1-B^{12}) - 1/(12(1-B))$, with $I_t^{(\tau_j)} = 1, \forall\, t \geq \tau_j$. For this study an identified seasonal break was defined as a detection at a given time point and then detection at the next three consecutive time points and the following three years. This definition avoids the possibility of spurious seasonal breaks being detected. Alternative definitions could have been used.

Results and Conclusion

Simulated monthly series (540 in total) were generated using a seasonal airline ARIMA model, $(1-B)(1-B^{12})y_t = (1-\theta_1 B)(1-\theta_{12}B^{12})a_t$, where $-0.9 \leq \theta_1, \theta_{12} \leq 0.9$. The model and parameter estimates were passed to X12-SEATS. This series was then contaminated by a known seasonal outlier. The seasonal break detection algorithm in X12-SEATS was iteratively applied until the first seasonal break was detected. The critical value was set at 3.75 since this is an appropiate value to use for the detection of unknown seasonal breaks. The *addone* detection method was used. The ratio of the irregular to seasonal component (I/S) was used as a measure of the relative volatility of each series. Table 1 summarises the detection results. Three relative volatilty groups were formed representing low $I/S < 3.30$, medium $3.30 \leq I/S < 5.6$ and high $I/S \geq 5.6$. When the seasonal break is small there are many runs that result in no detection due to the fact that these breaks are likely to be masked by noise. As the seasonal break increases there are more detections although not many of them are identified seasonal breaks (defined above). Apart from the case where the seasonal break magnitude is 0.1 with a low I/S ratio,

Table 1: Average detection time using X12-SEATS v3.0 (evaluation version), a is % of series where the true seasonal break was not detected, b is % of series where an indentified seasonal break was detected, c is average time until first detection (standard errors in brackets).

		Relative Volatility (I/S) Level					
		Low		Medium		High	
Magnitude		$\|\theta_{12}\| < 0.5$	$\|\theta_{12}\| \geq 0.5$	$\|\theta_{12}\| < 0.5$	$\|\theta_{12}\| \geq 0.5$	$\|\theta_{12}\| < 0.5$	$\|\theta_{12}\| \geq 0.5$
0.01	a	92%	83.3%	88%	72.7%	87.9%	81.8%
	b	0%	0%	0%	0%	0%	0%
	c	12 (0)	17.5 (7.7)	12.3 (0.6)	28 (13.8)	38.5 (36.1)	31 (13.4)
0.03	a	79.2%	53.8%	74.1%	56.3%	87.1%	73.7%
	b	0%	15.4%	3.2%	9.4%	0%	0%
	c	21 (20.1)	12.2 (0.4)	13 (1.2)	17.4 (10.1)	14 (2.2)	18.6 (7.2)
0.05	a	59.1%	43.8%	62.2%	47.8%	100%	53.9%
	b	9.1%	31.3%	2.7%	8.7%	0%	0%
	c	14 (3.5)	17.8 (10.3)	22.6 (21)	12.3 (0.6)	0 (-)	28.5 (25)
0.10	a	7.1%	30.8%	48.4%	36.4%	74%	70.6%
	b	42.9%	23.1%	13%	23%	0%	11.8%
	c	12.2 (0.4)	13.4 (4)	12.9 (3)	19.5 (18.1)	17.3 (6.5)	21.6 (21.5)

there seems to be an increase in performance when $|\theta_{12}| \geq 0.5$ which is consistent with a series with stable seasonality. If $|\theta_{12}| < 0.5$ the seasonality is generally evolving and the algorithm encounters more difficulty in seasonal break detection. A similar simulation was conducted using a critical value of 3.2 which is more likely to be used when there is a suggestion of a seasonal break at a specific point. In this case, the results showed that the number of identified detections increased. The case where the model parameters were not passed to X12-SEATS and had to be estimated was also considered. Further investigation will involve the definition of an identified seasonal break which may be different depending on the context of the series, assessment of alternative approaches to seasonal break detection such as the use of model based methods, wavelets, or a multivariate approach using related time series.

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RÉSUMÉ

Une série chronologique d'évaluations originales contient beaucoup d'influences. Des évaluations corrigées des variations saisonniéres peuvent être dérivées des évaluations originales en estimant et en enlevant les effets reliés par calendrier systématique, connus sous le nom de facteurs saisonniers. Le caractère saisonnier qui évolue lentement avec le temps peut être en juste proportion capturé par le procédé saisonnier d'évaluation de facteur. Cependant, parfois les facteurs saisonniers éprouvent les changements brusques il peut être difficiles détecter qu'et peuvent mener aux facteurs saisonniers de qualité inférieure et aux évaluations corrigées des variations saisonniéres. Cet article emploie une étude de simulation pour évaluer l'efficacité des approches courantes à détecter des changements des modèles saisonniers.