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Adjusting for calendar effects of real retail trade turnover time series

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Abstract. Fluctuations in economic activity are often influenced by calendar-based various factors. Such factors are non-working (non-trading) days, leap years, public holidays and the like. Most economic series are observed on a monthly or quarterly basis, but months (aggregated into quarters) are not comparable due to the different number of working and non-working days (different number of Mondays, Tuesdays, etc.). If the calendar effects are not properly adjusted, the identification of the ARIMA model for a given time series might not be correct, and the quality of seasonal adjustment is poor. An inappropriate calendar adjustment can generate false signals and negatively affect interpretation of adjusted data, which is particularly important for time series of retail sales and industrial productions. However, there is no general or unique procedure for correcting calendar effects in a pre-adjustment process of a time series. Therefore, this paper compares various regression models using alternative explanatory variables that take into account calendar effects and applied them to the time series of real retail trade turnover (RRT) in Croatia (monthly data observed from January 2001 to December 2013). The paper seeks to define a new explanatory variable (a regressor with time varying ratio between the average number of working days and the average number of non-working days) providing the most accurate correction of a RRT time series influenced by calendar effects. In addition, the assumption is that Saturdays and Sundays are working days of the week.

Key words: correction of calendar effects, real retail trade, pre-adjustment process

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1. Introduction

Short-term statistics are often characterized by seasonal fluctuations and other calendar effects, which can camouflage relevant short and long-term movements

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of series, and obstruct a clear understanding of analyzed economic phenomena. Therefore, the main objective of seasonal adjustment is to remove changes that are due to seasonal or calendar influences in order to produce a clearer picture of the underlying behavior of an analyzed series [4].

Most of economic series are observed on a monthly or quarterly basis, but months (aggregated into quarters) are not comparable due to the different number of working and non-working days (different number of Mondays, Tuesdays, etc.). This can have an impact on the observed variables such as retail sales, industrial productions and transportation. For example, retail sale turnover is likely to be more important on Saturdays than on other days of the week. Hence, there are two main reasons for revising data adjusted for seasonal effects and calendar effects: (1) revised gross data, based on improved information (in terms of coverage and/or reliability); or (2) a better estimated seasonality pattern, based on new information provided by new gross data, and based on the characteristics of filters and procedures that eliminate calendar and seasonal effects [4].

Two similar adjustment methods could be used; the method used by U.S. Census Bureau and the Eurostat method, although there is no paradigm on which method performs better [11]. The choice of method usually depends on experience and the policy of an organization, such as Croatian Bureau of Statistics. Calendar adjustment and seasonal adjustment is a source of constant debate, given that different methods can be used, in addition to the different tools and computer programs [6-8]. Moreover, the changes to original data due to seasonal adjustment is also brought into question.

According to the National Statistics Institute (INE) [11], seasonal fluctuations are movements occurring with a similar intensity each month (quarter) or each season of the year, and as such, are expected to continue occurring. Furthermore, calendar effects result from different structures of months (or quarters) in different years (in terms of length and composition), even if the remaining factors influencing the variable of interest remain constant. For example, March always has 31 days, and on average, it has more Mondays than February. The working-day adjustment should only be associated with the non-seasonal part of the effect.

According to Arteche et al. [1], calendar effects can be divided into two groups. The first group is the effects of working (or trading) days, whereas the second group deals with special calendar effects, such as Christmas, Easter or other (national) holidays. When processing data, these effects have to be considered as well as the associated various seasonal adjustment methods that are to be applied.

An inappropriate or poor quality seasonal and calendar adjustment can generate false signals and negatively affect interpretation of adjusted data. Bearing in mind all of this, the aim of this paper is to apply different correction methods to calendar effects influencing real retail trade turnover (RRT) in

Croatia and to define new explanatory variables that will provide most accurate correction of the RRTT time series. Therefore, new regressors in adjusting calendar effects will be defined.

The reminder of this paper provides the following sections. After the introduction in Section 2, an overview of different methods for correcting calendar effects based on previous research is presented. Section 3 describes the methodology, while Section 4 presents the results of the empirical analysis. Finally, Section 5 presents concluding remarks.

2. Overview of methods of calendar effects correction

Previous research has used linear regression incorporating different regressors for calendar adjustment of time series. Specifically, corrections for working (or trading) days are carried acquired from the estimated linear regression. Similar to Arteche et al. [1], the following calendar structure model using explanatory variables is defined as

$$y_t = z_t'\gamma + \varepsilon_t$$
$$\varphi(L)\delta(L)\varepsilon_t = \theta(L)v_t, \qquad t = 1,2,...,T \tag{1}$$

where y_t is a time series of interest, ε_t are error terms that follow an ARIMA process, $\varphi(L)$, $\delta(L)$ and $\theta(L)$ are finite polynomials of the lag operator L, z_t' is a vector of $(K\times 1)$ of K relevant regressors, γ is a $(K\times 1)$ vector of unknown parameters and v_t is an error term defined as white noise.

The component $z_t'\gamma$ represents nonstochastic effects, which are subtracted from the original time series before applying the ARIMA methodology for decomposition of the time series into a trend/cycle, seasonal and irregular component. The simplest nonstochastic effect is the average, in this case the regression constant. Effects that are more complex are for instance the intervention variables, atypical observations or calendar effects. Each time period is characterized by a different number of Mondays, Tuesdays, ..., Sundays. Arteche et al. [1] have compared different methods for processing calendar effects using spectral analysis, recursive estimation, information criteria and t-statistics applied to monthly data of the Industrial Production Index sourced from the Spanish province of Álava (Basque). The results are computed using the software packages TRAMO and SEATS. Five models are used, providing different corrections of calendar effects. The results indicated that simpler models can achieve better results, but may be insufficient for some time series, given that their duration and impact may vary between countries and sectors. They have concluded that atypical observations can have an important impact on processing calendar effects.

EUROSTAT [7] recommendations that the correction of calendar and seasonal effects and the extraction of a trend-cycle from a short term time-series should be carried out by applying ARIMA models along with TRAMO and SEATS modifications. This methodology is used by the main statistical offices throughout the world. TRAMO (Time Series Regression with ARIMA Noise, Missing Observations and Outliers) is a program for estimating, predicting and interpolating regression models using unobserved values and ARIMA errors, which in turn enables modelling of different types of anomalous values or outliers. TRAMO makes estimates using the maximum likelihood (or conditional least squares) of all the parameters in a selected model; detects and corrects anomalous observations or 'outliers' (additive, transitory or level shift); provides predictions of series and the corresponding mean square error; optimally interpolates non-observed values and calculates mean square errors. SEATS (Signal Extraction in ARIMA Time Series) decomposes a time series into unobservable components or signals. In addition, SEATS breaks down the linearized series, adhering to the specified model in TRAMO for the trend-cycle component (the trend includes long-term or low frequency movements, with a period exceeding 8 years). The cyclical component includes oscillations with a duration of between 2 and 8 years.

Leontitsis at al [12] have documented numerous stock return patterns related to calendar time. The list includes patterns related to the month-of-the-year, day-of-the-week and day-of-the-month. They have concluded that calendar anomalies are not in accordance with the concept of the Efficient Market Hypothesis. Their paper presents a nonlinear forecasting method for financial time series that takes into account calendar effects, improves the quality of forecasts and leads to the development of profitable trading strategies (excluding taxes, transaction and other costs). They used the daily returns from the NASDAQ Composite and TSE 300 Composite indices covering the period from 1984 to 2003.

Cano at al [3] used REGARIMA modelling techniques to account for calendar effects with month-specific explanatory variables. REGARIMA modelling combines standard regression analysis and ARIMA modelling. The REGARIMA models evaluate the variation in employment levels that are attributable to 11 separate survey interval variables, where one sis specified for each month except March, which always has a 4-week reporting interval from February. Smoothness statistics, t-statistics and joint tests for inclusion of explanatory variables provide supporting evidence for the majority of published employment series. The Bureau of Labor Statistics implemented the new X-12-ARIMA-based seasonal adjustment procedures with release of data from May 1996.

Monsell at al [13] have examined several alternative approaches to modelling Easter holiday effects including a method suggested by the Australian Bureau of Statistics. A more parsimonious technique for modelling trading day variation is examined by applying the day-of-week constraints from the weekday/weekend trading day contrast regressor found in TRAMO and X-12-ARIMA to the stock trading day. The final proposed Easter model is one that assumes that the change in the level of activity for weekend days (Friday, Saturday and Sunday) is different than the change for the weekdays leading up to Easter. This model will pool the effect for the weekend and weekdays, so that there is a single regressor for the weekend effect and a single regressor for the weekday effect.

Fale at al [9] describes the change to the seasonal adjustment of the SEEK and Trade Me Jobs vacancies series (the two main internet job boards) that are used to calculate the monthly Skilled Vacancy Index and All Vacancy Index. The change in the process is the result of an investigation into calendar effects in the series and comparisons of the performance of the day of the week and Easter effects regression models. The outcome of this modelling framework was a better identification of seasonal effects and a clearer picture of job vacancies, enhancing the Ministry of Business, Innovation and Employment's capacity to monitor and report on job vacancies. The modelling framework removes effects of the differing numbers of day of the week in each month, and the effect of Easter falling on different dates each year.

The adjustments were implemented using SAS software X-12 ARIMA to produce a combined regression and the ARIMA model for the time series by all and skilled vacancies for industries, occupations and regions. Standard statistical tests indicate that adjusting for these calendar effects in the vacancies series was consistent with the data in each month from Trade Me Jobs and SEEK.

3. Methodology

The working days effect differentiates working days from weekend days, so, in relevant literature, the variable $we_{m,T}$ is usually used to express the weighted difference between the number of working days in the month m from year T ($w_{m,T}$) and non-working days in the month m from year T ($nw_{m,T}$). The simplest way to compute the variable $we_{m,T}$ is:

$$we_{m,T} = \left(w_{m,T} - \frac{5}{2} nw_{m,T} \right). \tag{2}$$

Equation (2) gives the variable $we_{m,T}$, which is commonly used as a regressor in removing calendar effects. The weakness of the regressor defined in (2) and is a constant ratio between average number of working days and average number of non-working days, i.e. the number of non-working days is multiplied by 5/2 so that the average of the newly created variable is zero. This corresponds to the normalized composition-of-month effect. However, consideration must be given to the fact that the length and composition of each month has a seasonal part, which has to be captured in the seasonal component, and must not be eliminated. Moreover, the working-day adjustment must only be associated with the non-seasonal part of the effect. The non-seasonal part of the composition of working days of the month may be estimated by a deviation of this number of days from its long-term average. According to [4] and [11], in order to eliminate the seasonal part of this effect, the following working day regressor should be calculated using the following:

$$we^{*}_{m,T} = (w_{m,T} - \overline{w}_m) - \frac{\overline{w}}{\overline{\overline{nw}}} \cdot (nw_{m,T} - \overline{nw}_m) \quad m = 1,2,...,12 \, , \tag{3}$$

where, $w_{m,T}$ is the number of working days in the month m of year T, $\overline{w}_m$ is the average number of working days for each month in the series January, February,... December over the long-run (calculated over a 28-year calendar), $nw_{m,T}$ is the number of non-working days in the month m of year T, $\overline{nw}_m$ is the average number of non-working days for each month in the long run, and $\frac{\overline{w}}{\overline{\overline{nw}}}$ is the ratio between the average number of working days and the average number of non-working days, calculated over a 28-year calendar. In shorter series, this quotient is obtained using the calendar of the complete series, and is recalculated every year. The advantage of the regressor $we^{*}_{m,T}$ defined in (3) is that it includes both effects: the length-of-month effect and the composition-of-month effect. Even regressor $we^{*}_{m,T}$ exhibits better properties than $we_{m,T}$. It is erroneous to assume that working days $w_{m,T}$ are weekdays and non-working days $nw_{m,T}$ are Saturdays and Sundays, as is commonly set in most packages for time series analysis.

Furthermore, Eurostat and the European Central Bank emphasize the importance of leap year correction, which can be modelled using the following zero mean variable:

$$lpy_{m,T} \begin{cases} = 0{,}75 & \text{if } m = \text{February of a leap year} \\ = -0{,}25 & \text{if } m = \text{February of a non-leap year} \\ = 0 & \text{if } m = \text{other months} \end{cases} \tag{4}$$

The effect of public holidays as non-working days from Monday to Friday can also be analyzed separately by the following regressor:

$$phe_{m,T} = \left(ph_{m,T} - df\right), \tag{5}$$

where $ph_{m,T}$ is the number of non-working days corresponding to Monday, Tuesday, ..., Friday in the month m of year T, and df is the long run average of non-working days in the month excluding weekends. All three above-mentioned effects (working days effect, leap year effect and public holiday's effect) can be analyzed using a regression of a time series (monthly data observed over T years) with three independent variables:

$$y_{m,T} = \beta_0 + \beta_1 we_{m,T} + \beta_2 lpy_{m,T} + \beta_3 phe_{m,T} + \varepsilon_{m,T} , \quad (6)$$

Specifically, the regression model in equation (6) is the basic model which most European NSI use for correcting calendar effects. The alternative model can be a generalized model (6) that adds six new variables instead of $we_{m,t}$:

$$y_{m,T} = \beta_0 + \sum_{j=1}^{6} \beta_j w_{m,T}^j + \beta_7 lpy_{m,T} + \beta_8 phe_{m,T} + \varepsilon_{m,T} , \quad (7)$$

where $w_{m,T}^j$ are defined as follows:

$$\begin{aligned} w_{m,T}^1 &= \left(Mon_{m,T} - Sun_{m,T}\right) \\ w_{m,T}^2 &= \left(Thu_{m,T} - Sun_{m,T}\right) . \\ &\vdots \\ w_{m,T}^6 &= \left(Sat_{m,T} - Sun_{m,T}\right) \end{aligned} \quad (8)$$

Each variable $w_{m,T}^j$ represents the difference between the number of days j in month m of year T and the number of Sundays in month m of year T. Model (7) is the most popular model that combines standard regression analysis and ARIMA modelling before seasonal adjustment of the series. This model is known as the Reg-ARIMA model and is a part of the X-12-ARIMA technique. However, a disadvantage of model (7) is that it takes eight parameters to conduct an estimate, whereas model (6) has only three parameters. Model (6) and (7) can be modified by excluding some independent variables, thus allowing different corrections to calendar effects of a given time series. Based on that idea, models (6) and (7) can be simplified into one model using only one regressor, which can take into account all of the effects, i.e. the working days effect, public holidays' effect, as well as the Easter effect and implicitly the leap year effect:

$$y_{m,T} = \beta_0 + \beta_1 we^*_{m,T} + \varepsilon_{m,T} , \quad (9)$$

where $we^*_{m,t}$ is defined as in (3) but differs in the manner of counting working days and non-working days (regardless of whether it is a public holiday or Easter).

When building the regressor $we^*_{m,t}$, Croatian public holidays should be taken into account. In calculation both working and non-working days, the number of each of these days in each month in Croatia are taken into consideration.

According to abovementioned three models, only two are applied and compared. Namely, model (6) and model (9) are taken into consideration due to the parsimony principle that is compared to model (7). Moreover, model (7) assumes that Sunday is non-working day in the month, which does not hold true for Croatia. Since the objective of this paper is to define new a explanatory variable which will give the most accurate correction of the RRT time series, regressor $we^*_{m,t}$ in equation (9) is modified according two following assumptions:

- The ratio between the average number of working days and the average number of non-working days is not constant (it should be recalculated every year).
- Saturdays and Sundays are working days of the week.

It is rational to assume that Saturdays and Sundays are working days of the week due to retail sales in Croatia. Working on weekends, especially on Sundays, became an important marketing element and usual practice in Croatia, brought on by arrival of foreign retail chains and the formation of new national retail chains that mainly trade in food products and consumer goods. Large shopping centers are becoming a destination for family trips on Sundays, and skilled traders constantly are organizing specials and promotions to attract more customers.

The regressor $we_{m,t}$ in equation (6) is also be modified based on the same two assumptions. Therefore, the proposed modifications refer to manner variables $we_{m,t}$ and $we^*_{m,t}$ are computed according based on formulas (2) and (3) by taking into account new assumptions. After computing regressors $we_{m,t}$ and $we^*_{m,t}$, models (6) and (9) are estimated using OLS and are compared to reach the conclusion as to which of the two models provides a better correction of calendar effects. Input data for two regressors are presented in Table 1 and Table 2, while the empirical results are presented in the next section.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Jan	29	29	29	29	29	29	29	29	29	29	29	29	29
Feb	28	28	28	29	28	28	28	29	28	28	28	29	28
Mar	31	30	31	31	29	31	31	29	31	31	31	31	30
Apr	28	29	28	28	30	28	28	30	28	28	28	28	29
May	29	29	30	30	29	30	30	29	30	29	30	30	29
Jun	29	29	27	27	28	27	27	28	27	27	27	27	28
Jul	31	31	31	31	31	31	31	31	31	31	31	31	31
Aug	29	29	29	29	29	29	29	29	29	29	29	29	29
Sep	30	30	30	30	30	30	30	30	30	30	30	30	30
Oct	31	31	30	30	30	30	30	30	30	30	30	30	30
Nov	29	29	29	29	29	29	29	29	29	29	29	29	29
Dec	29	29	29	29	29	29	29	29	29	29	29	29	29

Table 1: *The number of working days of the month from 2001-2013.*

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Jan	2	2	2	2	2	2	2	2	2	2	2	2	2
Feb	0	0	0	0	0	0	0	0	0	0	0	0	0
Mar	0	1	0	0	2	0	0	2	0	0	0	0	1
Apr	2	1	2	2	0	2	2	0	2	2	2	2	1
May	2	2	1	1	2	1	1	2	1	2	1	1	2
Jun	1	1	3	3	2	3	3	2	3	3	3	3	2
Jul	0	0	0	0	0	0	0	0	0	0	0	0	0
Aug	2	2	2	2	2	2	2	2	2	2	2	2	2
Sep	0	0	0	0	0	0	0	0	0	0	0	0	0
Oct	0	0	1	1	1	1	1	1	1	1	1	1	1
Nov	1	1	1	1	1	1	1	1	1	1	1	1	1
Dec	2	2	2	2	2	2	2	2	2	2	2	2	2

Table 2: *The number of non-working days of the month from 2001-2013.*

4. Empirical analysis

The data set analyzed in this paper is a series of real Turnover Indices in Retail Trade for Croatia. The sample period ranges from January 2001 to December 2013 for a total of 156 monthly observations. According to the parasimony principle, two regression models are estimated using different regressors according to equations (6) and (9).

The first regression model uses three regressors, among which the variable $we_{m,t}$ is calculated according to equation (2) using data in Table 1 and 2. It should be emphasized once again that regressor $we_{m,t}$ accounts for only the composition-of-month effects. Figure 1 presents the results of this regression model using the OLS method.

	Coefficient	Std. Error	t-ratio	p-value
const	73.7791	13.0302	5.6622	0.0000
we	1.02670	0.491656	2.0882	0.0384
lpy	6.86919	9.58428	0.7167	0.4747
phe	5.44698	1.95289	2.7892	0.0060

Mean dependent var	100.8416	S.D. dependent var	14.81265
Sum squared resid	32185.57	S.E. of regression	14.55154
R^2	0.053623	Adjusted R^2	0.034944
$F(3, 152)$	2.870835	P-value(F)	0.038348
Log-likelihood	−637.0490	Akaike criterion	1282.098
Schwarz criterion	1294.297	Hannan–Quinn	1287.053
$\hat{\rho}$	0.653656	Durbin–Watson	0.651969

Figure 1: *Estimated OLS regression according to equation (6)*

As seen in Figure 1, the effect of additional working days (estimated coefficient of the variable *we*) is positive, meaning that on average, the retail trade turnover series should be upward corrected to 1.0267 for the additional working day. The conclusion is also that variable *lpy* is not statistically significant at a significance level of 5%, while the effect of an additional working day as well as the effect of a public holiday are significant. The public holiday effect is also positive, meaning that on average, the retail trade turnover series should be upward corrected to 5.4469. Public holidays are non-working days of the month, so they increase retail sales due to more intensive purchasing one or two days immediately before the public holiday.

However, the significance tests and other regression diagnostics are not as important as subtraction fitted values from the original series used to compute calendar adjusted values. Therefore, calendar adjusted values are residuals plus 100, which is exactly the mean of the retail trade turnover indices. Due to limited discussion, only actual values (RTT), fitted values and residuals for the year 2002 are presented in Table 3, while actual values and calendar-adjusted values are shown on Figure 2.

	rrt	fitted	residual
2002:01	73.909837	99.345776	-25.435939
2002:02	75.690667	96.288279	-20.597612
2002:03	90.827608	97.492229	-6.664621
2002:04	89.966721	101.912514	-11.945794
2002:05	96.350171	99.345776	-2.995605
2002:06	95.341871	112.806475	-17.464604
2002:07	107.768171	101.085663	6.682507
2002:08	104.990402	99.345776	5.644626
2002:09	99.497267	100.058968	-0.561701
2002:10	99.035243	106.532643	-7.497401
2002:11	92.101212	101.912514	-9.811302
2002:12	103.381128	104.792756	-1.411628

Table 3: *Actual values (RRT), fitted values and residuals for the year 2002 according to equation (6)*

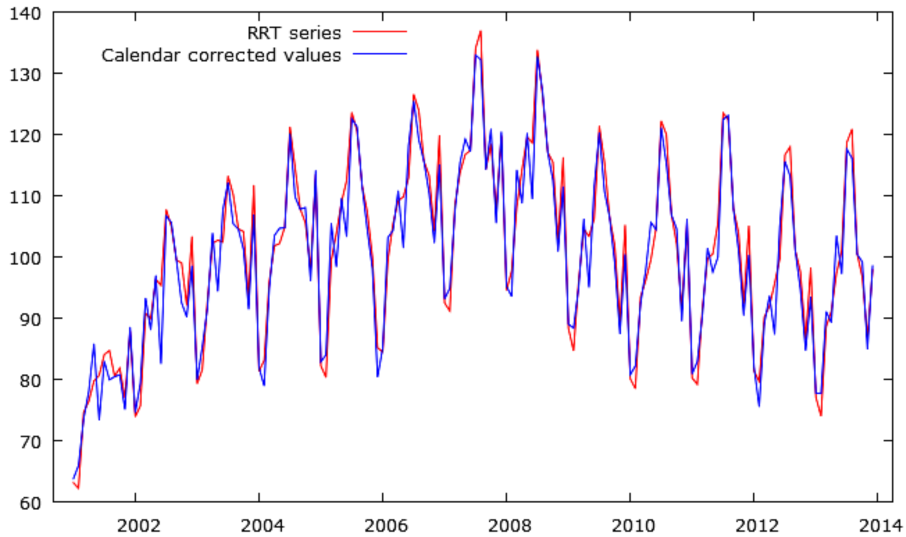

Figure 2: *Actual values of RRT series and calendar-adjusted values according to equation (6)*

The second regression model uses only one regressor $we^{*}_{m,t}$, which is calculated according to equation (3) using data in Table 1 and 2. It should be emphasized that regressor $we^{*}_{m,t}$ accounts for the composition-of-month effect and the length-of-the month effect, where both have been adjusted for the new assumptions given in Section 3. The results of this regression model are obtained within the OLS method and presented on Figure 3.

	Coefficient	Std. Error	t-ratio	p-value
const	100.868	1.17661	85.7274	0.0000
we2	2.76162	1.47708	1.8697	0.0634

Mean dependent var	100.8416	S.D. dependent var	14.81265
Sum squared resid	33254.41	S.E. of regression	14.69482
R^2	0.022195	Adjusted R^2	0.015846
$F(1, 154)$	3.495602	P-value(F)	0.063431
Log-likelihood	−639.5972	Akaike criterion	1283.194
Schwarz criterion	1289.294	Hannan–Quinn	1285.672
$\hat{\rho}$	0.667045	Durbin–Watson	0.622143

Figure 3: *Estimated OLS regression according to equation (9)*

According to Figure 3, the effect of additional working days (estimated coefficient of $we2$) results in a positive sign, meaning that on average, the retail trade turnover series should be upward corrected to 2.7616 when taking calendar effects into account. Calendar-adjusted values are residuals plus 100, which is exactly the mean of the retail trade turnover indices. Due to the limited discussion, only actual values (RRT), fitted values and residuals are presented for the year 2002 in Table 4, while actual values and calendar-adjusted values are presented in Figure 4.

	rrt	fitted	residual
2002:01	73.909837	101.337251	-27.427414
2002:02	75.690667	98.575631	-22.884964
2002:03	90.827608	98.575631	-7.748023
2002:04	89.966721	101.337251	-11.370530
2002:05	96.350171	101.337251	-4.987080
2002:06	95.341871	106.860491	-11.518620
2002:07	107.768171	98.575631	9.192539
2002:08	104.990402	101.337251	3.653151
2002:09	99.497267	98.575631	0.921636
2002:10	99.035243	101.337251	-2.302008
2002:11	92.101212	101.337251	-9.236039
2002:12	103.381128	104.098871	-0.717743

Table 4: *Actual values (RRT), fitted values and residuals for the year 2002 according to equation (9)*

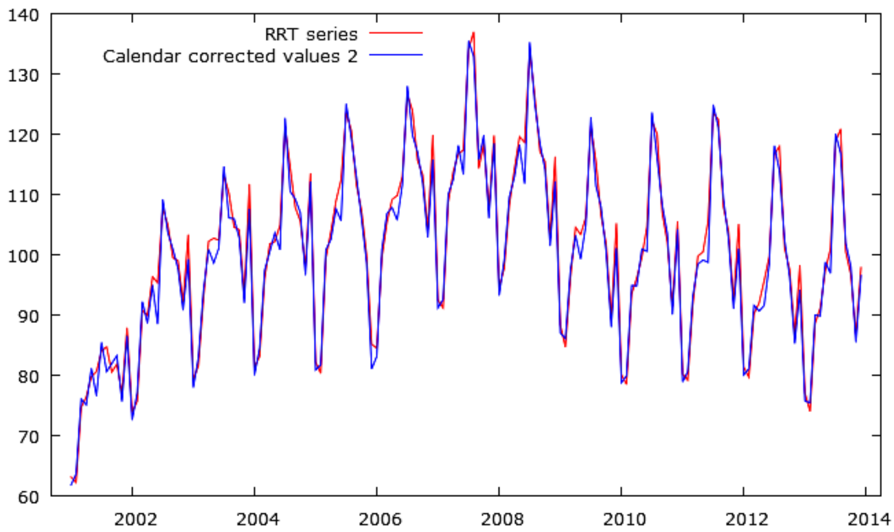

Figure 4: *Actual values of RRT series and calendar-adjusted values according to equation (9)*

In Table 5, two series of calendar-adjusted values are compared with the original series of retail trade turnover indices in Croatia (due to the limited discussion, only the results for 2001–2003 are presented). The first series of calendar-adjusted values (corrected_1) are obtained according to residuals of the first regression model with three regressors, while the second series of calendar-adjusted values (corrected_2) are obtained according to the residuals of the second regression model with one regressor.

	rrt	corrected_1	corrected_2
2001:01	63.1351	63.7893	61.7978
2001:02	62.2251	65.9368	63.6494
2001:03	74.6614	73.5758	76.0858
2001:04	76.4270	78.1079	75.0897
2001:05	79.7629	85.8641	81.1872
2001:06	80.6731	73.3136	76.5742
2001:07	84.0766	82.9910	85.5010
2001:08	84.7291	79.9363	80.6302
2001:09	80.5255	80.4665	81.9499
2001:10	81.8557	80.7700	83.2801
2001:11	76.9766	75.0641	75.6393
2001:12	87.9200	88.5742	86.5827
2002:01	73.9098	74.5641	72.5726
2002:02	75.6907	79.4024	77.1150
2002:03	90.8276	93.3354	92.2520
2002:04	89.9667	88.0542	88.6295
2002:05	96.3502	97.0044	95.0129
2002:06	95.3419	82.5354	88.4814
2002:07	107.7682	106.6825	109.1925
2002:08	104.9904	105.6446	103.6532
2002:09	99.4973	99.4383	100.9216
2002:10	99.0352	92.5026	97.6980
2002:11	92.1012	90.1887	90.7640
2002:12	103.3811	98.5884	99.2823
2003:01	79.2991	79.9534	77.9619
2003:02	81.5538	85.2655	82.9781
2003:03	92.7236	91.6380	94.1480
2003:04	102.2493	103.9302	100.9120
2003:05	102.7398	94.3536	98.6409
2003:06	102.4439	107.7182	101.1066
2003:07	113.2461	112.1605	114.6705
2003:08	110.2213	105.4285	106.1224
2003:09	104.5821	104.5231	106.0065
2003:10	104.1513	101.2121	102.8140
2003:11	93.3357	91.4232	91.9984
2003:12	111.7542	106.9615	107.6553

Table 5: *Two series of calendar-adjusted values (corrected˙1 and corrected˙2) compared with the original series of retail trade turnover indices for first three years of observation*

The model that provides a better fit for a correction of the calendar effect is the second model, because the two Schwartz and Hannan-Quinn information criteria have smaller values compared to the first model, due to a smaller number of regressors included in the regression equation. In other words, the model with the proposed regressor, which accounts for the composition-of-month effect and length-of-the month effect, is appropriate for calendar adjustment.

Moreover, the proposed regessor is modified according to the new introduced assumptions: the ratio between average number of working days and average number of non-working days is not constant (it is recalculated every year), and Saturdays and Sundays are working days of the week. These assumptions have changed the values of regressors used in the regression analysis. Standard diagnostic tests have shown that basic assumptions of the model have been met. The results of these diagnostic tests are available upon request.

5. Conclusion

Most of the economic series are observed on a monthly or quarterly basis, but some months (quarters) are not comparable due to the different number of working and non-working days. An inappropriate calendar adjustment can generate false signals and negatively affect the interpretation of adjusted data, which is particularly relevant for time series of retail sales and industrial productions. The straightforward use of existing methods by the Bureau of Statistics is not sufficient to capture calendar variations because they are not always periodic. Moreover, any calendar effects are masked by dominated seasonal effects. Therefore, the appropriate explanatory variables giving the most accurate calendar correction of a given time series should be chosen. An estimation of results shows that a single regression model with a newly proposed regressor $we^{*}_{m,T}$ is a better alternative for calendar adjustment of retail trade turnover series in Croatia, compared to multiple regression model. The advantage of the proposed regressor $we^{*}_{m,T}$ is that it accounts for all composition-of-month effects: working days effect, public holidays effect and implicitly the effect of leap years. Furthermore, it accounts for the length-of-month effect. The newly proposed regressor $we^{*}_{m,T}$ is adjusted by taking into account two assumptions: (1) the ratio between the average number of working days and the average number of non-working days is not constant (it is recalculated every year), and (1) Saturdays and Sundays are working days of the week. It is rational to assume that Saturdays and Sundays are working days of the week based on retail sales in Croatia. Working on weekends, especially on Sundays, has become an important marketing element and usual practice in Croatia, in line with the arrival of foreign retail chains and the formation of new national retail chains, which mainly trade in food products and consumer goods. Large shopping centers are becoming a regular destination for family trips on Sundays, where experienced traders constantly organize specials and promotions in order to attract more customers. In general, the conclusion is that an additional working day in the month has a positive effect on retail sales, i.e. retail trade turnover series should be upward corrected on average to 2.7616, when taking calendar effects into account.

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