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Seasonal adjustment with and without revisions: A comparison of X-13ARIMA-SEATS and CAMPLET

CAMA Working Paper 25/2015
July 2015

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Keywords

seasonal adjustment, real-time, seasonal pattern, simulations, employment, operational income, real GDP

JEL Classification

C22; E24; E32; E37

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*We would like to thank Pim Ouwehand for computational assistance and discussion, Dean Croushore and Jan De Gooijer for helpful suggestions, and participants at the Conference in Honour of Denise R. Osborn, Manchester, April 2014, in particular Farshid Vahid, a seminar at KOF Zurich, June 2014, the International Seminar of Forecasting, Rotterdam, June 2014, the 8th International Conference on Computational and Financial Econometrics (CFE 2014), University of Pisa, Italy, December 2014, and the 13th Conjunctuurdag, February 2015, The Hague for helpful comments.

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Keywords: seasonal adjustment, real-time, seasonal pattern, simulations, employment, operational income, real GDP

Seasonal adjustment is extraordinarily consequential

... we should think very carefully about how seasonal adjustment is done.

(Wright 2013, p65)

1 Introduction

Macroeconomic time series are typically seasonally adjusted before being used in economic and econometric analyses. Several procedures are in use, varying from the Census X-11 family (U.S. Census Bureau, Bank of Canada; for a brief overview see Monsell, 2009) to TRAMO/SEATS[1] and STAMP (Andrew Harvey and collaborators; `http://stamp-software.com/`). Recently, the two most popular methods, Census X-12-ARIMA and Tramo-Seats, merged into X-13ARIMA-SEATS, to become the industry standard. This paper compares X-13ARIMA-SEATS to CAMPLET[2], a new—but at the same time old—competitor, especially focusing on changes in seasonal pattern and the feature that the former method results in revisions when new observations become available while the latter does not.

Seasonality, which Hylleberg (1986, p. 23) defines as the systematic, although not necessarily regular or unchanging, intrayear movement that is caused by climatic changes, timing of religious festivals, business practices, and expectations, is often considered a nuisance in economic modeling. Consequently, a whole industry has come into existence that is devoted to seasonal adjustment. The U.S. Census Bureau Basic Seasonal Adjustment Glossary describes seasonal adjustment as 'the estimation of the seasonal component and, when applicable, also trading day and moving holiday effects, followed by their removal from the time series. The goal is usually to produce series whose movements are easier to

[1]Bank of Spain: `http://www.bde.es/bde/en/secciones/servicios/Profesionales/Programas_estadi/Notas_introduct_3638497004e2e21.html`

[2]CAMPLET is an acronym of its tuning parameters, as will become clear in Section 2.

analyze over consecutive time intervals and to compare to the movements of other series in order to detect co-movements.'

Underlying all seasonal adjustment methods is the decomposition of an observed series into non-seasonal or seasonally adjusted and seasonal components, after some pretreatment to adjust for outliers and trading-day and holiday effects. The aim is to extract the unobserved components from the observed series.

The approach adopted in the Census X-11 family is based upon the idea that large seasonal movements can obscure other movements of importance and that it is easier to see related movements in different series after seasonal adjustment. Consequently, the method produces seasonal effects that are relatively stable in terms of annual timing, within the same month or quarter, direction and magnitude (Monsell 2009). Trend-cycle and seasonal are extracted using sequential symmetric moving average (MA) filters and recently ARIMA models, with forecasts and backcasts to deal with the beginning and the end of the series.

One consequence of using MA filters and ARIMA models is that past values of the unobserved components change when new observations become available, thus causing revisions in real-time data. The current practice of changing seasonal factors only once a year implies the existence of annual revisions in vintages of time series, going back some three years; see, e.g., Croushore (2011).[3] Below we shall see however that these revisions are small for the series we investigated, U.S. non-farm payroll employment, especially when the seasonal factors are updated every period and for some observations also for real GDP in the Netherlands.

Recently, the view that seasonals must be relatively stable was challenged. In the aftermath of the 2008 recession the question was raised whether seasonal drift occurred, i.e. whether the 2008 recession had affected seasonals?; see, e.g., Bialik (2012), Kornfeld (2012), and Nomura (2012). This question has become especially relevant since seasonals

[3] In this paper we will not deal with the interesting philosophical question whether information that comes available at some future date can have a bearing on the seasonal pattern of the past—and modeling consequences. We also abstract from costs involved in revisions due to seasonal adjustment, both for data producers and users.

and seasonally adjusted values have been changed after the fact, which has led to diverging views on the current economic situation based on 'raw' and seasonally adjusted data.

Various responses can be observed. Lytras and Bell (2013) of the Census Bureau propose recession adjustments in the standard methodology using several *interventions*: outliers, ramps, different trend estimations. They find that the effects of the preadjustments on the seasonal adjustments are small. Tiller and Evans (2014) conclude that the standard methodology is reasonably robust to recession effects. Wright (2013) recommends outlier-robust filters to constrain the seasonal factors to vary less over time than the default filters used by U.S. statistical agencies. Swann (2011) takes the opposite route by advocating to look for changes in seasonal pattern: in particular to review series for degree of change, ad hoc approaches to capture seasonal patterns (shorten series; shorter MAs) or direct estimation of seasonals. As will be shown below, CAMPLET fits in the latter category, by explicitly allowing for changes in seasonal patterns if outliers persist.

The remainder of this paper is structured as follows. In Section 2, we provide some background information about the two methods. That is, we describe X-13ARIMA-SEATS briefly, and CAMPLET in more detail. In Section 3 we evaluate the outcomes of both methods in a controlled simulation framework using a variety of processes. In Section 4, we illustrate the differences between the two methods by analysing three time series: U.S. non-farm employment, operational income of Ahold, an international retailer, and real GDP in the Netherlands. Section 5 concludes.

2 Some background

To compare the seasonal adjustment methods we adopt the general decomposition of Ghysels and Osborne (2001, Equation (4.2)). An observed time series y_t is decomposed into a trend-cycle y_t^{tc}, seasonal y_t^{s}, irregular y_t^{i}, augmented by deterministic effects due to the length of months and the number of trading days y_t^{td} and holidays y_t^{h}. The additive version of the decomposition yields

$$y_t = y_t^{\mathrm{tc}} + y_t^{\mathrm{s}} + y_t^{\mathrm{td}} + y_t^{\mathrm{h}} + y_t^{\mathrm{i}}. \tag{1}$$

Basically, X-13ARIMA-SEATS and CAMPLET differ in their treatment of the deterministic effects and in the way the non-seasonals and seasonals are obtained.

X-13ARIMA-SEATS

The X-13ARIMA-SEATS seasonal adjustment consists of two steps. In the pretreatment or first step, the series is extended backwards and forwards using a regression model with ARIMA residuals, commonly referred to as a regARIMA model, while at the same time adjusting for outliers and trading-day and holiday effects. The second step, seasonal adjustment, consists of a combination of MA filters (the Census X-11 program) or ARIMA model-based adjustment from SEATS.

A detailed description of the method is beyond the scope of this paper. The Census X-11 program is described in, for instance, Ghysels and Osborn (2001, Chapter 4), whereas the appendix of Wright (2013) presents the X-12-ARIMA algorithm. Maravall (2008) presents the methodology behind the program SEATS (Signal Extraction in ARIMA Time Series). For further details see the X-13ARIMA-SEATS Seasonal Adjustment Program homepage at the U.S. Department of Commerce Census Bureau `http://www.census.gov/srd/www/x13as/`.[4]

CAMPLET

The CAMPLET program does not require pretreatment of a time series to adjust for outliers, trading day and holiday effects. In addition forecasting or backcasting is not necessary either, since the method does neither employ (symmetric) MA filters nor ARIMA

[4]The program can also be downloaded from this page. The R-package seasonal is an easy-to-use and (almost) full-featured interface to X-13ARIMA-SEATS. In the simulations below in Section 3 we use JDemetra+ (Grudkowska, 2015) and the Eviews implementation in the illustrations in Section 4.

models to do seasonal adjustment; only available information is used. The package including documentation and examples can be downloaded from `http://www.camplet.net`.

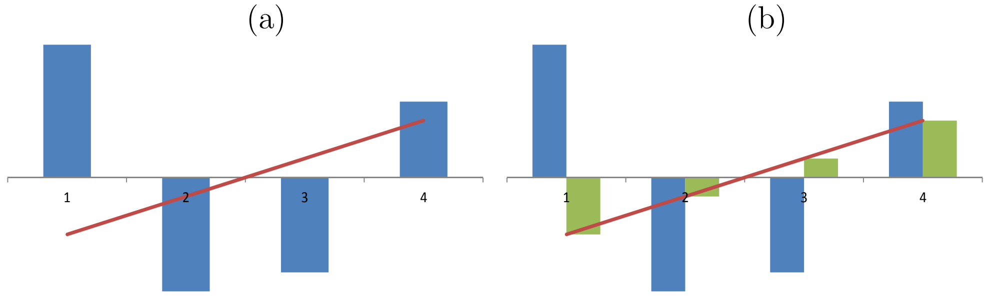
Seasonal factors

In contrast with X-13ARIMA-SEATS, the focus is on the seasonal: in each period a full set of (latent) seasonal factors is assumed to exist, which is updated when a new observation becomes available. The seasonal factor updating procedure is illustrated in Figures 1(a) and (b), assuming quarterly data. Each period t has a full set of seasonal factors, which add up to zero: $S_{t,1}+\cdots+S_{t,4}=0$. If the gradient, say g_t, of the non-seasonal component is assumed to be zero and a change (update) of a (say) is required in g_{t+1} to fit the new observation, then all seasonal factors change according to their distance from the center: $S_{t+1,1}=S_{t,1}+1.5a$, $S_{t+1,2}=S_{t,2}+0.5a$, $S_{t+1,3}=S_{t,3}-0.5a$, and $S_{t+1,4}=S_{t,4}-1.5a$. Generalizing for data with periodic frequency p, the updated seasonal factors become

$$S_{t+1,1+j}=S_{t,1+j}-[(j+1)-(p+1)/2]\times a, \qquad j=0,\ldots,p-1.$$

Note that $S_{\cdot,1+p}\equiv S_{\cdot,1}, S_{\cdot,2+p}\equiv S_{\cdot,2},\ldots,S_{\cdot,p+p}\equiv S_{\cdot,p}$.

Figure 1: (a) Seasonal factors (blue) before an adjustment a, and (b) updated seasonal factors (blue plus green) after an adjustment a is required.



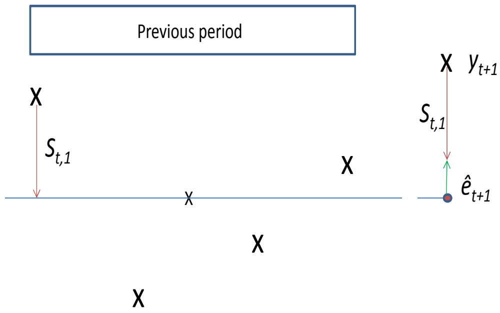
Key feature

Suppose we have a series of observations on a variable y with frequency p, i.e. p observations per year. At time t we know: the observed value y_t, the seasonally adjusted value

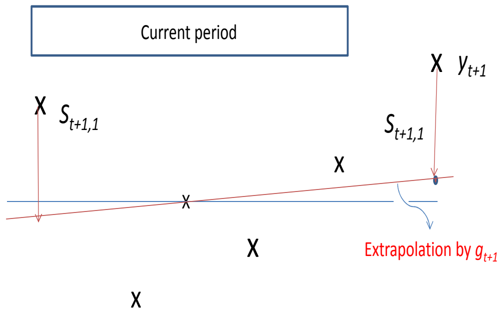
y_t^{SA}, the direction y_t^{SA} is going g_t, the so-called g-line, the seasonal factors $S_{t,1}, S_{t,2}, \ldots, S_{t,p}$ and the decomposition $y_t = y_t^{\mathrm{SA}} + S_t$, with $S_t = S_{t,i}$, where $i = 1 + [t-1] \mod p$. Given this setup, Figures 2(a) and (b) illustrate the key feature underlying the CAMPLET method to obtain the seasonally adjusted value y_{t+1}^{SA} using quarterly data assuming $g_t = 0$.

Figure 2: Illustration of the intuition of the CAMPLET method for seasonal adjustment.

(a)



(b)



Specifically, the left part of Figures 2(a) shows a hypothetical situation in the previous time period. If at time $t + 1$ a new observation y_{t+1} becomes available, the seasonal component $S_{t,1}$ is applied to obtain the provisional adjustment and y_t^{SA} is extrapolated with the g-line $g_t = 0$. The difference between the extrapolation and the provisional adjustment value is denoted by $\hat{e}_{t+1}$. Now in the current period (Figures 2(b)) the direction of y_t^{SA} changes: $g_{t+1} = g_t + \hat{e}_{t+1}/\ell$, where ℓ is equal to the **C**ommon **A**djustment (CA) length. For quarterly data we set $\ell = 6$; for monthly data $\ell = 15$. Changing the direction of y_t^{SA} leads to changes of the seasonal pattern, as shown above.

The above approach can be described more formally by the following steps.

1. Determine the seasonal factor that applies to period $t + 1$: $i = 1 + [(t + 1) - 1] \bmod p$.

2. Calculate what y_{t+1} would have been with extrapolated seasonal adjusted value and unchanged seasonal factor: $\hat{y}_{t+1} = y_t^{\mathrm{SA}} + g_t + S_{t,i}$.

3. Take the difference with respect to y_{t+1}: $\hat{e}_{t+1} = y_{t+1} - \hat{y}_{t+1}$.

4. The difference $\hat{e}_{t+1}$ is assumed to lead to a change in g_{t+1}, i.e., $g_{t+1} = g_t + \hat{e}_{t+1}/\ell$.

5. Consequently, **all** seasonal factors change according to:
   $S_{t+1,i+j} = S_{t,i+j} - [(j + 1) - (p + 1)/2]\, \hat{e}_{t+1}/\ell$, for $j = 0, \ldots, p - 1$.[5]

6. Finally, calculate the seasonally adjusted value y_{t+1}^{SA} as $y_{t+1}^{\mathrm{SA}} = y_{t+1} - S_{t+1} \equiv y_{t+1} - S_{t+1,i}$.

Outliers and change in seasonal pattern

Let $\bar{y}_{t+1} = \frac{1}{p} \sum_{i=1}^{p} |y_{t+1-i}|$ be the annual average of absolute values of the preceding p observations. An outlier is defined to occur if $100(\hat{e}_{t+1}/\bar{y}_{t+1}) > \mathrm{LE}$, where LE (**L**imit to **E**rror) is one of the tuning parameters of CAMPLET. We define that an outlier results in an increase in ℓ

$$\ell^{\mathrm{new}} = \ell + p \left(100 \left(\frac{\hat{e}_{t+1}}{\bar{y}_{t+1}} \right) - \mathrm{LE} \right) \times M,$$

where M is the tuning parameter **M**ultiplier, which takes as default value $M = 50$. For the next observation ℓ is reset to the Common Adjustment length value.

If the outlier persists, i.e. also occurs one year later, we assume that the seasonal pattern has changed. Instead of lengthening ℓ to put an upper limit to the change in the seasonals as in the outlier case, we now set ℓ to one year. Hence, the second time an outlier is detected, the seasonal of this observation becomes larger, while the other seasonals change correspondingly.

The tuning parameters **T**imes, which denotes the number of times an outlier returns before a change in seasonal pattern is assumed to have happened, and **P**attern, which

[5]Note that the seasonal factors are updated by a time-dependent parameter rather than by a fixed parameter, as with, for instance, the additive seasonal Holt-Winters method.

controls how fast the seasonal pattern is allowed to change, allow flexibility in dealing with outliers and changes in seasonal pattern.

Table 1 lists the default settings of CAMPLET.

Table 1: Defaul settings of CAMPLET.

Frequency of series	Quarterly	Monthly
Common **A**djustment (periods)	6	15
Multiplier	50	50
Pattern (periods)	4	12
Limit to **E**rror (%)	6	8
Times	1	1

Automatic parameter adjustment for volatile series

Volatile series contain frequent but unsystematic fluctuations, that are often much larger than seasonal fluctuations. Such series may occur, for example, in company interim results such as net profit and earnings per share. Strong and unsystematic fluctuations are recognized as outliers whose impact on the seasonal pattern and on the gradient of the g-line is reduced by increasing the Common Adjustment length of the series. If outliers occur frequently, a simultaneous change in the seasonal pattern or in the overall direction of the series' development may not be picked up. This is the more so, because the g-line is extended to the level of the new observation, seasonally adjusted but including the aberrant value. From there the g-line is extrapolated. This extrapolation will be way off if the next observation is in line with the original series' path but considered an outlier. One aberrant observation will therefore result in two outliers.

The objective of automatic parameter resetting is to reduce the number of outliers. To this end parameter Limit to Error (LE), the criterion for a new observation being aberrant or not, is raised by 5 percentage points whenever during the adjustment run the number of outliers identified is higher than 50% of the number of observations so far adjusted. This goes on until LE surpasses a threshold of 30%. For a quarterly series the default value of LE is 6%, which can be incremented in 5 steps of 5 percentage points each to a maximum of 31%. To mitigate the impact of fluctuations that are no longer regarded as aberrant, the Common Adjustment parameter (CA) is incremented at every step by $\frac{p}{2}$.

If parameter LE has reached its maximum value and outliers continue to occur at a rate of 50% or more of the number of observations adjusted, parameter Times (T), which denotes the number of times an outlier returns before a change in seasonal pattern is assumed to have happened, is increased from 1 to to 2, to ensure that frequent outliers do not cause too many shifts of the seasonal pattern. At the same time parameter Multiplier (M), which determines the impact of an increase of the Common Adjustment of the series, will be reduced from 50 to 25 to enhance the outliers' impact on the adjustment procedure. Whenever the proportion of outliers falls below 50% these steps are retraced in inverse order.

Initialisation

Starting values are required for y_0^{SA}, g_0, and the seasonal factors $S_{0,1}, \ldots, S_{0,p}$. These can be obtained from as short as one full year of observations—if no outliers are present—for example as follows:

- $y_0^{\mathrm{SA}} = \bar{y}^{\mathrm{SA}} = \bar{y}$, assuming the seasonal factors add up to zero over this period;
- assuming that y_i^{SA} does not change during a year, we have $g_0 = 0$, and $S_{0,i} = y_i - y_0^{\mathrm{SA}},\ i = 1, \ldots, p$.

If these first period values include an outlier, this aberrant value also figures in the initial seasonal pattern. To avoid this situation the adjustment procedure is applied for the first three years of the series, then the resulting g-line is extrapolated to the first observation of the series and the procedure is repeated for the full series, now with a more appropriate seasonal pattern.

3 Simulations

We evaluate both seasonal adjustment methods with controlled simulations using a variety of Data Generating Processes (DGPs).[6] For a general discussion of criteria to judge the quality of seasonal adjustment procedures see e.g. Bell and Hillmer (1984). Fok, Franses and Paap (2006) apply a number of diagnostic and specification tests concerning the presence of seasonal patterns before and after seasonal adjustment, using several DGPs that are observed in practice. We simulate 24 DGPs based on a stylized representation of the trend-cycle-seasonal decomposition (1) introduced in Section 2 above and compare the simulated non-seasonal observations and the seasonal adjusted values using standard accuracy measures, as described in e.g. Armstrong (1985, pp. 346–356) or Kennedy (2008, pp. 334–335).

Design

Our starting point is the Basic Structural Model (Harvey, 1990), in state space form

$$
\begin{aligned}
y_t &= \mu_t + \gamma_t + \sum_{i=1}^{k} \beta_i d_{it} + \varepsilon_t, & \varepsilon_t &\sim \text{NID}(0, \sigma_\varepsilon^2) \\
\mu_t &= \mu_{t-1} + \eta_t, & \eta_t &\sim \text{NID}(0, \sigma_\eta^2) \\
\gamma_t &= -\gamma_{t-1} - \gamma_{t-2} - \gamma_{t-3} + \omega_t, & \omega_t &\sim \text{NID}(0, \sigma_\omega^2),
\end{aligned}
$$

where y_t is the simulated series, μ_t the level, γ_t are seasonal factors, k is the number of outliers, the size of outlier i is equal to β_i, while d_{it} defines when the outlier occurs. For additive outliers d_{it} equals zero except for the period of the outlier, where d_{it} is equal to one. For a level shift, the value of d_{it} is zero up to the period of the shift and zero thereafter.

For each DGP we generate 1000 series for 35 years of quarterly observations. Observations for the first 10 years are discarded to reduce the impact of starting values. Hence, our simulated series consist of 100 observations.

[6]This section draws upon Ouwehand (2015).

We make the following parameter choices:

- the starting value of the level, μ_0, equals zero;
- starting values for the seasonal factors for $t = 1, \ldots, 3$ are drawn from a uniform distribution $U[-20,\ 20]$, while $\gamma_4 = -\gamma_1 - \gamma_2 - \gamma_3$;
- σ_ε gets a low noise of value 3 and a high noise value of 7;
- σ_η gets a value of 1 and a value of 10 to mimic series with slow and strong development in the level of the series, respectively;
- σ_ω gets the value 0 for a constant seasonal pattern and the value of 2 for a varying seasonal pattern; in addition we simulate seasonal breaks in an arbitrary period between the 10th and the 90th observation for series with a constant seasonal pattern by generating a new random seasonal pattern that begins from a period that is drawn from a uniform distribution between the 10th and the 90th observations.

When adding outliers,

- the series are not simulated again to be able to analyse the pure effect of outliers;
- we simulate one level shift in a random chosen period between the 10th and the 90th observation, and five single period outliers in random periods between observation 0 and 100;
- the size of the additive outliers is drawn from a uniform distribution $\pm(2\sigma_\varepsilon, 5\sigma_\varepsilon)$; a level shift is treated as an extraordinary event and drawn from $\pm(4\sigma_\varepsilon, 5\sigma_\varepsilon)$.

By this we obtain 12 DGPs without outliers and 12 DGPs with outliers. Table 2 summarizes the simulation settings.

Quality measures

Let $\{y_t\}$, $t = 1, \ldots, T$ be a simulated series with non-seasonal component $y_t^{\text{ns}} \equiv y_t - y_t^{\text{s}}$ and y_t^{sa} the seasonal adjusted value. We calculate three quality measures:

Table 2: Simulation settings.

DGP	σ_ε	σ_η	σ_ω	season break	outliers
1	3	1	0	no	no
2	7	1	0	no	no
3	3	1	2	no	no
4	7	1	2	no	no
5	3	1	0	yes	no
6	7	1	0	yes	no
7	3	10	0	no	no
8	7	10	0	no	no
9	3	10	2	no	no
10	7	10	2	no	no
11	3	10	0	yes	no
12	7	10	0	yes	no
13	3	1	0	no	yes
14	7	1	0	no	yes
15	3	1	2	no	yes
16	7	1	2	no	yes
17	3	1	0	yes	yes
18	7	1	0	yes	yes
19	3	10	0	no	yes
20	7	10	0	no	yes
21	3	10	2	no	yes
22	7	10	2	no	yes
23	3	10	0	no	yes
24	7	10	0	no	yes

1. Root Mean Squared Error: $RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{T}(y_t^{\text{sa}} - y_t^{\text{ns}})^2}$;
2. Mean Absolute Percentage Error: $MAPE = \frac{1}{N}\sum_{t=1}^{T}\left|\frac{y_t^{\text{sa}} - y_t^{\text{ns}}}{y_t^{\text{ns}}}\right| \times 100\%$;
3. Mean Error: $ME = \frac{1}{N}\sum_{t=1}^{T}(y_t^{\text{sa}} - y_t^{\text{ns}})$.

We calculate the quality measures for three different horizons: (i) all observations: $t = 1, \ldots, 100; N = 100$, (ii) the last four observations: $t = 97, \ldots, 100; N = 4$ and (iii) the final observation: $t = 100 : N = 1$. Finally we compute averages and standard deviations over the 1000 simulated series for each DGP, where the mean errors (ME) of the simulated series are taken in absolute values.

Implementation in seasonal adjustment packages

Whereas CAMPLET works automatically and does not require additional parameter settings from the ones listed in Table 1, working with X-13ARIMA-SEATS is more involved. We use default settings as much as possible in the pretreatment step (type of decomposition; ARIMA model; no working day patterns; determination of outliers) and in the seasonal adjustment step (length of season and trend-cycle filter).

Results

The simulation outcomes are listed in full detail in the Appendix. Here we summarize the simulations in Table 3, which shows the fraction of the 1000 series for which the CAMPLET quality measures are better than the X-13ARIMA-SEATS measures. A first conclusion is that X-13ARIMA-SEATS generally performs better than CAMPLET in terms of all quality measures distinguished and all horizons, but that the relative performance of CAMPLET improves for shorter horizons. The exception is ME outcomes for the 100-period horizon. For the 100-period horizon CAMPLET ME outcomes are better than X-13ARIMA-SEATS ME outcomes in more that 50% of the 1000 simulations if the DGP has a change in the seasonal pattern or a seasonal break. Both conclusions carry over to the DGPs with outliers (DGP13–DGP24).

The conclusion that RMSE and MAPE outcomes favor X-13ARIMA-SEATS over CAMPLET for all horizons is in line with our expectations. These quality measures penalize strong deviations in single periods. By construction X-13ARIMA-SEATS 'smoothens' the seasonal pattern over time which also results in smooth adjusted values; CAMPLET does not share this property. Moreover changes in seasonal patterns and seasonal breaks cannot occur in the first ten and the last ten observations and thus do not affect the CAMPLET outcomes for the last four observations and the final observation positively compared to the X-13ARIMA-SEATS outcomes. Nevertheless CAMPLET quality outcomes becomes relatively better for the shorter horizons.

Table 3: Relative quality measures.

	100 observations			last 4 observations			final observation		
DGP	RMSE	MAPE	ME	RMSE	MAPE	ME	RMSE	MAPE	ME
1	0.000	0.001	0.371	0.180	0.208	0.112	0.360	0.360	0.360
2	0.003	0.002	0.362	0.186	0.200	0.133	0.352	0.352	0.352
3	0.004	0.004	0.497	0.256	0.268	0.388	0.399	0.399	0.399
4	0.003	0.005	0.453	0.288	0.298	0.327	0.405	0.405	0.405
5	0.001	0.008	0.663	0.324	0.326	0.152	0.435	0.435	0.435
6	0.004	0.005	0.607	0.280	0.299	0.160	0.393	0.393	0.393
7	0.011	0.046	0.254	0.199	0.216	0.067	0.345	0.345	0.345
8	0.011	0.056	0.268	0.215	0.219	0.075	0.348	0.348	0.348
9	0.003	0.031	0.424	0.250	0.279	0.247	0.401	0.401	0.401
10	0.009	0.045	0.363	0.277	0.307	0.255	0.394	0.394	0.394
11	0.002	0.046	0.596	0.268	0.281	0.075	0.402	0.402	0.402
12	0.006	0.057	0.534	0.304	0.309	0.094	0.404	0.404	0.404
13	0.010	0.005	0.386	0.179	0.195	0.108	0.355	0.355	0.355
14	0.013	0.009	0.333	0.207	0.222	0.124	0.363	0.363	0.363
15	0.008	0.009	0.495	0.281	0.286	0.373	0.410	0.410	0.410
16	0.001	0.000	0.412	0.019	0.019	0.519	0.100	0.100	0.100
17	0.004	0.008	0.658	0.323	0.321	0.158	0.424	0.424	0.424
18	0.003	0.010	0.586	0.301	0.300	0.143	0.400	0.400	0.400
19	0.009	0.049	0.243	0.197	0.203	0.055	0.338	0.338	0.338
20	0.017	0.063	0.267	0.231	0.239	0.089	0.393	0.393	0.393
21	0.003	0.031	0.418	0.253	0.277	0.258	0.398	0.398	0.398
22	0.008	0.057	0.385	0.296	0.306	0.258	0.412	0.412	0.412
23	0.001	0.039	0.595	0.308	0.313	0.077	0.404	0.404	0.404
24	0.008	0.053	0.530	0.297	0.290	0.099	0.415	0.415	0.415

Notes. For all 1000 series we determine per series whether CAMPLET produces a smaller value of the quality measure than X-13ARIMA-SEATS. The numbers in the table indicate the fraction of the 1000 series for which this the case.

4 Illustration

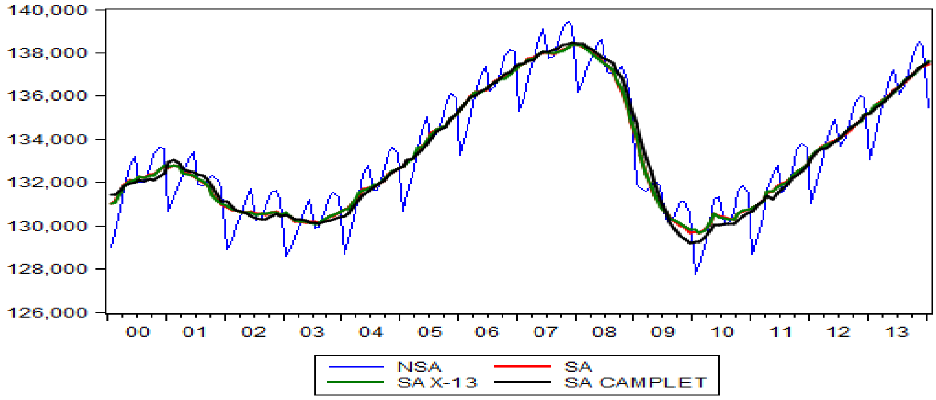
U.S. non-farm payroll employment

There are not many series that are available real-time, both in seasonally adjusted and non-seasonally adjusted form. One of the exceptions is non-farm payroll employment. Wright (2013) looks at this series too. The source of the series is Bureau of Labor Statistics / Alfred, Federal Reserve Bank of St. Louis. Seasonally adjusted values are only available for the 2014M2 vintage, the latest vintage when we downloaded the data, and cover the 1939M1–2014M1 period. We retrieved raw data, i.e. non-seasonally adjusted figures, for the vintages from 2008M9 up to and including 2014M2; all vintages start in 1939M1. Our non-farm payroll employment data trapezoid consists of initial revisions with changes in the most recent observations, annual (seasonal) revisions in February due to updated seasonal factors and the confrontation of quarterly with annual information resulting in changes up to three years back, and historical, comprehensive or benchmark revisions in February 2013 and February 2014, possibly related to changes in e.g. statistical methodology, which affect the whole vintage. Generally, revisions in the employment series are small.

Figure 3 shows the 2014M2 vintage of seasonally unadjusted non-farm payroll employment data from 2000M1 onwards, together with the published seasonally adjusted figures and the seasonally adjusted values obtained from the Census X-13 routine in EViews[7] and CAMPLET with the default settings of Table 1. The first finding is that the differences between all seasonal adjusted series are quite small. CAMPLET seasonally adjusted figures are very close to the official SA figures and the EViews X-13 outcomes. A second finding is that the seasonally adjusted figures of CAMPLET are slightly lower towards the end of 2009 than the other two SA series. Apparently, the trough in the raw data enters into the SA series of CAMPLET instead of in the seasonal.

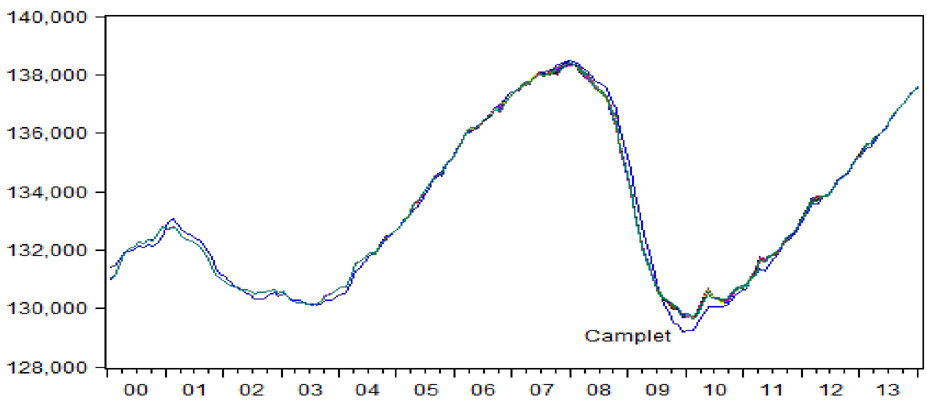
[7] In all computations we use the Auto (None / Log) transform, no ARIMA model and default X-13 settings for seasonal adjustment.

Figure 3: Latest vintage U.S. non-farm payroll employment.



To investigate the impact of new information becoming available, we do a quasi real-time analysis and compute seasonally adjusted figures with X-13ARIMA-SEATS and CAMPLET for the latest vintage, starting from the 2000M1-2008M8 sample and adding one observation at the time. Figure 4 shows the outcomes. CAMPLET outcomes do not change when new observations become available, in contrast with X-13ARIMA-SEATS figures. However, the application of the X-13ARIMA-SEATS approach does not yield large revisions in (quasi-) real-time, if seasonal factors are updated for every observation. This point has been noted by, e.g., Wallis (1982). Because the quasi real-time outcomes are so close and revisions due to Census-type of seasonal adjustment cause data revisions as noted in the Introduction, we have not yet done a real-time analysis using all vintages of non-farm payroll employment.

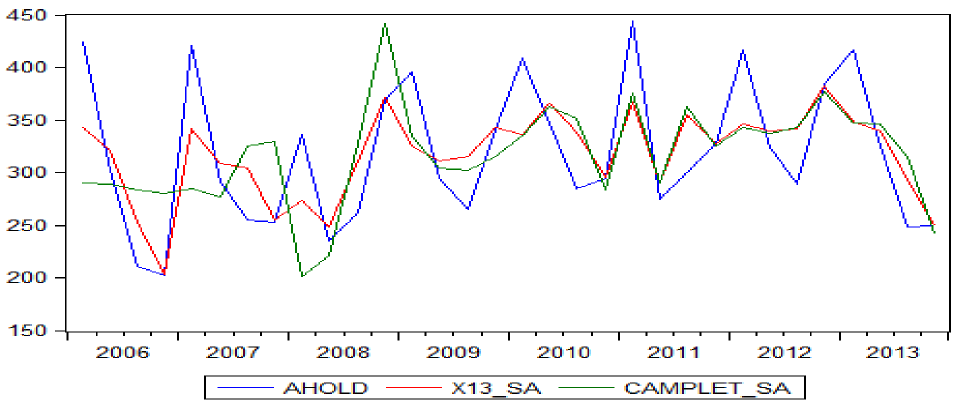
Figure 4: Quasi real-time analysis.



Ahold

The U.S. non-farm payroll employment series has a fairly constant seasonal pattern with small seasonals. Our second illustration is operating income of Ahold, an international retailer based in Zaandam. Figure 5 reveals that this series, with quarterly observations from 2006Q1 up to and including 2013Q4 is much more volatile, with a stronger seasonal pattern. Again, CAMPLET seasonally adjusted figures are fairly close to the X-13ARIMA-SEATS outcomes, but there are striking differences in 2006 through 2008.

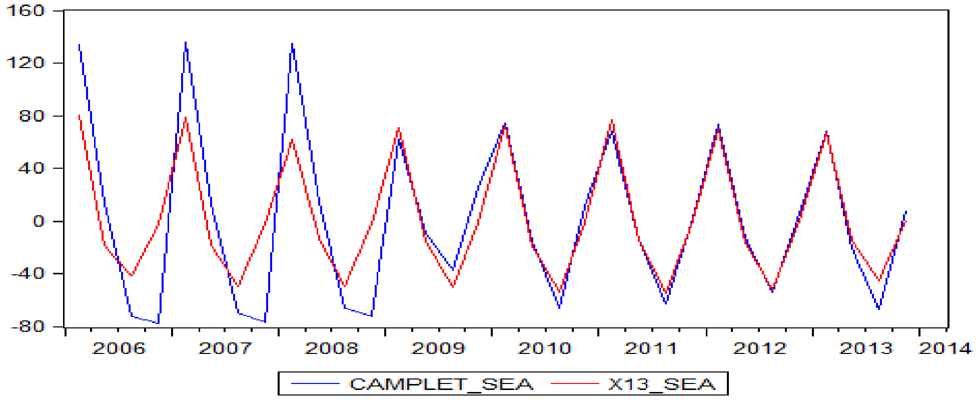
Figure 5: Ahold Operating income. Source: Ahold Quarterly Bulletin (various issues).



In the beginning of 2008 Ahold announced a change in accounting policies: "As of 2008, Ahold has applied IFRS 8 "Operating segments". IFRS 8 introduces new disclosure requirements with respect to segment information. This adoption of IFRS 8 did not have an impact on Ahold's segment structure, consolidated financial results or position; however, segment results no longer include intercompany royalties." See Ahold Quarterly Bulletin Q1 2008. Consequently, operating income decreased from €421 million in 2007Q1 to €336 million in 2008Q1.

Figure 6 shows the seasonal patterns as identified by CAMPLET and X-13ARIMA-SEATS. Whereas the latter finds a constant seasonal pattern throughout the sample, CAMPLET picks up a change! Future research in the form of a (quasi-) real time analysis will reveal how the seasonal pattern of X-13ARIMA-SEATS evolves over time.

Figure 6: Ahold operating income: Seasonal pattern.



Real GDP in the Netherlands

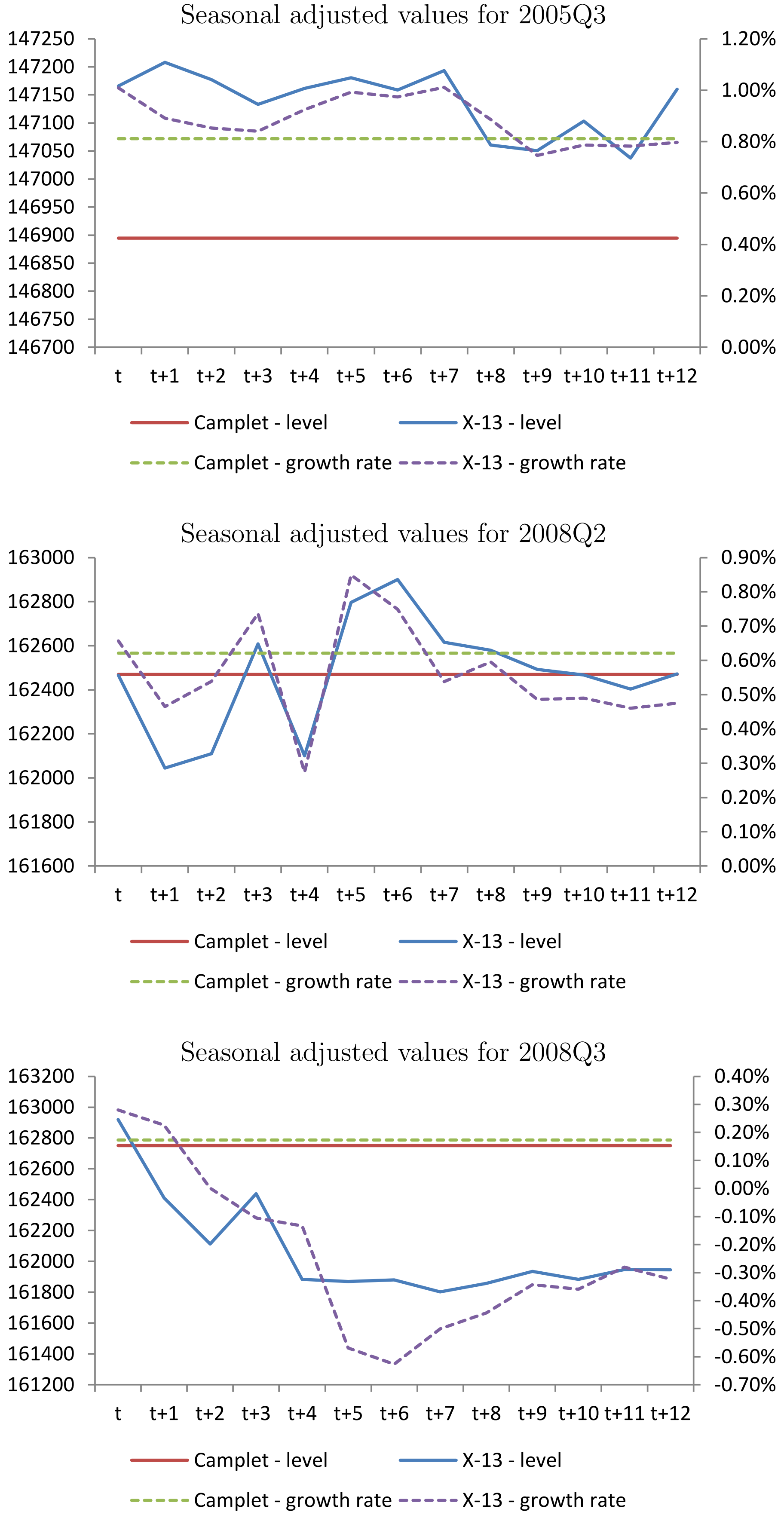
To investigate whether CAMPLET seasonal adjusted values are similar to first and subsequently revised X-13ARIMA-SEATS outcomes, we do a quasi real-time analysis using the 2014Q3 vintage of real GDP in the Netherlands. We calculate seasonal adjusted values of levels and corresponding growth rates for all observations between 2005Q1 and 2011Q3, allowing X13-ARIMA-SEATS outcomes to be revised up to three years backwards.[8]

Figure 7 shows successive seasonal adjusted values of X-13ARIMA-SEATS (abbreviated as X-13) and CAMPLET both in levels (left axis) and growth rates (right axis) for three quarters: 2005Q2, 2008Q2 and 2008Q3. The outcomes are representative for the other quarters as well. Whereas X-13ARIMA-SEATS seasonal adjusted values are subject to revision when observations are added to the series, CAMPLET outcomes stay the same.

In some cases the CAMPLET seasonal adjusted value is already close to the final X-13ARIMA-SEATS outcome (middle panel) of both the level of real GDP in the Netherlands and its growth rate; for other quarters the X-13ARIMA-SEATS outcomes deviate from the CAMPLET ones, like in the top and bottom panel. So, CAMPLET predicts X-13ARIMA-SEATS outcomes for some observations, but not for all.

[8]The settings of X13-ARIMA-SEATS are the same as in Section 3, but here we also detect working day patterns.

Figure 7: Real GDP in the Netherlands (levels: left axis; growth rates: right axis) .



5 Conclusion

Seasonal adjustment can be defined as purging any variation in economic data that is predictable using the calendar alone. It is an ongoing debate whether seasonals should be reasonably stable or external shocks can affect the seasonal pattern. And whether seasonal adjustment should lead to revisions has not been questioned often before either.

This paper compared the seasonal adjustment methods X-13ARIMA-SEATS and CAMPLET focusing on changes in seasonal pattern and the feature that the former leads to revisions in seasonally adjusted values after the fact while the latter does not. The simulations revealed that X-13ARIMA-SEATS generally outperforms CAMPLET except for data generating processes with a change in seasonal pattern or a seasonal break. Our illustrations showed that both methods generally produce similar seasonal adjusted figures. In addition, X-13ARIMA-SEATS does not produce large revisions in a quasi real-time analysis in U.S. non-farm payroll employment, but CAMPLET does not show any revisions at all. CAMPLET non-seasonals fall deeper in 2009 than X-13ARIMA-SEATS seasonal adjusted figures. Our second illustration involving operating income of Ahold shows that X-13ARIMA-SEATS does not pick up changes in seasonal patterns, in contrast to CAMPLET. Our third illustration revealed in a quasi real-time analysis of real GDP in the Netherlands that CAMPLET predicted X-13ARIMA-SEATS seasonal adjusted values for some observations, but not for all.

Over the years, seasonal adjustment has become standard in empirical macroeconomic research and many other fields where periodic time series are being used and analysed. We wholeheartedly endorse the three changes to the practice of seasonal adjustment that Wright (2013, p101) proposes: (i) for statistical agencies to always provide unadjusted data, (ii) for these agencies to publish a full history of revised seasonal factors with every data release (not just at the time of annual benchmark revisions), and (iii) to make the seasonal adjustment process entirely replicable by outside researchers. However in our view this may not be sufficient. We hope that our paper helps in challenging the self-evidence of seasonal adjustment leading to revisions when new observations become available.

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A Detailed simulation outcomes

Table A.1: CAMPLET quality measures.

	100 observations			last 4 observations			final observation		
DGP	RMSE	MAPE	ME	RMSE	MAPE	ME	RMSE	MAPE	ME
1	1.61	1.30	0.01	1.46	1.27	0.27	1.26	1.28	1.26
2	3.92	3.17	0.04	3.61	3.16	0.63	3.11	3.18	3.11
3	3.13	2.50	0.05*	2.91	2.55	0.56	2.66	2.70	2.66
4	5.07	4.13	0.06*	4.60	4.06	0.84	3.95	4.07	3.95
5	4.29	2.14	0.10*	1.54	1.34	0.29	1.26	1.28	1.26
6	6.07	4.10	0.11*	3.86	3.38	0.62	3.27	3.34	3.27
7	4.08	26.51*	0.05	3.68	9.87	0.77	3.24	6.58	3.24
8	5.33	25.86	0.06	4.75	9.00	0.84	4.28	9.23	4.28
9	5.26	31.37	0.07	4.87	35.70	1.00	4.17	28.33	4.17
10	6.36	80.42	0.08	5.88	22.67	1.01	5.09	29.87	5.09
11	6.15	61.83	0.11*	3.83	65.97	0.84	3.22	9.87	3.22
12	7.19	34.41	0.12*	5.01	28.19	0.95	4.30	29.44	4.30
13	1.98	1.56	0.02	1.70	1.50	0.31	1.44	1.47	1.44
14	4.64	3.97	0.04	4.00	4.08	0.65	3.38	3.96	3.38
15	3.44	2.77	0.05*	3.17	2.81	0.59	2.85	2.94	2.85
16	18.52	17.28	0.08	20.25	20.73	0.41	21.43	25.04	21.43
17	4.49	2.44	0.10*	1.84	1.64	0.35	1.51	1.58	1.51
18	6.77	5.04	0.12*	4.45	4.52	0.69	3.75	4.45	3.75
19	4.28	36.72	0.05	3.82	14.42	0.80	3.30	9.97	3.30
20	5.92	23.99	0.07	5.13	22.75	0.88	4.48	25.72	4.48
21	5.45	37.97	0.07	5.01	74.86	0.98	4.29	12.97	4.29
22	6.98	52.25*	0.08	6.30	21.60	1.09	5.41	19.83	5.41
23	6.31	31.20	0.11*	3.96	11.65	0.85	3.40	12.64	3.40
24	7.76	45.59	0.13*	5.56	16.71	0.98	4.68	17.69	4.68

Note: An asterisk denotes that the CAMPLET measure is smaller than the corresponding X-13ARIMA-SEATS measure of X-13.

Table A.2: X-13ARIMA-SEATS quality measures.

	100 observations			last 4 observations			final observation		
DGP	RMSE	MAPE	ME	RMSE	MAPE	ME	RMSE	MAPE	ME
1	1.05	0.86	0.01	1.07	0.93	0.05	0.98	0.99	0.98
2	2.38	1.96	0.03	2.48	2.19	0.12	2.25	2.31	2.25
3	2.25	1.80	0.05	2.33	2.04	0.40	2.25	2.28	2.25
4	3.33	2.70	0.06	3.69	3.28	0.44	3.25	3.34	3.25
5	1.76	1.20	0.23	1.27	1.11	0.08	1.11	1.13	1.11
6	3.17	2.43	0.21	2.89	2.53	0.15	2.49	2.54	2.49
7	2.39	28.89	0.02	2.47	7.57	0.06	2.34	5.51	2.34
8	3.24	17.19	0.03	3.32	6.98	0.07	3.14	7.18	3.14
9	3.31	21.97	0.06	3.84	20.80	0.40	3.62	21.68	3.62
10	4.04	76.04	0.06	4.69	17.27	0.41	4.18	17.89	4.18
11	3.20	21.77	0.17	2.89	60.34	0.08	2.61	8.53	2.61
12	4.04	22.14	0.15	3.81	20.51	0.09	3.50	22.01	3.50
13	1.19	0.96	0.02	1.16	1.02	0.05	1.04	1.07	1.04
14	2.67	2.34	0.03	2.77	2.82	0.11	2.46	2.95	2.46
15	2.44	1.96	0.06	2.57	2.27	0.41	2.42	2.48	2.42
16	3.69	3.20	0.07	4.09	4.22	0.45	3.51	4.17	3.51
17	2.00	1.37	0.22	1.44	1.29	0.09	1.27	1.31	1.27
18	3.60	2.92	0.20	3.29	3.35	0.14	2.78	3.28	2.78
19	2.52	18.51	0.02	2.59	10.05	0.06	2.42	6.26	2.42
20	3.58	15.21	0.04	3.72	11.01	0.08	3.48	12.62	3.48
21	3.43	30.27	0.06	3.96	36.72	0.40	3.68	11.89	3.68
22	4.40	86.36	0.07	4.96	18.19	0.41	4.41	14.71	4.41
23	3.34	21.10	0.16	3.04	9.14	0.08	2.77	11.37	2.77
24	4.46	32.40	0.16	4.23	14.42	0.10	3.86	17.22	3.86

Table A.3: Standard deviations of CAMPLET quality measures.

	100 observations			last 4 observations			final observation		
DGP	RMSE	MAPE	ME	RMSE	MAPE	ME	RMSE	MAPE	ME
1	0.23*	0.22	0.01	0.63	0.61	0.23	0.98	1.03	0.98
2	0.64	0.63	0.03*	1.61	1.54	0.62	2.45	2.58	2.45
3	0.35	0.39	0.03*	1.28	1.22	0.47	2.15	2.23	2.15
4	0.70	0.70	0.05*	1.99	1.92	0.78	3.11	3.35	3.11
5	1.67	0.53	0.08*	0.71	0.64	0.29	0.99	1.02	0.99
6	1.83	0.95	0.08*	2.22	2.14	0.66	3.13	3.29	3.13
7	0.71	217.96*	0.04	1.74	51.56	0.73	2.66	14.21 *	2.66
8	1.01	127.99	0.05	2.27	24.60	0.90	3.36	37.35	3.36
9	0.77	141.06	0.06	2.00	511.66	0.84	3.26	228.96 *	3.26
10	0.99	1000.29*	0.06	2.45	127.06	0.97	3.91	444.42	3.91
11	1.65	927.83	0.09*	1.94	1367.77	0.83	2.68	40.04	2.68
12	1.81	180.18	0.09*	2.50	221.37	1.03	3.50	324.87	3.50
13	0.36	0.33	0.02*	0.85	0.86	0.29	1.19	1.27	1.19
14	0.91	1.34	0.04*	2.09	2.91	0.69	2.81	3.75	2.81
15	0.43	0.52	0.04*	1.43	1.46	0.50	2.32	2.52	2.32
16	6.78	7.91	0.06*	8.78	13.41	0.32*	16.01	22.37	16.01
17	1.65	0.64	0.08*	1.00	0.94	0.36	1.32	1.42	1.32
18	1.92	1.69	0.09*	2.56	3.67	0.80	3.53	5.50	3.53
19	0.74	447.85	0.04	1.71	136.84	0.75	2.58	57.66	2.58
20	1.17	88.08	0.05*	2.43	303.67	0.95	3.50	482.38	3.50
21	0.81	215.75*	0.05	2.09	1866.69	0.87	3.28	52.08 *	3.28
22	1.20	425.23*	0.06	2.77	84.02	1.08	4.34	175.05	4.34
23	1.66	270.93	0.09*	1.98	46.27	0.82	2.78	82.54	2.78
24	1.90	410.16	0.10*	2.91	56.53 *	1.10	4.26	121.86 *	4.26

Note: An asterisk denotes that the standard deviation of CAMPLET is smaller than the corresponding standard deviation of X-13.

Table A.4: Standard deviations of X-13ARIMA-SEATS quality measures.

	100 observations			last 4 observations			final observation		
DGP	RMSE	MAPE	ME	RMSE	MAPE	ME	RMSE	MAPE	ME
1	0.23	0.21	0.01	0.49	0.45	0.07	0.80	0.84	0.80
2	0.56	0.51	0.04	1.12	1.06	0.18	1.75	1.89	1.75
3	0.24	0.25	0.06	0.95	0.89	0.30	1.69	1.74	1.69
4	0.44	0.44	0.08	1.53	1.48	0.37	2.55	2.72	2.55
5	0.68	0.36	0.31	0.59	0.55	0.11	0.88	0.92	0.88
6	0.67	0.54	0.29	1.31	1.20	0.20	2.06	2.11	2.06
7	0.52	488.56	0.02	1.16	41.90	0.05	1.84	18.65	1.84
8	0.73	93.65	0.03	1.57	20.85	0.08	2.44	34.05	2.44
9	0.45	109.60	0.06	1.59	213.79	0.29	2.74	241.34	2.74
10	0.64	1516.40	0.06	2.04	96.29	0.32	3.25	170.57	3.25
11	0.71	271.78	0.19	1.35	1079.71	0.12	2.10	30.56	2.10
12	0.80	158.46	0.14	1.78	170.78	0.11	2.72	227.09	2.72
13	0.29	0.26	0.02	0.60	0.58	0.08	0.84	0.89	0.84
14	0.68	0.88	0.06	1.43	1.92	0.19	2.16	3.25	2.16
15	0.29	0.32	0.13	1.10	1.09	0.32	1.89	1.97	1.89
16	0.61	0.92	0.15	1.83	2.90	0.37	2.80	4.16	2.80
17	0.72	0.40	0.30	0.76	0.73	0.14	1.04	1.12	1.04
18	0.85	1.03	0.28	1.66	2.47	0.25	2.47	3.60	2.47
19	0.55	150.82	0.02	1.19	67.13	0.05	1.89	22.24	1.89
20	0.84	55.59	0.07	1.92	75.79	0.11	2.84	119.30	2.84
21	0.50	314.38	0.05	1.70	786.48	0.29	2.82	74.19	2.82
22	0.72	1687.96	0.06	2.23	81.62	0.32	3.49	80.62	3.49
23	0.71	261.23	0.17	1.40	31.96	0.12	2.20	76.59	2.20
24	0.88	275.15	0.20	2.13	74.47	0.12	3.30	207.50	3.30