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SEASONAL ADJUSTMENT OF DAILY DATA WITH CAMPLET

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Seasonal adjustment of daily data with CAMPLET

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Abstract/Résumé

In the last decade large data sets have become available, both in terms of the number of time series and with higher frequencies (weekly, daily and even higher). All series may suffer from seasonality, which hides other important fluctuations. Therefore time series are typically seasonally adjusted. However, standard seasonal adjustment methods cannot handle series with higher than monthly frequencies. Recently, Abeln et al. (2019) presented CAMPLET, a new seasonal adjustment method, which does not produce revisions when new observations become available. The aim of this paper is to show the attractiveness of CAMPLET for seasonal adjustment of daily time series. We apply CAMPLET to daily data on the gas system in the Netherlands.

Au cours de la dernière décennie, de vastes ensembles de données sont devenus disponibles, tant en termes de nombre de séries chronologiques que de fréquences plus élevées (hebdomadaires, quotidiennes et même supérieures). Toutes les séries peuvent souffrir d'une saisonnalité, qui masque d'autres fluctuations importantes. C'est pourquoi les séries temporelles sont généralement désaisonnalisées. Cependant, les méthodes standard de désaisonnalisation ne peuvent pas traiter les séries dont la fréquence est supérieure au mois. Récemment, Abeln et al. (2019) ont présenté CAMPLET, une nouvelle méthode de désaisonnalisation, qui ne produit pas de révisions lorsque de nouvelles observations sont disponibles. L'objectif de cet article est de montrer l'attrait de CAMPLET pour l'ajustement saisonnier des séries temporelles quotidiennes. Nous appliquons CAMPLET à des données quotidiennes sur le réseau de gaz aux Pays-Bas.

Keywords/Mots-clés: daily data; seasonal adjustment; calendar effect; gas system; the Netherlands. / données quotidiennes ; ajustement saisonnier ; effet de calendrier ; système de gaz ; les Pays-Bas.

JEL Codes/Codes JEL: C22; Q47

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1 Introduction

In the last decade large data sets have become available, both in terms of the number of time series and at higher frequencies (daily and even higher). All series may suffer from seasonality, which hides other important fluctuations. Therefore time series are typically seasonally adjusted before being used in (economic) analysis. Seasonal adjustment aims at estimating the seasonal components, followed by its removal from the time series. In this paper we focus on daily data. Here, seasonal adjustment refers to the process of estimating and adjusting all periodically recurring systematic effects with a cycle length of less than or equal to one year. For daily data, there can typically be weekly, monthly and annually recurring patterns.

Several seasonal adjustment methods have been proposed for daily data. Ladiray et al. (2018) present some ideas to adapt the X11 family, i.e. methods based on moving averages like X11 (see e.g. Ladiray and Quenneville (2001)), X12-ARIMA (see the appendix of Wright (2013)) and X13-ARIMA-SEATS (for details see the X-13ARIMA-SEATS Seasonal Adjustment Program homepage at the U.S. Department of Commerce Census Bureau `https://www.census.gov/srd/www/x13as/`), and methods based on ARIMA models like TRAMO-SEATS (Gómez and Maravall, 1996) to daily data. A second group of methods is based on STL (a Seasonal-Trend decomposition procedure based on Loess), a non-parametric method introduced by Cleveland et al. (1990). Ollech (2021) proposes a method for daily time series, based on STL. A third class of methods employs structural time series models or unobserved components models. Koopman and Ooms (2003), De Livera et al. (2011), McElroy et al. (2018) and Proieti and Pedregal (2021) show applications for daily data.

Recently, Abeln et al. (2019) presented a new seasonal adjustment method CAMPLET, an acronym of its tuning parameters. The method consists of a simple procedure to extract the seasonal and the non-seasonal component from an observed time series.

Once this process is carried out, there will be no need to revise these components at a later stage when new observations become available. The aim of this paper is to show that CAMPLET is very attractive for seasonal adjustment of daily time series.

We apply the method to the daily data on the Dutch gas system over the period 2006 to 2014. The Netherlands used to be a major gas producer exporting significant volumes of gas to neighbouring countries, while the domestic consumption was relatively large as well. As the gas was mainly used for heating, both production and consumption show strong seasonal patterns. By removing the seasonal pattern the remaining fluctuations in the gas production and consumption become clear.

The paper is structured as follows. Section 2 describes issues in the seasonal adjustment of daily data. Section 3 presents CAMPLET, whereas Section 4 describes and analyzes changes that are necessary for seasonal adjustment of daily data. Section 5 compares seasonal adjustments of CAMPLET for annual and monthly cycles for three different series of Ollech (2021), and to his Daily Seasonal Adjustments (DSA) outcomes. Section 6 presents and analyzes our seasonal adjusted outcomes for gas production and consumption in the Netherlands, including imports and exports. Section 7 concludes.

2 Seasonal adjustment of daily data

An observed time series y_t can be decomposed into a trend-cycle y_t^{tc}, seasonal y_t^s, irregular y_t^i component, and deterministic effects due to the number of trading days y_t^{td}, and holidays y_t^h, such as Easter and Christmas (Ghysels and Osborne 2001, Section 4.2). Assuming weekly y_t^{sw}, monthly y_t^{sm} and yearly seasonal fluctuations y_t^{sy} exist and using the additive version of the decomposition, we get

$$y_t = y_t^{tc} + \underbrace{y_t^{sy} + y_t^{sm} + y_t^{sw}}_{\text{seasonal effects}} + \underbrace{y_t^{td} + y_t^{h}}_{\text{calendar effects}} + y_t^{i}, \qquad t = 1, \ldots, T. \tag{1}$$

Seasonal adjustment of daily time series has special problems: (i) daily time series can exhibit different seasonal patterns; here we distinguish weekly, monthly and yearly fluctuations; (ii) the data are not exactly periodic: the length of the month and the year are not constant in terms of the number of days; and (iii) calendar effects such as trading days and moving holidays (Easter, Christmas) may be taken into account; the same holds for outliers in the data.

Several solutions have been proposed to handle different seasonal patterns. Cleveland et al. (1990) suggested to adjust seasonal fluctuations sequentially, to start with weekly cycles, then adjust for monthly cycles, and then yearly cycles. This suggestion is followed by e.g. Ollech (2021). Below we analyze the impact of the order in CAMPLET.

To deal with time-varying lengths of cycles in terms of days, several data transformations are used. Ollech (2021) deletes the observations of 29 February in leap years and thus obtains equal-sized years of 365 days. In the structural time series analysis of Koopman and Ooms (2003) month and year lengths are fixed; missing observations are estimated/interpolated by the Kalman filter. The method we adopt in CAMPLET is related to theirs as shown in the next section.

Calendar effects and outliers are typically adjusted for in a pre-treatment step, with a regression with dummies capturing trading days, holidays and outliers (Ladiray et al 2018; McElroy et al. 2018), the so-called regARIMA equation. CAMPLET does not require pre-treatment of a time series to adjust for calendar effects and outliers, as shown in Abeln et al. (2019) and in Section 3 below.

3 CAMPLET

CAMPLET[1] is based on the decomposition of an observed series (y_t) into a non-seasonal (y_t^{ns}) and seasonal (y_t^s) component

$$y_t = y_t^{ns} + y_t^s, \qquad t = 1, \ldots, T. \tag{2}$$

Differences between average values of groups of corresponding observations of a time series of a number of full years can be decomposed into seasonal and a non-seasonal (NS) components. It is assumed that the NS change is, on average, the same between the groups of variables. If the average change of one group differs from the others, this would be a seasonal effect. The NS components constitute a linear progression, with the average NS change equal to the difference. Average seasonal components are then the differences between group averages of raw data and NS components. In every period a time series has a full set of latent seasonal components.

CAMPLET seasonally adjusts a time series on a period-by-period basis. If a new observation becomes available in period $t + 1$, the seasonal factor from the previous period t that corresponds to this observation applies. If the new observation fits the extrapolation of the linear NS progression and this seasonal factor, then the average NS change and the corresponding seasonal factor are also valid for the new observation $t + 1$. The corresponding average seasonal factor of period t can be applied to adjust the new observation in period $t + 1$. This adjustment is final. In our view, future events cannot have an impact on the decomposition of past observations. Every observation is seasonally adjusted as if it is the final observation of a time series. The seasonal and NS components are determined on the basis of the new observation and on what preceded.

[1]For details on CAMPLET we refer to Abeln et al. (2019, Section 2). The package including documentation and examples is available at `http://www.camplet.net`.

It is more likely that a new observation does not fit the extrapolation of the linear NS progression and the corresponding seasonal factor of the previous observation. To adjust the new observation, the change of the NS progression is updated. The difference between the observed value y_{t+1} and the extrapolated value for $t+1$ based on information available in t is denoted by the *extrapolation error* $\hat{e}_{t+1}$. The extrapolation error in period $t+1$ is divided over changes in the seasonal and changes in the NS change in period $t+1$. We assume that the NS change g_t rotates according to $g_{t+1} = g_t + \hat{e}_{t+1}/\ell_{t+1}$, where ℓ_{t+1} is the *common adjustment length*, a parameter in CAMPLET which is assumed to be equal to $1.5\times$ the length of the seasonal cycle. The change of the NS progression also affects the seasonal components. Once we know the value of the new seasonal component in period $t+1$, y^s_{t+1}, we can calculate the seasonally adjusted value y^{sa}_{t+1} from decomposition (2).

CAMPLET needs starting values for the the seasonally adjusted value y^{sa}_0, the NS change g_0, and the seasonal components in the starting period. These can be obtained from one seasonal cycle, if there are no outliers. An outlier in the first seasonal cycle also occurs in the initial seasonal pattern. To avoid this situation we apply CAMPLET for the first three seasonal cycles, extrapolate the NS change backwards to the first observation, and adjust the full series.

The period-by-period seasonal adjustment in CAMPLET allows dealing with calendar effects, including outliers. To mitigate the effects of an outlier on the seasonal components, we increase the adjustment length for that period, but reset it to common adjustment length of one-and-a-half cycle for the next observation. If the outlier also occurs one seasonal cycle later, we assume that the seasonal pattern has changed. The second time an outlier is detected, the adjustment length is shortened to one cycle to adopt the new seasonal pattern. This property of CAMPLET makes it well suited to capture breaks in seasonal patterns.

4 Adjustments in CAMPLET for daily data

CAMPLET does not require much special adjustments for daily data. All parameters of CAMPLET remain the same. The cycle length enters the adjustment length, which determines the NS change when extrapolation errors occur. Since the cycle length enters the denominator of the NS change, a difference of one day in the length of the year does not have a huge impact. Observations for one full seasonal cycle are required for initialisation. Four cycles are necessary to obtain stable seasonal adjustments.

Updating latent seasonal components

Define $a_{t+1,p} \equiv \hat{e}_{t+1}/\ell_{t+1}$, where ℓ_{t+1} is the *common adjustment length*, a parameter in CAMPLET which is assumed to be equal to 1.5× the length of the seasonal cycle p. In the previous section we described that the change of the NS progression also affects the evolution of the latent seasonal components $S_{t+1,1+j},\ j = 0, \ldots, p-1$. The general updating rule for a cycle with length p is as follows

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

This implies for quarterly data and an annual cycle $p = 4$

$$S_{t+1,1+j} = S_{t,1+j} - [(j+1) - (4+1)/2] \times a_{t+1,4}, \qquad j = 0, \ldots, 3$$

and for monthly data with an annual cycle $p = 12$

$$S_{t+1,1+j} = S_{t,1+j} - [(j+1) - (12+1)/2] \times a_{t+1,12}, \qquad j = 0, \ldots, 11.$$

We distinguish three types of cycles in daily data: a weekly cycle, a monthly cycle and an annual cycle. For daily data with weekly cycles $p = 7$, the updating rule becomes

$$S_{t+1,1+j} = S_{t,1+j} - [(j+1) - (7+1)/2] \times a_{t+1,7}, \qquad j = 0, \ldots, 6.$$

Months do not have equal lengths. Some months have 30 days, others 31 days, and February has 28 days and in leap years 29 days. We can model this in three different ways:

1. assuming a monthly cycle of $p = 30$ days. The updating rule for seasonal components then becomes

$$S_{t+1,1+j} = S_{t,1+j} - [(j+1) - (30+1)/2] \times a_{t+1,30}, \qquad j = 0, \ldots, 29.$$

2. assuming a monthly cycle of 31 days, with updating rule

$$S_{t+1,1+j} = S_{t,1+j} - [(j+1) - (31+1)/2] \times a_{t+1,31}, \qquad j = 0, \ldots, 30.$$

3. our preferred model on logical frounds, 31 (var) days, does not assume fixed month length of 30 or 31 days. Instead 31 seasonal components are updated as in the previous method and we take the seasonal component corresponding to the previous day in the change of the NS regulate the extrapolation error and then update the seasonal components.

In the next section we compare the three ways empirically.

To allow for annual cycles, we can assume a cycle of 365 or 366 days with corresponding seasonal components updating rules:

$$S_{t+1,1+j} = S_{t,1+j} - [(j+1) - (365+1)/2] \times a_{t+1,365}, \qquad j = 0, \ldots, 364$$
$$S_{t+1,1+j} = S_{t,1+j} - [(j+1) - (366+1)/2] \times a_{t+1,366}, \qquad j = 0, \ldots, 365.$$

Since the annual cycle enters in the denominator of the common adjustment length, we expect that the impact of the cycle length is small. We include both lengths in the comparison below.[2]

Order of seasonal adjustment

Since we cannot adjust daily data for weekly, monthly and annual cycles in one step, we have to compute SAs sequentially. Here we have two options: (i) starting with adjusting for the weekly cycle, then adjusting the SAs of the weekly cycle for the monthly cycle, and the resulting SAs for the annual cycle, or (ii) begin with the adjustment for the annual cycle, adjust the SAs of the annual cycle for the monthly cycle, and finally adjust the SAs of the second step for the weekly. Ollech (2021) chooses to go from short to long cycles. Below we compare both options.

5 Comparisons

In this section we compare seasonal adjustments of three series of daily data provided by Ollech (2021): currency in circulation, electricity consumption and NO2 immissions. The first series runs from January 1, 2011 to May 22, 2020. The series is interpolated in a similar way as in Ollech's article. Missing weekend observations are replaced by Friday

[2] In theory, we could implement a similar method as the 31 (var) days for monthly cycles, updating 366 seasonal components and taking the component that applies in the NS progression. However, we do not expect a large effect from this method because leap years occur only once every four years.

values, missing holiday observations by the latest available observation. The series of electricity consumption starts January 1, 2015 and the series of NO2 immissions in January 2016. Both end May 22, 2020. The seasonal adjustments below are based on the largest possible sample. However, some figures show outcomes for shorter samples.

Seasonal adjustments of monthly cycles with fixed length of 31 days are done with CAMPLET Version 4, available at `camplet.net`. All other seasonal adjustments are carried out with CAMPLET Version 6, which is especially designed to deal with monthly cycles with varying lengths and available upon request.[3]

Seasonal adjustment with annual cycles

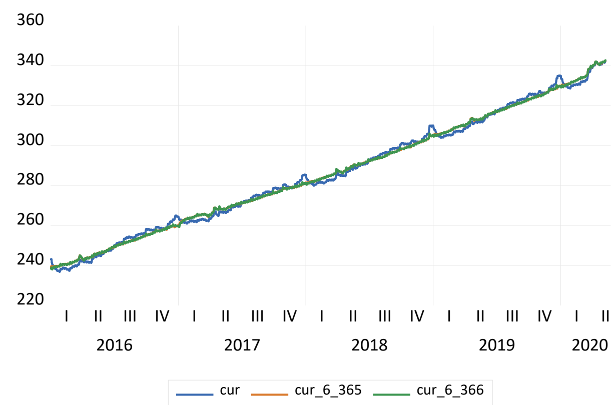
Figure 1 shows the three raw series together with SAs of CAMPLET based on annual cycles of 365 and 366 days for the period January 1, 2016 – May 22, 2020. Eyeballing the three panels suggests that differences between the raw series and the two CAMPLET seasonal adjustments based on annual cycles are small. Our next step is to test for equality of the CAMPLET seasonal adjustments assuming annual cycles.

Table 1 compares seasonal adjustments assuming cycles of 365 and 366 days. Instead of seasonality tests, we show outcomes of t-tests for equality of means and outcomes of F-tests for equality of variances of seasonally adjusted series. For currency in circulation means and standard deviations between seasonal adjustments based on annual cycles of 365 and 366 days are close, and the equality tests do not reveal differences. Variances however do differ for the other two series. For electricity consumption and NO2 immissions the variance of seasonal adjustments assuming a cycle of 365 days is smaller than taking an annual cycle of 366 days. Therefore we prefer an annual cycle of 365 days in the seasonal adjustment with CAMPLET.

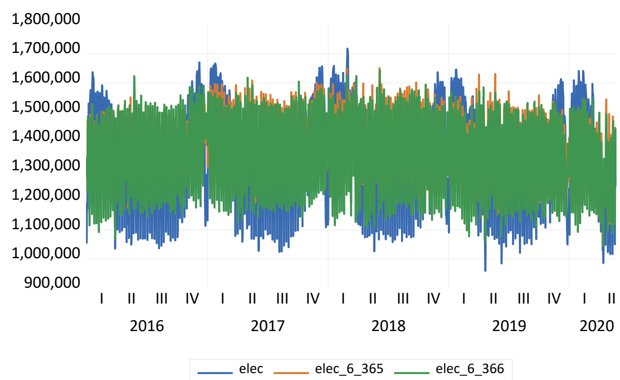
[3] In CAMPLET 5 a bug is fixed to make seasonal adjustments of single series the same whether they are read separately or in a group.

Figure 1: Seasonal adjustments of three series of Ollech (2021) based on annual cycles of 365 and 366 days

currency in circulation (Germany, billion euros)



electricity consumption (Germany, GWh)



NO2 immissions (Europe, μ g/m^3)

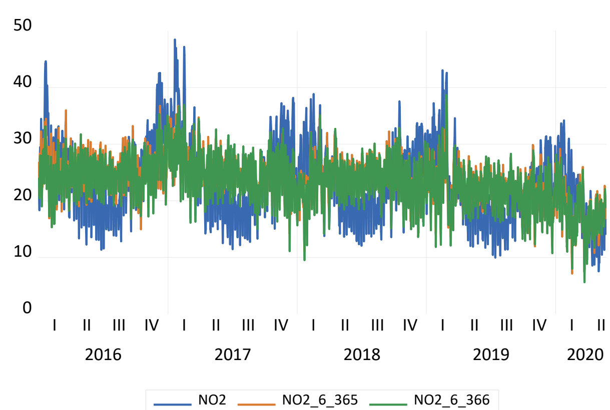


Table 1: CAMPLET seasonal adjustments of three series of Ollech (2021) based on cycles of 365 and 366 days: descriptive statistics and tests of equality

	365 days	366 days
	currency in circulation (Germany, billion euros)	
mean	236.2119	236.2157
st. dev.	54.0251	54.0160
equality of means	-0.003	
equality of variances	1.000	
	electricity consumption (Germany, GWh)	
mean	1372161	1371366
st. dev.	103881	124902
equality of means	0.217	
equality of variances	1.446***	
	NO2 immissions (Europe, μ g/m^3)	
mean	23.638	23.623
st.dev.	4.161	4.417
equality of means	0.099	
equality of variances	1.127**	

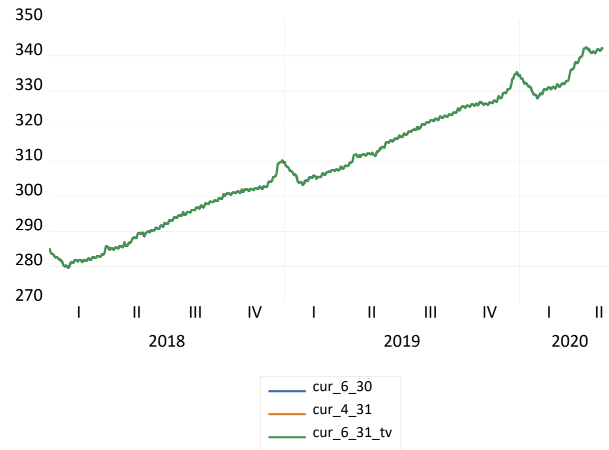
Notes: equality of means test of seasonally adjustments shows outcome of t-test; equality of variance test of seasonally adjusted series shows outcome of F-test. Three (two) asterisks denote significance at the 1% (5%) level.

Seasonal adjustment with monthly cycles

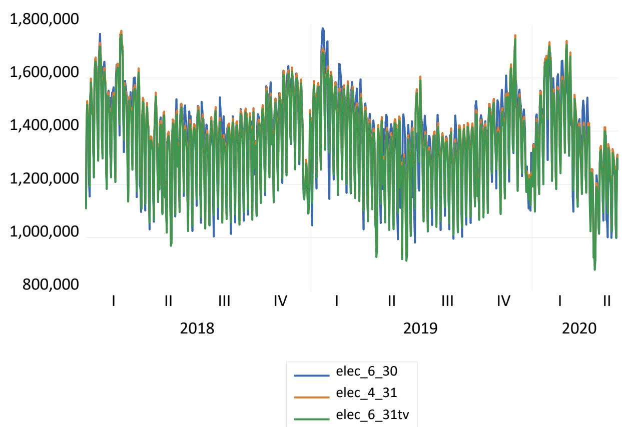
Above we described three ways of modelling the length of monthly cycles in CAMPLET: 30 days fixed, 31 days fixed, and the method we prefer 31 (var) days in which for each period 31 latent seasonal components are updated as with 31 days fixed, but only one seasonal component applies. For e.g. March 31 we take the 31th component and for April 30 the 30th component of the previous period. Figure 2 shows seasonal adjustments of CAMPLET based on monthly cycles of 30, 31 and 31 (var) days assuming varying length of month.

Figure 2: CAMPLET seasonal adjustments of three series of Ollech (2021) with monthly cycles

currency in circulation (Germany, billion euros)



electricity consumption (Germany, GWh)



NO2 immissions (Germany, GWh)

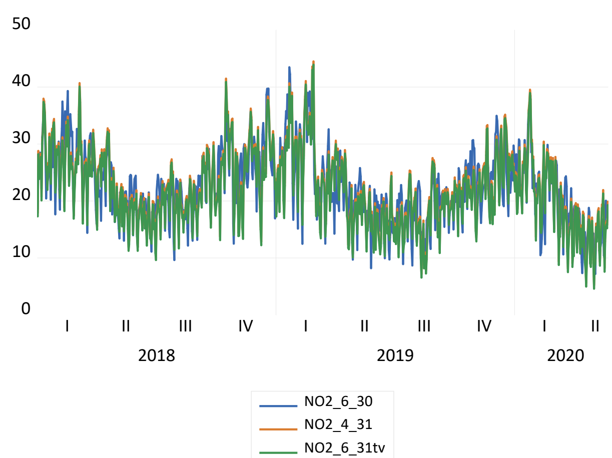


Table 2: CAMPLET seasonal adjustments of three series of Ollech (2021) with monthly cycles: descriptive statistics and tests of equality

	30 days		31 days		31 (var) days
	currency in circulation (Germany, billion euros)				
mean	236.3302		236.3306		236.3091
st. dev.	54.0754		54.0749		54.0749
equality of means		-0.000			
				0.016	
equality of variances		1.000			
				1.000	
	electricity consumption (Germany, GWh)				
mean	1374635		1374183		1359110
st. dev.	170585		161202		161211
equality of means		0.085			
				2.932***	
equality of variances		1.446***			
				1.000	
	NO2 immissions (Europe, μ g/m^3)				
mean	23.680		23.664		23.070
st.dev.	6.874		6.965		7.007
equality of means		0.068			
				2.404**	
equality of variances		1.027			
				1.012	

Notes: equality of means test of seasonally adjustments shows outcome of t-test;
equality of variance test of seasonally adjusted series shows outcome of F-test.
Three (two) asterisks denote significance at the 1% (5%) level.

Table 2 lists outcomes of means, standard deviations and equality tests of seasonally adjusted values. Again, seasonal adjustments of currency in circulation are equal for the three monthly lengths we distinguish. In addition, we find that for the electricity series that while the means of the seasonal adjustments are equal the variance assuming a cycle of 31 days is smaller that the variance of the seasonal adjustments with a cycle of 30 days (F-outcome: 1.120); comparison of monthly cycles of 31 days and our preferred method of 31 (var) days yields that our method produces seasonal adjustments with a smaller mean. Results for NO2 immissions are similar, although we do not find equality of means and variances between seasonal adjustments produced with the fixed length monthly cycles. Means between seasonal adjustments with a cycle of 31 days and 31 (var) days are different.

Order of seasonal adjustment in CAMPLET and comparison with DSA outcomes

Figure 3 shows two types of seasonal adjustments by CAMPLET, one produced by first adjusting for annual cycles, then monthly cycles, and finally weekly series, the other by first adjusting for weekly cycles, then monthly cycles and annual cycles, and the seasonal adjustments generated by the DSA method.

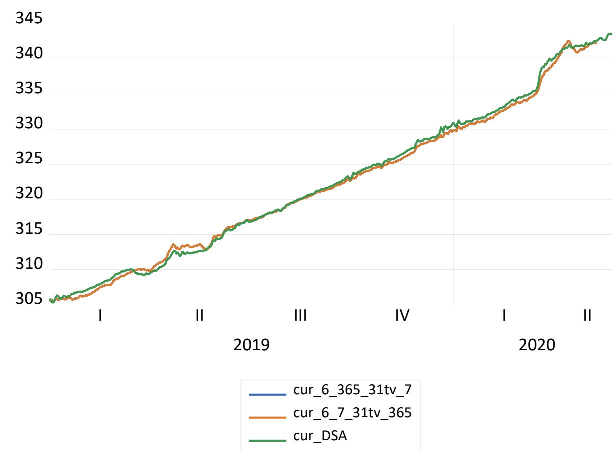
Comparison of adjusting for a weekly cycle, a monthly cyclus of 31 (var) days followed by an annual cycle of 365 days and the other way around (first year, then month, followed by week) leads again to no differences for seasonal adjustments of the currency in circulation series.

For electricity consumption means and variances differ, but we get the ambiguous outcome that the mean of the week-month-year order seasonal adjustment is larger whereas the variance is smaller for this series. For the NO2 series we find that the order of adjusting does not affect the mean of the seasonal adjustments, but does have an impact on the equality of the variance. Here, the order of week-month-year is clearly preferred.

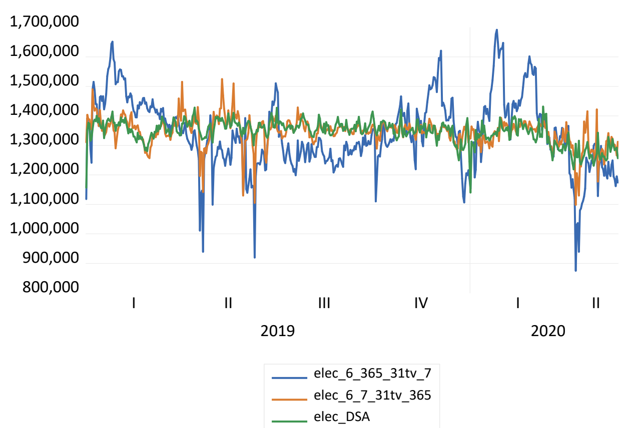
We also compare the CAMPLET seasonal adjustments applying the order week-month-year to the DSA seasonal adjustment outcomes. For currency in circulation and NO2 immissions no differences are found in the means and variances. DSA seasonal adjustments have smaller variances than CAMPLET outcomes produced in order week-month-year.

Figure 3: Order of seasonal adjustments in CAMPLET and daily seasonal adjustments (DSA) outcomes of Ollech (2021)

currency in circulation (Germany, billion euros)



electricity consumption (Germany, GWh)



NO2 immissions (Europe, μ g/m^3)

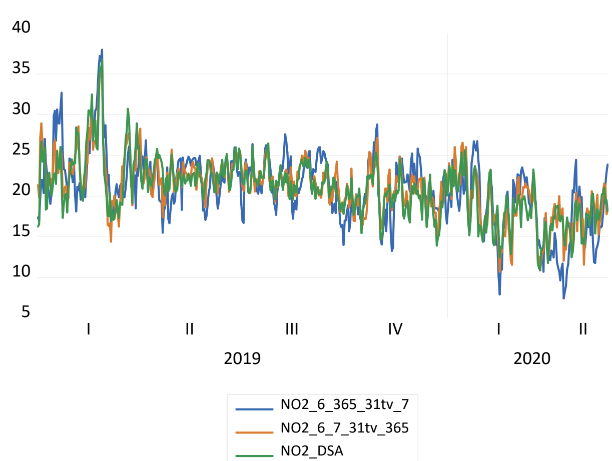


Table 3: Order of seasonal adjustment in CAMPLET and comparison with daily seasonal adjustments (DSA) outcomes of Ollech (2021): descriptive statistics and tests of equality

	year-month-year		week-month-year		DSA
	currency in circulation (Germany, billion euros)				
mean	236.1982		236.1945		236.3958
st. dev.	54.0754		54.0247		54.0236
equality of means		0.003			
				-0.486	
equality of variances		1.000			
				1.011	
	electricity consumption (Germany, GWh)				
mean	1359130		1368421		1370298
st. dev.	111069		46472		36248
equality of means		-0.910			
				-1.142	
equality of variances		5.712***			
				1.644***	
	NO2 immissions (Europe, μ g/m^3)				
mean	23.519		23.644		23.499
st.dev.	4.197		3.497		3.637
equality of means		-0.910			
				1.146	
equality of variances		1.441***			
				1.082	

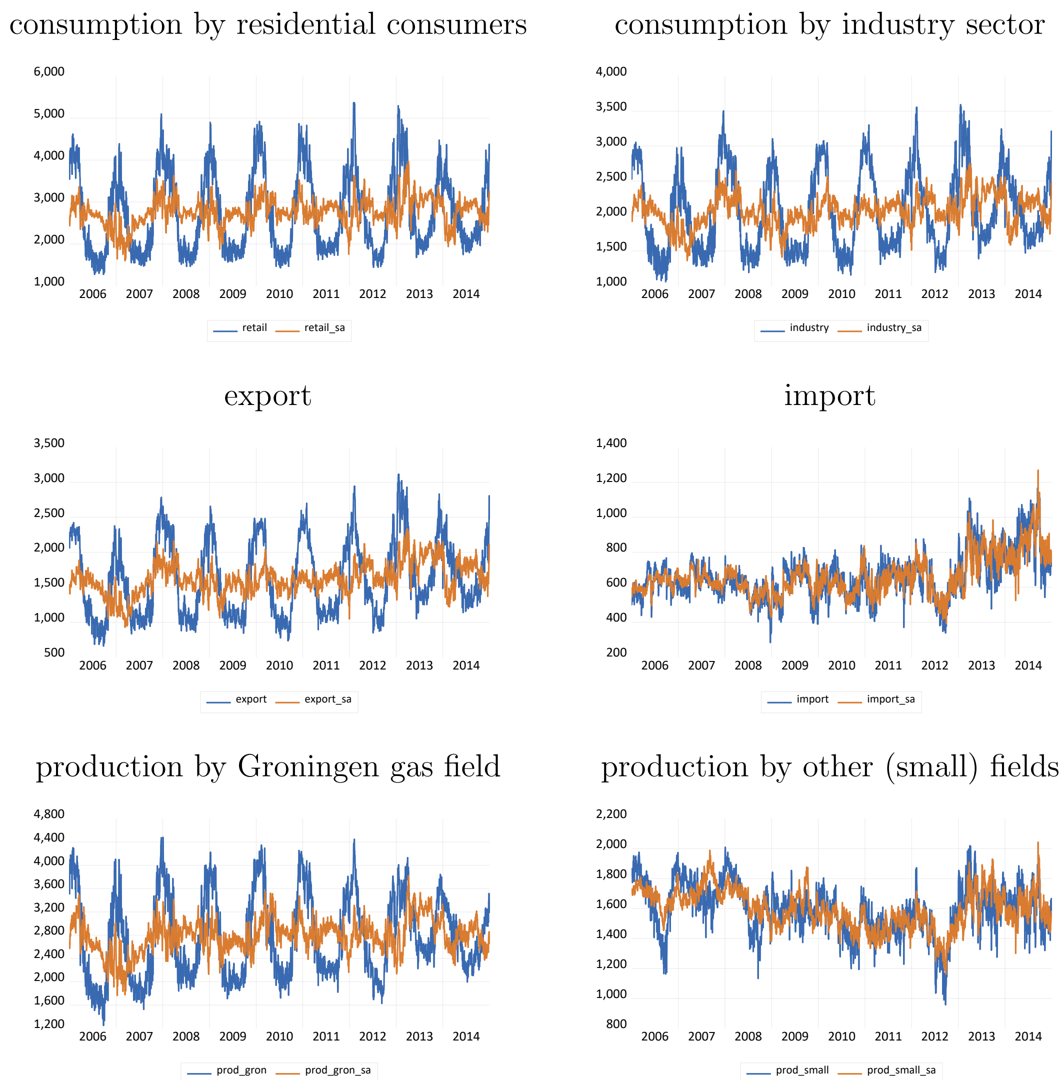
Notes: equality of means test of seasonally adjustments shows outcome of t-test; equality of variance test of seasonally adjusted series shows outcome of F-test. Three (two) asterisks denote significance at the 1% (5%) level.

6 Gas consumption and production in the Netherlands

The Netherlands used to have a well developed gas system because of the presence of one of the largest onshore gas fields in Europe, the so-called Groningen field. This gas field has several unique properties. Besides its size, the main characteristic is its ability to quickly adapt production levels. As a result, this field was able to provide flexibility to the system, which is in particular important as most of the gas demand, not only domestically, but also in the neighbouring countries, is related to heating. This heating demand is strongly related to the outside temperature, which gives rise to a very strong seasonal effect (see Figure 8). The Groningen gas field was in particular used to accommodate its production levels to the changes in consumption because of its characteristics. Therefore, the Groningen gas field was also called a swing supplier (Schipperus and Mulder, 2015).

Figure 4 clearly shows the seasonality in consumption by residential users, the industrial sector and also the export to the neighbouring countries. The production by the Groningen gas field is quite similar to these seasonal patterns, while the production from the so-called small fields hardly shows a seasonal pattern. The latter is related to the fact that it is way more costly to produce the gas from these small fields in a strongly fluctuating manner. The same holds for the import supply (from Norway and Russia mainly): the economics of this import make that a relatively flat supply is the most efficient option to use the infrastructure.

Figure 4: Gas consumption and production in the Netherlands, per day from 2006–2014



Source: Authority for Consumers & Markets (ACM), `www.acm.nl`

6.1 Seasonal cycles

The main aims of seasonal adjustment are to remove seasonality to produce series whose movements are easier to analyze over consecutive time intervals and to compare to the movements of other series in order to detect co-movements (U.S. Census, Time Series and Seasonal adjustment `https://www.census.gov/topics/research/seasonal-adjustment.html`). In addition, by removing the seasonal patterns, it becomes clear which other (non-seasonal) fluctuations exists in the various variables. These fluctuations are in this case strongly related to day-to-day fluctuations in weather circumstances The removed seasonal patterns are also of interest by themselves, for example to get a picture of how much gas is on average (in 'normal' winter circumstances) needed in peak periods and to prepare capacity and/or stocks for the coming period. It should be kept in mind that seasonal components do not have to add up to zero for a full cycle, that property holds for seasonal components in each period. It does not either for subsections of the cycle. The deviation from zero of a subsection can be seen as the difference from the annual average.

Figure 5: Intra-week seasonality, industry 2014

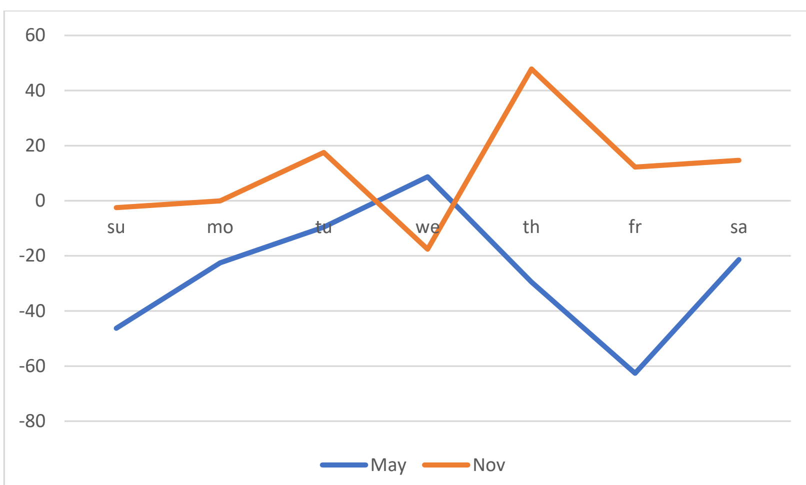
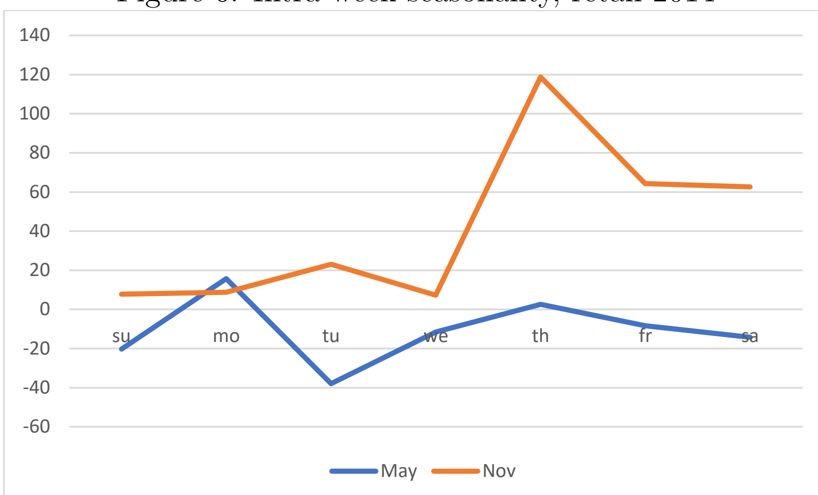


Figure 5 shows the daily use of gas by industry (except the electricity sector) for the months May and November of the year 2014. For each month the average seasonality of four Sundays, four Mondays, ..., four Saturdays have been calculated. Clearly the use in November is above the annual average, while the use in May is below.

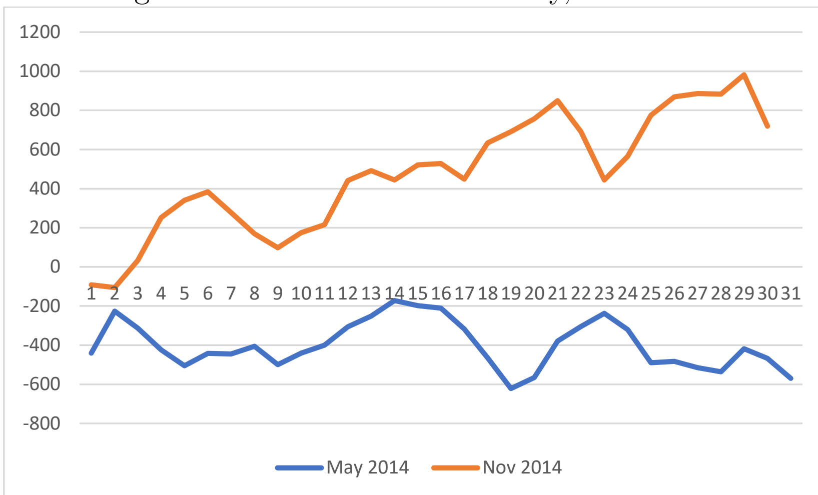
The daily consumption of gas by residential users has a similar seasonal pattern, be it that at the end of week (Thursday through Saturday) the increment in November is more pronounced than in the industry graph. This is related to the fact that residential consumers spend more time in their premises during the weekends, which raises their gas consumption, while industrial gas consumption is lower during the weekends for the same reason.

Figure 6: Intra-week seasonality, retail 2014



After removing the intra-week fluctuations we adjust the series for intra-month seasonality with the (varying) cycle 31. Again we look at the outcomes for May and November 2014 in Figure 7. The use in May is below the annual average and the use in November is above the annual average and rising, which makes sense as the outside temperatures are going down (on average) as the month November proceeds.

Figure 7: Intra-month seasonality, retail 2014

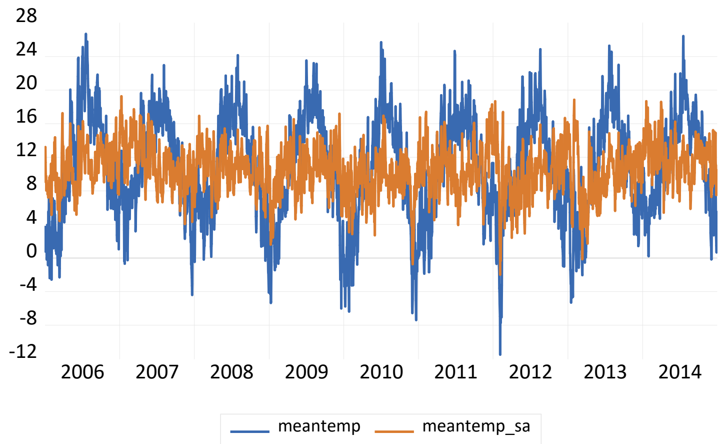


6.2 Gas consumption and production, and mean temperature

Mean temperature, as shown in Figure 8, plays an important role in gas consumption and production in the Netherlands (Schipperus and Mulder, 2015). The lower the temperature, the higher gas consumption and gas production.

Table 4 shows outcomes of regressions of gas consumption and gas production, gas exports and gas imports on a constant and a slope parameter, both for non-seasonally adjusted and seasonally adjusted values. We find significant negative slopes for all categories distinguished except gas imports. Seasonal adjustment still produces significant negative slopes, except for gas production by small fields and gas imports. However, seasonal adjustment picks up part of the explanation of the regressions.

Figure 8: Mean temperature in the Netherlands, daily from 2006–2014



Source: KNMI, `https://dataplatform.knmi.nl/`

Table 4: Gas consumption and production, and mean temperature in the Netherlands, non-seasonally adjusted (NSA) and seasonally adjusted (SA)

		constant	st.dev	slope	st.dev	adj. R^2
gas consumption						
retail	NSA	4230.567	29.582	−137.482	2.388	0.838
retail	SA	3530.512	40.327	−72.781	3.851	0.415
industry	NSA	2922.092	23.237	−79.258	1.765	0.760
industry	SA	2444.697	30.220	−35.450	2.835	0.215
export	NSA	2417.802	22.781	−73.689	1.780	0.744
export	SA	1970.375	33.032	−32.859	3.121	0.176
gas production						
Groningen	NSA	3851.363	26.089	−99.723	2.242	0.778
Groningen	SA	3410.986	38.369	−58.459	3.584	0.328
small fields	NSA	1698.635	12.899	−9.893	1.067	0.133
small fields	SA	1607.769	18.556	−0.991	1.662	0.000
import	NSA	635.612	11.254	2.231	0.977	0.012
import	SA	665.413	16.627	−0.274	1.503	−0.000

Notes. St. dev. are HAC standard errors.

7 Conclusion

Three problems arise when seasonally adjusting daily data: daily time series can exhibit different seasonal patterns, the data are not exactly periodic, in particular the length of the month and the year are not constant in terms of number of days, and calendar effects such as trading days and moving holidays (Easter, Christmas) and outliers have to be dealt with. We have shown in this paper that CAMPLET, a new seasonal adjustment procedure, can easily cope with all three problems. In combination with its property that no revisions are produced when new observations become available, this makes CAMPLET an attractive competitor in the seasonal adjustment of daily data.

We analyzed seasonal adjustments of CAMPLET on the basis of three daily series provided by Ollech (2021): currency in circulation, electricity consumption and NO2 immissions. Based on these series we conclude that adjusting with an annual cycle of 365 days is to be preferred to a cycle of 366 days, and our way of dealing with monthly cycles produces smaller variances than using fixed length monthly series. We also compared CAMPLET seasonal adjustment outcomes to DSA outcomes of Ollech (2021). DSA outcomes are similar for two of the three series analyzed, but its variance is smaller for electricity consumption. More research, especially a thorough simulation study, is necessary to validate CAMPLET for daily data.

An application to daily data on the gas system in the Netherlands reveals seasonal cycles and shows the impact of seasoanal adjustment on the relation between gas consumption and production and mean temperature.

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