# Seasonal Adjustment and Calendar Correction of Weekly Household Consumption Indicators Using Daily Payment Card Data

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**Abstract.**

*This paper presents a methodological framework for seasonal adjustment and calendar correction of a weekly household consumption indicator derived from daily payment card data. The increasing use of high-frequency data in official statistics creates challenges for traditional seasonal adjustment methods designed for monthly or quarterly data. We analyse both daily and weekly time series and compare indirect and direct modelling approaches. The proposed framework combines regression-based calendar correction with an Unobserved Components Model (UCM), allowing flexible modelling of trend, seasonal and cyclical behavior. A detailed empirical evaluation based on statistical diagnostics, revision stability and smoothness demonstrates that a direct application of UCM to weekly data provides robust and interpretable results. The approach is suitable for production use and can be extended to other high-frequency indicators.*

**Keywords:** seasonal adjustment; calendar correction; weekly consumption indicator; payment card data; unobserved components model

## 1. Introduction

### *a. Background*

This paper presents a framework for seasonal adjustment and calendar correction of a weekly household consumption indicator derived from daily payment card data.

Users of official statistics require time series adjusted for seasonal and calendar effects to analyse underlying trends. This task may be easily handled when the seasonal adjustment procedure is to be applied to monthly or quarterly time series. These routines are well-developed and there are also extensive documents from different sources that support such procedures; see e.g. ESS Guidelines for seasonal adjustment (Eurostat, 2025).

However, the methods and routines developed for monthly and quarterly data are not directly applicable to higher-frequency data. As high-frequency data become more common in official statistics, there is a need for robust methods that can handle weekly and daily series.

In this work we focus on specific time series data, namely weekly household consumption indicator, obtained from daily card payment data, but the approach presented here may easily be modified to treat high frequency time series of different kind.

### b. *Problem formulation*

Weekly time series present challenges such as varying numbers of weeks per year and difficulties in separating seasonal and calendar effects. Moving holidays and weekday effects complicate modelling, particularly at higher frequencies, and must often be approximated in weekly data. Weekly series may also exhibit complex and non-integer seasonal cycles that traditional tools cannot capture. High volatility and noise further complicate the identification of stable patterns.

These challenges require flexible approaches such as structural time series models, while standardized tools, such as X-13-Arima-Seats or Tramo-Seats remain limited.

### c. *Data*

The original data used in this study consists of daily time series covering the period from January 1, 2019, to January 31, 2025. This roughly corresponds to a six-years (unbroken) period.

Only two household consumption time series are treated here, one expressed in the fixed prices (SEK million) and another one expressed in the current prices

(SEK million). Corresponding weekly time series are derived by summing daily observations for each week into a single observation per week.

## 2. Approaches and methodology

### *a. Modelling approaches*

The modelling framework combines a regression component capturing calendar effects and a time series decomposition component. The regression part is mainly used to estimate calendar effects and potential outlier effects and "clean" time series in order to facilitate decomposition of the time series. The decomposition separates the series into trend, seasonal, cyclical and irregular components. Both sequential and simultaneous strategies for applying the regression and time series decomposition components are evaluated using daily data. In this case, seasonally adjusted daily data were aggregated to adjusted weekly data, which is referred to as indirect approach of data processing. Another approach of data processing assumes direct modelling of weekly data. Only the simultaneous strategy was applied under the direct approach.

In the current analysis, two types of regression models were applied, namely the ordinary linear regression model, which ignores the autocorrelation among errors when estimating variances of the estimates, and time series regression model with autocorrelated errors.

For seasonal adjustment purposes, a version of structural time series model (STS), known as an *Unobserved Component Model* (UCM), has been used. The model may be applied on the data of high frequencies. Also, multiple seasonal factors combined with certain periodic cycles may simultaneously be treated within the same procedure. This model is robust and it may be applied simultaneously, incorporating both the regression part and the decomposition part in a single step.

The basic model representation for UCM may be expressed as follows:

$$Y_t = \mu_t + \gamma_t + \psi_t + \sum_j^m \beta_j X_{j,t} + \epsilon_t$$

or as follows in case the UCM is fitted to the residuals from the regression model

$$\epsilon_{Regression\ Model\ t} = \mu_t + \gamma_t + \psi_t + \epsilon_t, \quad t = 1, 2, \dots, T$$

where $\mu_t$ is the trend component, $\gamma_t$ is the seasonal component, $\psi_t$ is the cyclical component and $\epsilon_t$ is the irregular component.

The UCM defined above is an extension of the so-called Basic Structural Model (BSM), which includes only trend, seasonal and irregular components. Importantly, each component in this model is stochastic, meaning that each follows its own model with its own error term. Due to the properties of the current data, the trend component is treated without a slope, assuming it is roughly constant over whole length of time series, with no obvious persistent upward or downward movements. This version is called random walk (RW) and is expressed as follows:

$$\mu_t = \mu_{t-1} + \eta_{t,} \quad \eta_t \sim iid\left(0, \sigma_\eta^2\right)$$

The cyclical component captures multiple overlapping periodicities beyond the ordinary seasonal fluctuations and various calendar effects modelled in the regression part of the UCM. The seasonal component, in turn, may also include multiple seasonalities. Moreover, in the present analysis, its specification is trigonometric. The irregular component is assumed to satisfy the assumption of mutually and identically distributed observations.

All models in this study are implemented using SAS procedures PROC REG, PROC AUTOREG and PROC UCM (SAS/ETS® User's Guide, 2025). A practical guide to implementation of UCM using SAS may be found in (Rajesh Selukar, SAS Institute, 2009).

*b. Evaluation criteria*

Different model specifications may arise depending on data frequency, explanatory variables, and treatment of time series components. The models analysed were evaluated based on following criteria.

Expected and statistically significant regression parameters (at least at the 10% level); Goodness-of-fit measures: $R^2$ and adjusted $R^2$ (higher is better), RMSE and AIC (lower is better); Reasonable cycle estimates when not fixed; An irregular component without seasonal patterns and satisfying independence and normality assumptions (with caution in cases of high variance); Stability of revisions, assessed by fitting models to nine expanding datasets and comparing adjusted series using the Change Rate:

$$ChangeRate_t = \frac{\hat{y}_{tp}^{SA} - \hat{y}_{t(p-1)}^{SA}}{\hat{y}_{t(p-1)}^{SA}} * 100\%, \;\; p = 2, 3, \dots, 9.$$

The eight resulting Change Rate series were summarized by their average, minimum, and maximum at each time point. Models with the smallest values are preferred, and ideally the maximum Change Rate should not exceed 1%;

The adjusted series should be sufficiently smooth to allow meaningful comparison of consumption between weeks, with substantive knowledge guiding the final assessment.

## 3. Analysis and numerical results

A preliminary analysis was conducted to explore data properties and identify relevant calendar factors for the regression model (Section 2.a), using both graphical inspection and simple regression tests. Results for daily and weekly data are summarized below.

### *a. Preliminary analysis of daily data*

The daily series appear stationary in both mean and variance, motivating a level-only trend specification in the UCM. Autocorrelation indicates a clear 7-day cycle, justifying a seasonal component with weekly periodicity and 52 yearly blocks. The cycle component is treated as unknown and estimated.

Calendar effects are important: consumption is lowest on Sundays and highest on Fridays, with a strong additional effect during salary payment periods, especially through an interaction between Fridays and salary payments. The coronavirus pandemic has a clear negative effect and is included as a separate regression variable rather than as part of seasonal or cyclical components.

Holiday periods (Midsummer, Christmas, Easter) show distinct sub-period patterns with increases followed by drops, requiring detailed modelling. Black Week effects appear weak, likely due to missing online transactions. Leap-year effects were tested but are expected to be small. Among tested interactions, only Friday–salary effects were retained.

### *b. Preliminary analysis of weekly data*

Aggregation to weekly data reduces calendar effects, leading to fewer relevant variables. However, strong effects, particularly salary payments, remain important. Suitable variables were selected based on preliminary regression analysis.

### *c. Results*

Based on the preliminary analysis, 22 models were evaluated. Most satisfied standard criteria, but only a few showed an acceptable revision stability. Models with month-length effects performed poorly in this regard, while models within the direct approach showed stable results. For fixed prices, four candidate models were identified and further compared in terms of smoothing. A preferred specification models the Midsummer effect as a calendar effect with varying periodicity across years.

The final model applies a UCM directly to weekly data, including level, irregular, and a fixed cycle (4.35 weeks), with a 52-week seasonal component. Calendar effects are treated as seasonal and removed in the adjusted series, except for the coronavirus effect. The adjusted series is given by:

$$\hat{y}_t^{SA} = \hat{\beta}_{CP} X_{t,CP} + \hat{\mu}_t + \hat{\varepsilon}_t,$$

where $X_{t,CP}$ indicates the Corona period (week 11, 2020 to week 13, 2022).

Figure 1 illustrates non-adjusted and adjusted weekly series for selected models.

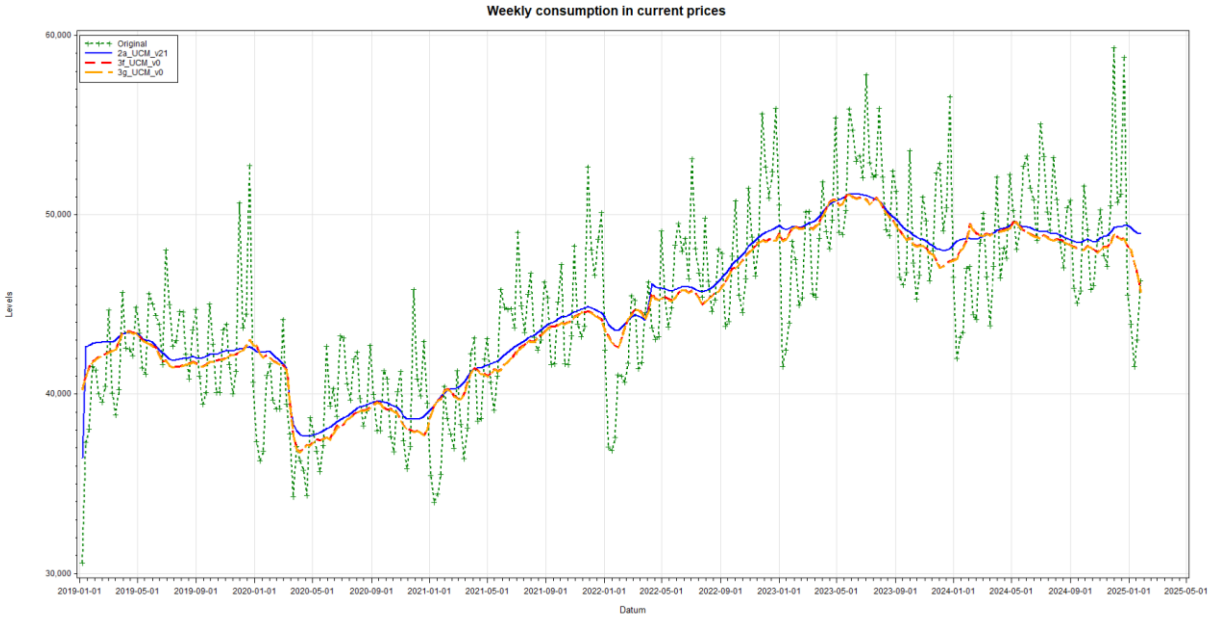


**Figure 1. Non-adjusted and adjusted weekly series for a few candidate models. The price type is current prices (SEK million).**

## 4. Conclusions and recommendations

The aim of the current study is to investigate and compare the performance of several possible approaches for performing seasonal adjustment and calendar correction of the weekly household consumption indicator derived from daily payment card data. Using various evaluation criteria, a final approach has been proposed. In terms of practical implementation, the proposed approach meets the technical requirements for software in statistical production processes at Statistics Sweden.

Methodologically, a key characteristic of the approach is that it includes a so-called Unobserved Component Model (UCM), which is to be applied in a single step directly to the weekly data. A comparative analysis with other possible approaches based on the idea of deriving weekly adjusted series by aggregating daily adjusted series (where the adjustment of daily series is done either by applying a UCM in a single step or in combination with a regression model), indicated that the one-step application of a UCM directly to weekly data is the most suitable for obtaining adjusted series with the desired properties.

To begin with, the proposed approach has demonstrated a high stability of the revised adjusted series, which partly depends on the relatively high degree of smoothing of the adjusted series. Furthermore, the degree of smoothing was not too high, as for other competing approaches, whose adjusted series resemble a trend rather than a seasonally adjusted and calendar corrected series.

Yet another advantage of the proposed approach is that the regression part of the UCM used to estimate calendar effects is fairly simple and easy to interpret. However, it is probably too simple to obtain a comprehensive description of calendar effects causing fluctuations in the underlying daily consumption.

As a final comment, we would like to emphasize that the final model cannot be generalized to any similar time series because the current study has only been concerned with a very specific weekly time series. Nevertheless, the experiences from the empirical work are genuine and are likely to have some important implications on future work with this kind of data.

## 5. Appendix: List of references


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