https://doi.org/10.26219/heal.aueb.5891

ΟΙΚΟΝΟΜΙΚΟ
ΠΑΝΕΠΙΣΤΗΜΙΟ
ΑΘΗΝΩΝ

ATHENS UNIVERSITY
OF ECONOMICS
AND BUSINESS

SCHOOL OF INFORMATION SCIENCES & TECHNOLOGY
DEPARTMENT OF STATISTICS
POSTGRADUATE PROGRAM

Comparison of seasonally adjusted time series for composite (aggregated) quantities

By
Petrina I. Stivakta

A THESIS
Submitted to the Department of Statistics
of the Athens University of Economics and Business
in partial fulfilment of the requirements for
the degree of Master of Science in Statistics

Athens, Greece
August 2022

https://doi.org/10.26219/heal.aueb.5891

https://doi.org/10.26219/heal.aueb.5891

ΣΧΟΛΗ ΕΠΙΣΤΗΜΩΝ & ΤΕΧΝΟΛΟΓΙΑΣ ΤΗΣ ΠΛΗΡΟΦΟΡΙΑΣ
ΤΜΗΜΑ ΣΤΑΤΙΣΤΙΚΗΣ
ΜΕΤΑΠΤΥΧΙΑΚΟ ΠΡΟΓΡΑΜΜΑ

Σύγκριση εποχικά διορθωμένων χρονοσειρών για σύνθετα (συγκεντρωτικά) μεγέθη

Πετρίνα Ι. Στιβακτά

ΔΙΑΤΡΙΒΗ
Που υποβλήθηκε στο Τμήμα Στατιστικής
του Οικονομικού Πανεπιστημίου Αθηνών
ως μέρος των απαιτήσεων για την απόκτηση
Διπλώματος Μεταπτυχιακών Σπουδών στη Στατιστική

Αθήνα
Αύγουστος 2022

https://doi.org/10.26219/heal.aueb.5891

DEDICATION

To my beloved mother, Helen

https://doi.org/10.26219/heal.aueb.5891

ACKNOWLEDGMENTS

During my postgraduate studies at the Department of Statistics of Athens University of Economics and Business, I had the honor of meeting a lot of interesting people. One of them, is my supervisor Prof.Evangelos Ioannidis, whom I would like to thank for all his help and guidance that provided me. This work would not have been possible without his support.

I also want to thank my family, for their patience, guidance and support throughout my studies. *I appreciate you beyond words, and I am forever indebted to you!*

https://doi.org/10.26219/heal.aueb.5891

https://doi.org/10.26219/heal.aueb.5891

VITA

I was born in Athens, Greece, on June 11, 1993. In September 2012, I entered the Department of Mathematics at the National and Kapodistrian University of Athens and in April 2021, I received my bachelor degree. I enrolled the Master of Science in Statistics at Athens University of Economics and Business in September 2020.

https://doi.org/10.26219/heal.aueb.5891

https://doi.org/10.26219/heal.aueb.5891

ABSTRACT

This thesis shows how to seasonally adjust aggregate time series using the TRAMO/SEATS program, supported by the software JDemetra+. By performing seasonal adjustment an aggregate series can be seasonally adjusted either directly or indirectly by adjusting its components and adding the results. We describe the basic principles of the TRAMO/SEATS, as well as the two seasonal adjustment approaches. Then, we perform seasonal adjustment of the Greek Industrial Production Index using the direct and indirect approach for two possible models, one with log-transformation of the data and the other without transformation.

The choice between the direct and the indirect seasonal adjustment is made taking into account the quality of the seasonally adjusted data, the consistency between the two approaches and the magnitude of revisions. It is interesting that the two approaches provide almost similar results for the two models, however in terms of roughness measures (Gómez and Maravall (1999)) and revisions, it appears that the direct method is preferred over the indirect for both models.

https://doi.org/10.26219/heal.aueb.5891

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ΠΕΡΙΛΗΨΗ

Η παρούσα διατριβή δείχνει πώς να προσαρμόσουμε εποχικά συγκεντρωτικές χρονοσειρές με τη χρήση του προγράμματος TRAMO/SEATS, το οποίο υποστηρίζεται από το λογισμικό JDemetra+. Με την εποχική προσαρμογή μια συγκεντρωτική σειρά μπορεί να προσαρμοστεί εποχικά είτε άμεσα είτε έμμεσα με την προσαρμογή των συνιστωσών της και την πρόσθεση των αποτελεσμάτων. Περιγράφουμε τις βασικές αρχές του TRAMO/SEATS, καθώς και τις δύο προσεγγίσεις εποχικής προσαρμογής. Στη συνέχεια, πραγματοποιούμε εποχική προσαρμογή του Δείκτη Βιομηχανικής Παραγωγής της Ελλάδας χρησιμοποιώντας την άμεση και έμμεση προσέγγιση για δύο πιθανά μοντέλα, το ένα με λογαριθμικό μετασχηματισμό των δεδομένων και το άλλο χωρίς μετασχηματισμό.

Η επιλογή μεταξύ άμεσης και έμμεσης εποχικής προσαρμογής γίνεται λαμβάνοντας υπόψη την ποιότητα των εποχικά προσαρμοσμένων δεδομένων, τη συνέπεια μεταξύ των δύο προσεγγίσεων και το μέγεθος των αναθεωρήσεων. Είναι ενδιαφέρον ότι οι δύο προσεγγίσεις παρέχουν σχεδόν παρόμοια αποτελέσματα για τα δύο μοντέλα, ωστόσο όσον αφορά τα μέτρα τραχύτητας (Gómez και Maravall (1999)) και τις αναθεωρήσεις, φαίνεται ότι η άμεση μέθοδος προτιμάται έναντι της έμμεσης και για τα δύο μοντέλα.

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1

INTRODUCTION

A common practice nowadays is to perform seasonal adjustment (SA) in order to interpret published statistics. By separating the non-seasonal part from the seasonal and calendar effects it is likely to obtain a refined picture about the underlying movement of the time series observations. Hence, the SA-procedure eliminates the estimated seasonal and calendar effects from the original time series and obtain the SA estimates. Such estimates are likely to reveal what is new in a time series, which is a crucial issue related to seasonal adjustment. The European Statistical System (ESS) developed a set of guidelines on seasonal adjustment (Eurostat, 2009) and the new software JDemetra+ (Eurostat, 2012), which supports TRAMO/SEATS (developed by the Bank of Spain and promoted by Eurostat), a seasonal adjustment approach based on ARIMA modeling.

The ARIMA-model-based (AMB) approach for seasonal adjustment (Gómez and Maravall [1]) is an alternative to the X13-ARIMA-SEATS (or X13) seasonal adjustment program, developed and supported by the U.S. Census Bureau (Monsell B. (2007)). The X13 implements the two most widely used seasonal adjustment methods: the moving average X-11 method (uses linear filters) and the ARIMA model-based SEATS method. The X13-ARIMA-SEATS uses filter that applies to every single series in the same manner regardless of the structure of the seasonal and non-seasonal components. Conversely, the SEATS uses filter that adapts itself to the particular structure of the series.

Specifically, TRAMO/SEATS consists of two main programs and runs through the following steps. In the first step, the TRAMO program is applied to fit an appropriate ARIMA model for the time series under analysis. During this process, outliers are automatically detected and other regression variables such as calendar-day variations and holiday effects are also estimated, in order to produce the "linearized" series, which is the original series corrected for outliers and calendar effects.

In the second step, TRAMO passes the linearized series to the SEATS program, which carries out the actual decomposition. The pre-adjusted series (y) is decomposed into the following components: trend-cycle (t), seasonal component (s) and irregular component (i). The decomposition can be: additive ($y = t + s + i$) or multiplicative ($y = t \cdot s \cdot i$). To do this, the approach consists of estimating an ARIMA model for the original (pre-adjusted) series and deriving consistent ARIMA models for the unobserved components (trend-cycle, seasonality, irregular). Then, it finds the roots of the AutoRegressive (AR) polynomial that are close to the seasonal frequencies, and these roots are assigned to the seasonal component. The rest of the roots are attributed to the other components. The roots may be allocated to the different components according to the behavior they induce in the series. Thus, the AR polynomials of the components are identified and can be obtained from the AR polynomial in the model for the observed series. On the basis of these models, appropriate filters are developed to extract each component from the series (Maravall [16]).

In the SEATS process, the unobserved components are assumed to be orthogonal. In order to apply a symmetric filter, missing values are replaced by their forecasts or backcasts. SEATS derives the final estimate of seasonally adjusted series by estimating the parameters of the trend-cycle component and seasonal adjustment factor, and re-introducing the outliers and the various effects into these estimated components. The final seasonally adjusted series shall be free of seasonal and calendar-related movements.

The two programs are structured so as to be used together, both for in depth analysis of a few series (as done at the Bank of Spain) or for automatic routine applications to a large number of series (as presently done at Eurostat).

A seasonal time series can be the result of adding up two or more sub-series (possibly weighted). From the point of view of the seasonal adjustment policy, two natural alternatives arise to seasonally adjust the aggregated series:

1. the aggregated series is seasonally adjusted on its own (direct method)

2. the aggregated seasonally adjusted series is obtained as a sum of seasonally adjusted sub-series (indirect method).

The results for the two methods will rarely be identical. To preserve additivity, it is often preferred to indirectly adjust many series. However, in some instances this may lead to an adjustment with residual seasonality, large revisions, or less stable results than direct seasonal adjustment. Therefore, it is important to always check the quality of the adjustment. This applies to the direct and the indirect adjustment, as well as the adjustments of all the sub-series. In this thesis, we address the problem of comparing the two approaches mentioned above in order to determine the best quality of the seasonal adjustment of the Greek Industrial Production Index (IPI). The comparison of the two adjustments is achieved with some quality measures (Dagum ([2]), Pfefferman et al. ([5]), Gómez and Maravall ([11])).

The rest of this thesis is organized as follows:

Chapter 2 provides information relevant to the TRAMO/SEATS program.

Chapter 3 discusses the issue of direct and indirect seasonal adjustment and proposes some useful criteria, which can contribute to the choice between the direct and the indirect approach.

Chapter 4 presents the application for the discussed seasonal adjustment procedure to the example of the IPI. It compares the direct and the indirect approach using some useful quality measures, in order to determine which method is better.

Chapter 5 concludes this thesis.

https://doi.org/10.26219/heal.aueb.5891

2

SEASONAL ADJUSTMENT WITH JDEMETRA+

2.1 TRAMO/SEATS

TRAMO/SEATS is a model-based seasonal adjustment method which has been developed by Maravall and Gómez (1996) at the Bank of Spain and it consists of two linked programs: TRAMO and SEATS.

2.1.1 *The TRAMO program*

TRAMO ("Time Series Regression with ARIMA Noise, Missing Observations, and Outliers") performs estimation and forecasting of regression models with possibly nonstationary (ARIMA) errors and any sequence of missing values. The program interpolates these values, identifies and corrects for several types of outliers, and estimates special effects such as Trading Day and Easter Effect and eventually produces a linear purely stochastic process (i.e., the ARIMA model). Fully automatic ARIMA model identification and outlier correction procedures are available. With reference to the automatic procedure for ARIMA model identification, it is worth emphasising that model identification is the most important step in the model building process influencing parameters estimates, forecasting and decomposition. The availability of a powerful automatic procedure for model identification is the most widespread procedure used for seasonal adjustment (Gómez and Maravall (2001)). TRAMO/SEATS has greatly simplified the seasonal adjustment, allowing a massive treatment and decomposition of many seasonal time series and enhancing the overall quality of data.

The ARIMA-model-based methodology for seasonal adjustment developed from the work of Cleveland and Tiao (1976), Burman (1980), Hillmer and Tiao (1982), Bell and Hillmer (1984) and Maravall and Pierce (1987).

Thus, the first step consists of pre-adjusting the original series with a regression-ARIMA model, where the original series is corrected for any deterministic effects and missing observations. This step is also reffered as linearization of the original series. The program fits the regression model:

$$y_t = w_t'\beta + x_t \tag{1}$$

where:

- y_t is the original series

- $\beta = (\beta_1, ..., \beta_n)'$ is a vector of regression coefficients

- $w_t' = (w_{1t}, ..., w_{nt})$ denotes n regression variables (outliers, calendar effects (e.g. Easter effect), user-defined variables) and

- the monthly or quarterly series x_t is a disturbance that follows the stochastic general ARIMA model

$$\phi(B)\delta(B)x_t = \theta(B)a_t \tag{2}$$

where B is the backshift operator $(By_t = y_{t-1})$, a_t is assumed a white-noise variable with zero mean and a constant variance, and $\delta(B)$, $\phi(B)$, $\theta(B)$ are finite polynomials in B that have the multiplicative form:

$$\delta(B) = (1-B)^d(1-B^s)^D$$

$$\phi(B) = (1+\phi_1 B + ... + \phi_p B^p)(1+\Phi_1 B^s + ... + \Phi_P B^{s\times P})$$

$$\theta(B) = (1+\theta_1 B + ... + \theta_q B^q)(1+\Theta_1 B^s + ... + \Theta_Q B^{s\times Q})$$

https://doi.org/10.26219/heal.aueb.5891

where:

- p - the number of regular AR terms (in ’JDemetra+’ $p \leq 3$)
- P - the number of seasonal AR terms (in ’JDemetra+’ $P \leq 1$)
- q - the number of regular MA terms (in ’JDemetra+’ $q \leq 3$)
- Q - the number of seasonal MA terms (in ’JDemetra+’ $Q \leq 1$)
- s denotes the number of observations per year.

More specifically $\delta(B)$ is a non-stationary autoregressive (AR) polynomial in B that contains the unit roots associated with differencing (d-regular (non-seasonal) differencing order (in ’JDemetra+’ $d \leq 2$) and D-seasonal differencing order (in ’JDemetra+’ $D \leq 1$)), $\phi(B)$ is a stationary autoregressive polynomial in B and in B^s containing regular and seasonal unit roots, and $\theta(B)$ denotes the (invertible) moving average polynomial in B and in B^s.

Initial estimates of the parameters can be input by the user, set to the default values, or computed by the program. Additionally, the regression variables can be input by the user or generated by TRAMO. The variables that can be generated are e.g. Trading day, Easter effect.

JDemetra+ uses notation: P, D, Q, BP, BD, BQ instead of p, d, q, P, D, Q respectively. Therefore, the structure of the ARIMA $(p,d,q)(P,D,Q)$ model is denoted in JDemetra+ as ARIMA $(P,D,Q)(BP,BD,BQ)$.

Moreover, TRAMO:

1) estimates by exact maximum likelihood (or unconditional/conditional least squares) the parameters in (1) and (2)
2) computes optimal forecasts for the series, together with their MSE
3) yields optimal interpolators of the missing observations and their associated MSE

TRAMO has a facility for detecting outliers and removing their effect. The outliers can be entered by the user or they can be automatically detected by the program, using the original appoach, as proposed by Tsay (1986) and Chen and Liu (1993). The procedure used to incorporate or reject outliers is similar to the stepwise regression procedure for selecting the *best* regression equation.

Therefore, TRAMO contains the pre-adjustment phase of a time series. This comprises adjustment for working days, i.e. allowing for the impact of weekends, public holidays and the Leap Day. Extreme observations (outliers) in the data are also addressed at the pre-adjustment phase.

TRAMO/SEATS can observe three types of outliers. These are distinguished by the way the time series returns to the level prior to the outlying observation.

1. ***The isolated additive outlier (AO)***. In this case, the time series returns back to its starting level immediately after the outlying observation.

2. ***Transitory change (TC)***. In the case of a transitory change, the level of the time series changes abruptly but then gradually returns to its starting level over the next few observations.

3. ***Level shift (LC)***. It is concerned when the level of the time series changes but does not return to the level prior to this change over the next few observations.

   There is another type of outlier, the seasonal, that user has to enable its detection.

4. ***Seasonal outlier (SO)***. A seasonal outlier is an event that affects one period (month or quarter) of a time series permanently.

TRAMO also contains a facility to pre-test for the log-level specification and if appropriate for the possible presence of trading day and Easter effect. The default model in TRAMO is the so-called Airline (ARIMA (0,1,1)(0,1,1)) model, introduced by Box and Jenkins (1970), who used it to study a time series of the number of airline passengers. The Airline model is given by the equation:

$$\nabla\nabla_s x_t = (1+\theta B)(1+\Theta B^s)a_t, \qquad -1 \leq (\theta,\Theta) \leq 1.$$

Thus, TRAMO can be used as a pre-adjustment process to SEATS, which decomposes then the linearized series and its forecasts into its stochastic components.

2.1.2 *The SEATS program*

SEATS ("Signal Extraction in ARIMA Time Series") computes the components for seasonal adjustment. It is a program for estimation of unobserved components in time series following the ARIMA-model-based method. It uses signal extraction with filters derived from an ARIMA-type time series model that describes the behavior of the series. The input for the model based signal extraction procedure is always provided by TRAMO and includes the original series y_t, the linearized series x_t (i.e. the original series y_t with the deterministic effects removed), the ARIMA model for the stochastic time series x_t and the deterministic effects (calendar effects, outliers and other regression variable effects).
SEATS decomposes the linearized series (and the ARIMA model) into trend, seasonal, transitory and irregular components, provides forecasts for these components, together with the associated standard errors, and finally assigns the deterministic effects to each component yielding the final components. The Minimum Mean Square Error (MMSE) estimators of the components are computed with a Wiener-Kolmogorov filter applied to the finite series extended with forecasts and backcasts.

Following the genuine TRAMO algorithm it is possible to choose between an additive and a multiplicative decomposition model by adjusting the fractional Airline model (0,1,1)(0,1,1) to the raw data and to the log-transformed data and comparing the quality of the adjustments. Unless JDemetra+ finds a more specific model, it applies the Airline model.

Completed the preliminary treatment, aimed at removing the calendar effects, the outliers and other deterministic effects and estimating possible missing values, the resulting time series are decomposed into the unobserved components trend-cycle, seasonality and irregular.

The seasonal adjustment methods available in JDemetra+ aim to decompose a time series into components and remove seasonal fluctuations from the observed time series. The main components, each representing the impact of certain types of phenomena on the time series (X_t), are:

1. The trend (T_t) that captures long-term and medium-term behaviour, and consists of 2 sub-components:
    a) The long-term evolution of the series
    b) The cycle, that represents the smooth, almost periodic movement around the long-term evolution of the series.
2. The seasonal component (S_t) representing intra-year, monthly or quarterly fluctuations, that are repeated more or less regularly year after year.
3. The irregular component (I_t) combines all the other more or less erratic fluctuations not covered by the previous components.

For some data series, SEATS will identify and estimate a transitory component. While the irregular component is defined as white noise, the transitory component identifies and removes short-term variation other than that, which would otherwise influence the estimation of the seasonal component. Once the components are estimated, the irregular and transitory component are treated together. Adding the transitory component improves the performance of the trend-cycle and SA series.

To ensure the optimal identification of the components of an unadjusted series, outliers are removed from a series prior to the actual seasonal adjustment process. However, since the outliers include important information, they are generally re-introduced as part of the final seasonally adjusted data, and therefore they remain observable after seasonal adjustment. The exception is with seasonal outliers, as these should not be evident in the seasonally adjusted data.

The following table (Table 2.1) shows which components are assigned the different type of outliers as well as some other features of the outliers.

https://doi.org/10.26219/heal.aueb.5891

Type of outlier	Component	Durability of impact	Visible in SA data
Additive outlier	Irregular	Temporary	Yes
Transitory change	Irregular	Temporary	Yes
Level shift	Trend-cycle	Permanent	Yes
Seasonal outlier	Seasonal	Permanent	No

Table 2.1: Characteristics of different types of outliers.

For seasonal adjustment TRAMO/SEATS do not separate the long-term trend from the cycle as these two components are usually too short to perform their reliable estimation. However, the method may separate the long-term trend from the cycle through the Hodrick-Precsott filter using the output of the standard decomposition. More specifically JDemetra+ refers to the trend-cycle as trend (T_t).

The decomposition made by SEATS, assumes that all components in a time series, i.e. seasonal, trend and irregular/transitory, are independent of each other. There are two decomposition models considered by TRAMO/SEATS:

a. **The additive model:**

$$X_t = T_t + S_t + I_t$$

which assumes that the components of the series behave independently of each other. In this case, the magnitude of seasonal or irregular variations does not change as the level of the trend changes. Series with zero or negative values are additive.

b. **The multiplicative model:**

$$X_t = T_t \cdot S_t \cdot I_t$$

which implies that as the trend of the series increases, the magnitude of the seasonal spikes also increases. Most of the series show the characteristics of a multiplicative decomposition. If the series has a decreasing level, with positive values close to zero and no negative values, it is multiplicative.

In the additive decomposition additive components have the same scale as the original series and the expected value of the irregular component is 0, while in the multiplicative or log-additive decomposition only the trend (and consequently the SA series) is expressed in the original scale and the expected value of the irregular component is 1.

The decomposition is performed for the ARIMA model identified by TRAMO. However, in some cases, the ARIMA model chosen by TRAMO is changed by SEATS. It is done, for example, when the ARIMA model selected by TRAMO leads to a non-admissible decomposition, such as when the ARIMA-model-based decomposition of the ARIMA model cannot yield components all of which have non-negative spectra, thus the model cannot be decomposed and SEATS replaces it with a decomposable approximation.

On of the main assumptions is that the linearized time series x_t follows the ARIMA model

$$\phi(B)\delta(B)x_t = \theta(B)a_t$$

or

$$\phi_r(B)\phi_s(B^s)\nabla^d\nabla_s^D x_t = \theta(B)a_t$$

where $\phi(B)$, $\delta(B)$ and $\theta(B)$ are the polynomials defined in TRAMO with $\phi_r(B)$, $\phi_s(B^s)$ denoting the stationary regular and seasonal polynomials

$$\phi_r(B) = 1 + \phi_{r,1}(B) + ... + \phi_{r,p}(B^p)$$

$$\phi_s(B^s) = 1 + \phi_{s,1}(B^s) + ... + \phi_{s,P}(B^{s\times P})$$

Factoring the stationary regular AR polynomial as

$$\phi_r(B) = \prod_{j=1}^{p}(1-\lambda_j B)$$

https://doi.org/10.26219/heal.aueb.5891

where λ_j is a root for B^{-1} and each root is associated with a frequency ω_j. For example, if λ_j is a positive real number, then $\omega_j = 0$ and the root will be associated with a trend. For monthly time series, a pair of complex conjugate roots for a frequency $\omega_j = \frac{\pi}{6} j$, $(j = 1, 2, ..., 5)$ will be associated with the j-times-a-year seasonal frequency, and a real negative root with the 6-times-a-year frequency.

Thus, it might happen that seasonal roots are solutions of the equation $\phi_r(B) = 0$ and hence the polynomial can be factored as

$$\phi_r(B) = \phi_{rn}(B)\phi_{rs}(B)$$

where $\phi_{rn}(B)$ contains the non-seasonal roots and ϕ_{rs} the seasonal ones.

The same can happen for the stationary seasonal AR polynomial ϕ_s, which may contain non-seasonal roots. Specifically, when $\phi_s > 0$, the polynomial $(1 + \phi_s B^s)$ contains non-seasonal roots because the spectral peaks it produces are not at seasonal frequencies. On the other hand, when $\phi_s < 0$, the polynomial factors as:

$$(1 + \phi_s B^s) = (1 - \lambda B)(1 + \lambda B + ... + \lambda^{s-1} B^{s-1})$$

where $\lambda = \phi_s^{1/s}$. The first root will be associated with the trend and the polynomial

$$S_\lambda = 1 + \lambda B + ... + \lambda^{s-1} B^{s-1}$$

contains the seasonal frequency. Thus the polynomial ϕ_s can be factorized as

$$\phi_s(B^s) = \phi_{sn}(B)\phi_{ss}(B)$$

where $\phi_{sn}(B)$ contains the non-seasonal roots and $\phi_{ss}(B)$ the seasonal ones. The polynomial ϕ_{sn} consists roots that are part of the trend-cycle and/or the transitory component.

Denoting $\varphi(B) = \phi(B)\delta(B)$, the above ARIMA model (2) can be written as

$$\varphi(B)x_t = \theta(B)a_t \tag{3}$$

where $\varphi(B)$ contains both the stationary and the non-stationary roots.

Grouping the seasonal and the non-seasonal roots in the two following polynomials

- $\varphi_s(B) = \phi_{rs}(B)\phi_{ss}(B)S^D$ (contains only seasonal roots)
- $\varphi_n(B) = \phi_{rn}(B)\phi_{sn}(B)\nabla^{d+D}$ (contains only non-seasonal roots)

where $S = 1 + B + ... + B^{s-1}$ includes unit roots for the seasonal frequencies. Therefore, the ARIMA model (3) can be written as

$$\varphi_n(B)\varphi_s(B)x_t = \theta(B)a_t \tag{4}$$

In the following we consider the additive decomposition, thus SEATS decomposes the linearized series x_t as

$$x_t = s_t + n_t$$

where s_t denotes the seasonal component and n_t the SA series. This additive decomposition is obtained from the partial fractions decomposition (PFD) of (4) as

$$x_t = \frac{\theta(B)}{\varphi_n(B)\varphi_s(B)}a_t = \frac{\theta_n(B)}{\varphi_n(B)}a_{nt} + \frac{\theta_s(B)}{\varphi_s(B)}a_{st}$$

The first term in the PFD provides the model for the SA series and the second term, the model for the seasonal component

$$\varphi_n(B)n_t = \theta_n(B)a_{nt}, \qquad a_{nt} \sim WN(0, V_n)$$

$$\varphi_s(B)s_t = \theta_s(B)a_{st}, \qquad a_{st} \sim WN(0, V_s)$$

https://doi.org/10.26219/heal.aueb.5891

The MA polynomials $\theta_n(B)$ and $\theta_s(B)$ can be obtained from the relationship

$$\theta(B)a_t = \varphi_s(B)\theta_n(B)a_{nt} + \varphi_n(B)\theta_s(B)a_{st}$$

In SEATS, the SA series is further split into trend-cycle, irregular and (possibly) transitory components. The trend-cycle is decomposed into trend plus cycle. In essence, the trend-cycle captures the peak at frequency 0 in the series spectrum, the irregular is white noise and the transitory component captures peaks for frequencies that are not zero, nor seasonal. The decomposition is said to be admissible, if the minimum of the sum of the spectra of all the components is non-negative.

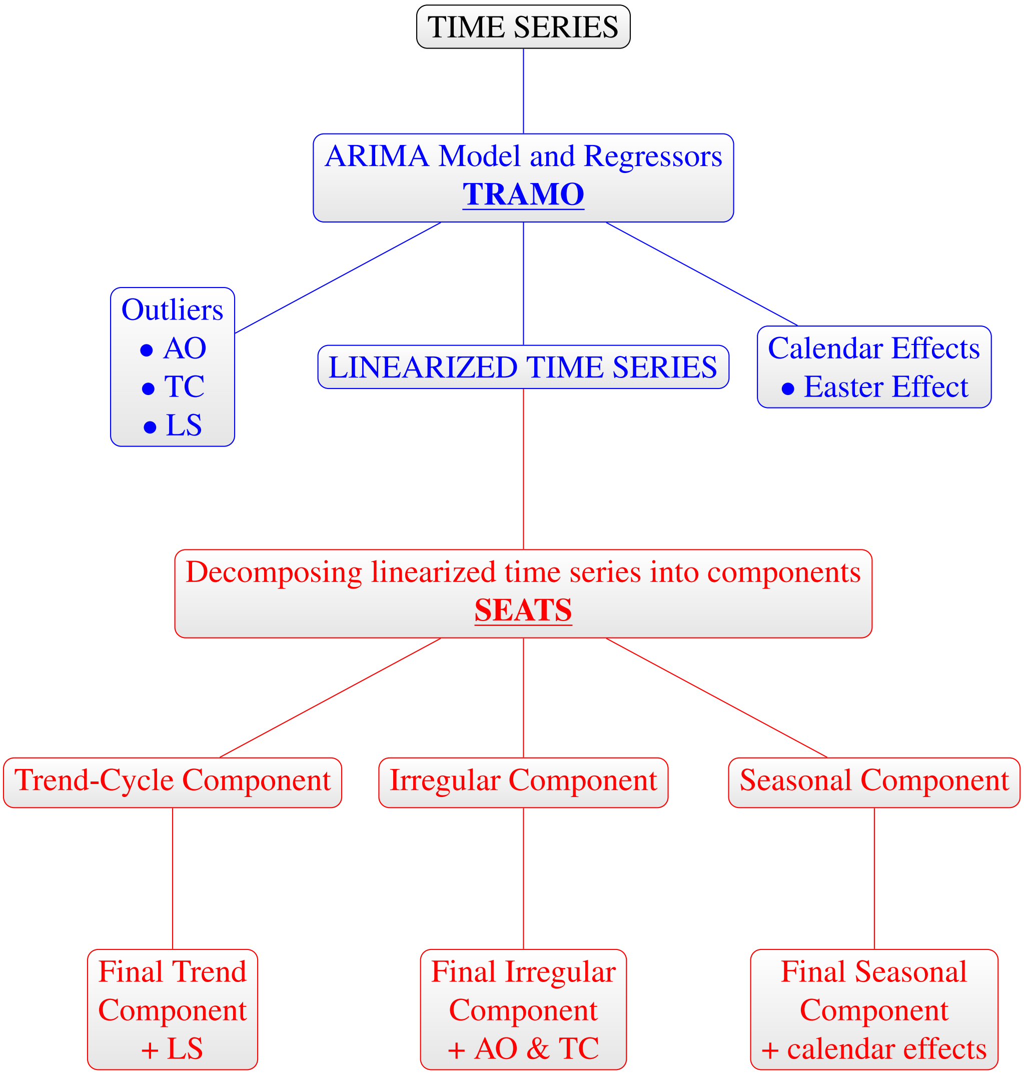

Figure 2.1: The TRAMO/SEATS procedure in brief.

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3

THE DIRECT-INDIRECT APPROACH

3.1 DIRECT VS INDIRECT SEASONAL ADJUSTMENT

If a time series can be constructed as the sum of several time series it is called an aggregate series. An aggregate time series can be seasonally adjusted in two natural alternative ways:

- **Direct approach** - we apply the seasonal adjustment procedure directly to the aggregate data.
- **Indirect approach** - we apply the seasonal adjustment for components of time series (with the same method and software), then we sum the seasonally adjusted time series.

The indirect approach implies estimation of missing raw and seasonally adjusted data, so different models have to be estimated, checked and updated. More control over outcomes with direct adjustment, so easier to ensure adequacy (i.e., the resulting adjustment does not exhibit seasonality).

Under most circumstances the direct and indirect adjustments for an aggregate series are not identical. The two strategies could produce quite different results. While the aggregate is a linear combination of the components and the seasonal adjustment is a non-linear process, direct and indirect approaches ***do not generally coincide***, except for some very limited situations, particularly if the adjustments are additive. For a multiplicative decomposition, the conditions required for identical adjustments are more restrictive (for more information see Pfefferman, Salama, and Ben-Turvia [5]). Especially, TRAMO/SEATS uses filter which is derived from the characteristics of the series. As a different filter is associated to each series, direct and indirect adjustments would never coincide.

3.2 CRITERIA FOR CHOOSING THE DIRECT OR INDIRECT APPROACH

If the performance of direct and indirect approach has to be compared, both methods should exhibit some desirable features such as smoothness, residual seasonality, etc. Conceptually, neither the direct approach nor the indirect approach is optimal. There are arguments in favor of both approaches. Studies (Dagum and Morry [3]) have shown that the quality of the seasonally adjusted data and especially estimates of the trend-cycle component, may be improved, by seasonally adjusting aggregates directly. For aggregates, the direct adjustment may give the best results if the component series show similar seasonal patterns and the trend-cycles are highly correlated. In such cases, aggregation often reduces the amplitude of the irregular in the component series, which at the most detailed level may be too dominant for proper seasonal adjustment (Dagum [2]). The aggregation will produce a smoother series with no loss of information on the seasonal pattern.

On the other hand, the indirect approach may give the best results when the component series show very different seasonal patterns. Aggregation may cause large, highly volatile seasonality overshadow stable seasonal effects, making it difficult to identify seasonality in the aggregate series. Additionally, it may be easier to detect outliers and calendar effects in detailed series than directly from the aggregates, because at the detailed level these effects may display a simpler pattern and be more interpretable. The indirect method is also better choice than direct when there is a strong demand by users for a coherence or consistency between the aggregates at different levels (for example, additivity).

Unless specific conditions are fulfilled (Campolongo and Planas [4]), the results provided by the two approaches differ. There are some selection criteria than can be helpful for deciding whether to adjust directly or indirectly, such as the following.

1. Residual Seasonality in the Seasonally Adjusted Series

The most fundamental requirement of a seasonal adjustment, regarding quality, is the lack of any significant residual seasonality and calendar effects left in the SA series. Residual seasonality is the presence of estimable seasonal effects in either the seasonally adjusted series or the detrended seasonally adjusted series (i.e, in the irregular component).

The existence of residual seasonality in the SA series when this is obtained with the direct approach can result from an inadequate adjustment procedure, or from the existence of seasonality difficult to estimate in the original series. A seasonal adjusted series obtained indirectly by aggregating the SA components, might show residual seasonality when the seasonal patterns present in the components series are not similar and are not properly estimated, leaving residual effects in the adjusted series.

The spectral diagnostics, such as the Periodogram and the AutoRegressive Moving Average Spectrum for residual seasonality are the most important diagnostics. The spectrum of an observed time series shows the strength, or amplitude, of each frequency component when the data are decomposed into such components. For monthly series with a strong seasonal effect, we will see peaks in the spectrum at the frequencies : $\frac{\pi}{6}$, $\frac{2\pi}{6}$, $\frac{3\pi}{6}$, $\frac{4\pi}{6}$, $\frac{5\pi}{6}$, π, which are equivalent to 1, 2,... cycles per year, while for quarterly data there are two seasonal frequencies: $\frac{\pi}{2}$ (one cycle per year) and π (two cycles per year).

It is necessary to remove any very strong frequency components from the adjusted series before the spectrum calculation to enable the spectrum to reveal the presence of the seasonal component. If a series has strong long-term trend movements, the low frequencies associated with the long-term trend movements will have amplitudes that dominate the spectrum. It is also possible to have two series with no apparent residual seasonality, but to have residual seasonality in the aggregate series. In conclusion, a seasonal adjustment has a good quality if the peaks in the seasonal frequencies of the original data do not appear in the SA data.

2. Sign concordance of growth rates

A further step concerns the consistency between the growth rates of the SA aggregated series and their adjusted components, which should evolve in the same direction. The seasonally adjusted series should deliver more or less the same message and their annual growth rates should have the same sign. Therefore, to measure the degree of consistency in annual growth rates, we use the statistics C1, which is calculated on the basis of the ratio of annual growth rates for the same observations of similar sign. The statistics C1 measures the percentage of concordance between the direct and indirect series. The sequential annual growth rate was calculated accordingly, using the following formulas:

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- $g_t = \frac{SA_t - SA_{t-12}}{SA_{t-12}}$ and

- $g_t = \frac{SA_t - SA_{t-12}}{SA_{t-12}} \approx ln(SA_t) - ln(SA_{t-12})$, for logarithmic data

and the statistics C1 is calculated with the formula

$$C1 = \frac{G_t}{N-12}$$

where $\{SA_t : 1 \leq t \leq N\}$ is the seasonally adjusted series, $G_t =$ the number of annual growth rates with the same sign for direct and indirect approach, and N is the length of the series.

3. Analysis of smoothness

One of the aspects taken into consideration in the choice between direct and indirect seasonal adjustment is the roughness of the SA series, although the smoothness of the seasonally adjusted series is not actually a quality measure. On the contrary, the irregular component is a part of the seasonally adjusted series. Dagum ([2]) proposed two measures of roughness or lack of smoothness, of the SA series, that measure the size of their deviations from a smooth trend (e.g. the size of an “irregular component”), and are based on the first difference filter applied to the SA series. The involved filter removes most of the low frequencies components that correspond to the trend-cycle variations. Thus, the measure is defined as:

$$R_1 = \sum_{t=2}^{N} (SA_t - SA_{t-1})^2 = \sum_{t=2}^{N} (\nabla SA_t)^2$$

The third measure suggested by Pfefferman *et al.* ([5]), was a *"natural"* measure, a measure of similarity between seasonally adjusted data and trend:

$$R_3 = \sum_{t=1}^{N} (SA_t - TC_t)^2$$

where $\{TC_t : 1 \leq t \leq N\}$ are the estimates of the trend.

Gómez and Maravall ([11]) prefer to use the following quality measures for the seasonality and the trend-cycle:

$$Mar(S) = \sum_{t=1}^{N} [(1 + B + B^2 + ... + B^{11})S_t]^2$$

The smoothness of the trend-cycle is measured by the L_2-norm of the first and the second differences:

$$Mar_1(TC) = \sum_{t=2}^{N} (\nabla TC_t)^2$$

$$Mar_2(TC) = \sum_{t=3}^{N} (\nabla^2 TC_t)^2$$

where $1 + B + B^2 + ... + B^{11}$ is the annual aggregation operator. These statistics can be calculated: for each couple of possible approaches; for the seasonally adjusted series, the trend-cycle estimates and the seasonal components; on the complete series and on the last three years.

4. Revision Analysis

Stability of the seasonally adjusted series is a desirable characteristic. Whenever a new observation is added to the current end of a time series, and the series is then seasonally adjusted, there will be revisions to seasonally adjusted estimates, particularly in the most recent time periods. Seasonally adjusted estimates that are subject to relatively small revisions over time are said to be stable (Maravall and Sánchez [10]). Measure the size of the future revisions based on past history (by forecasting) using specific measures (Guardabascio, Iaconelli and Iannaccone [15]), such as:

- Mean Revision: $$MR = \frac{1}{N}\sum_{t=1}^{N}\left(Final_t - Initial_t\right) = \frac{1}{N}\sum_{t=1}^{N} R_t$$
- Mean Absolute Revision: $$MAR = \frac{1}{N}\sum_{t=1}^{N}\left|Final_t - Initial_t\right| = \frac{1}{N}\sum_{t=1}^{N} \left|R_t\right|$$
- Mean Squared Revision: $$MSR = \frac{1}{N}\sum_{t=1}^{N}\left(Final_t - Initial_t\right)^2 = \frac{1}{N}\sum_{t=1}^{N} R_t^2$$

  which represents the variance of the revision process.
- Standard Deviation of Revision: $$SDR = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(R_t - MR\right)^2}$$

where:
$Initial_t$ = the first seasonally adjusted data at time t, the initial publication of data
$Final_t$ = the final seasonally adjusted data at time t, the last publication of data

https://doi.org/10.26219/heal.aueb.5891

4

SEASONAL ADJUSTMENT OF THE GREEK INDUSTRIAL PRODUCTION INDEX: DIRECT VERSUS INDIRECT

4.1 THE GREEK INDUSTRIAL PRODUCTION INDEX

In this chapter we will compare the seasonal adjustment produced by the direct and the indirect method for the Greek Industrial Production Index (IPI). First, we will introduce the IPI, then we will describe the basic methodology underlying the procedure of the seasonal adjustment, and we will perform seasonal adjustment (direct and indirect) for the IPI. More specifically, for the indirect approach we will seasonally adjust the five Main Industrial Groupings (MIGs) which refer to a breakdown of the industry sector into the: "**Energy**", "**Intermediate Goods Industry**", "**Capital Goods Industry**", "**Durable Consumer**" as well as "**Non-Durable Consumer Goods Industry**", and then we will sum their seasonally adjusted series using the respective weights. Finally, we will compare the two seasonal adjustments using some useful quality measures in order to examine which approach is better for the IPI.

The chart analysis (Figure 4.1) allows us to assume some important points about the Greek Industrial Production Index for the period from January 2000 to December 2021, such as:

- It was strongly affected by the World as well as the Greek Crisis at the end of 2008. We can observe a decline in the index during this period until the end of 2014.

- Seasonal behavior, from January to July the index has increased while in the other months, decreased. This behavior is repeated every year.

- Trend seems stable (no growth or abrupt falls) from the beginning of the observed time (2000) until 2008. From 2009 until the end of 2014 there was an downward trend. After this period it shows an increase, starting from July 2015.

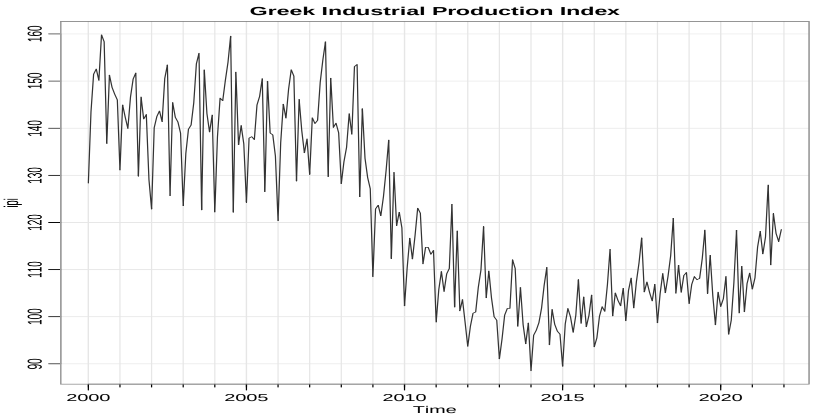

Figure 4.1: Greek Industrial Production Index, January 2000 - December 2021 (base year 2015 = 100).

The five Main Industrial Groupings are the component series which compose the IPI and they are illustrated in the Figure 4.2 below. From the figure we can assume that:

- The variance of the given component series is not constant, which causes us to conclude that it’s necessary to transform the series. Hence, it stabilises the variance of the original time series.

- Additional, the indices of the Intermediate, Capital and Durable Consumer Goods appear to have similar seasonal patterns.

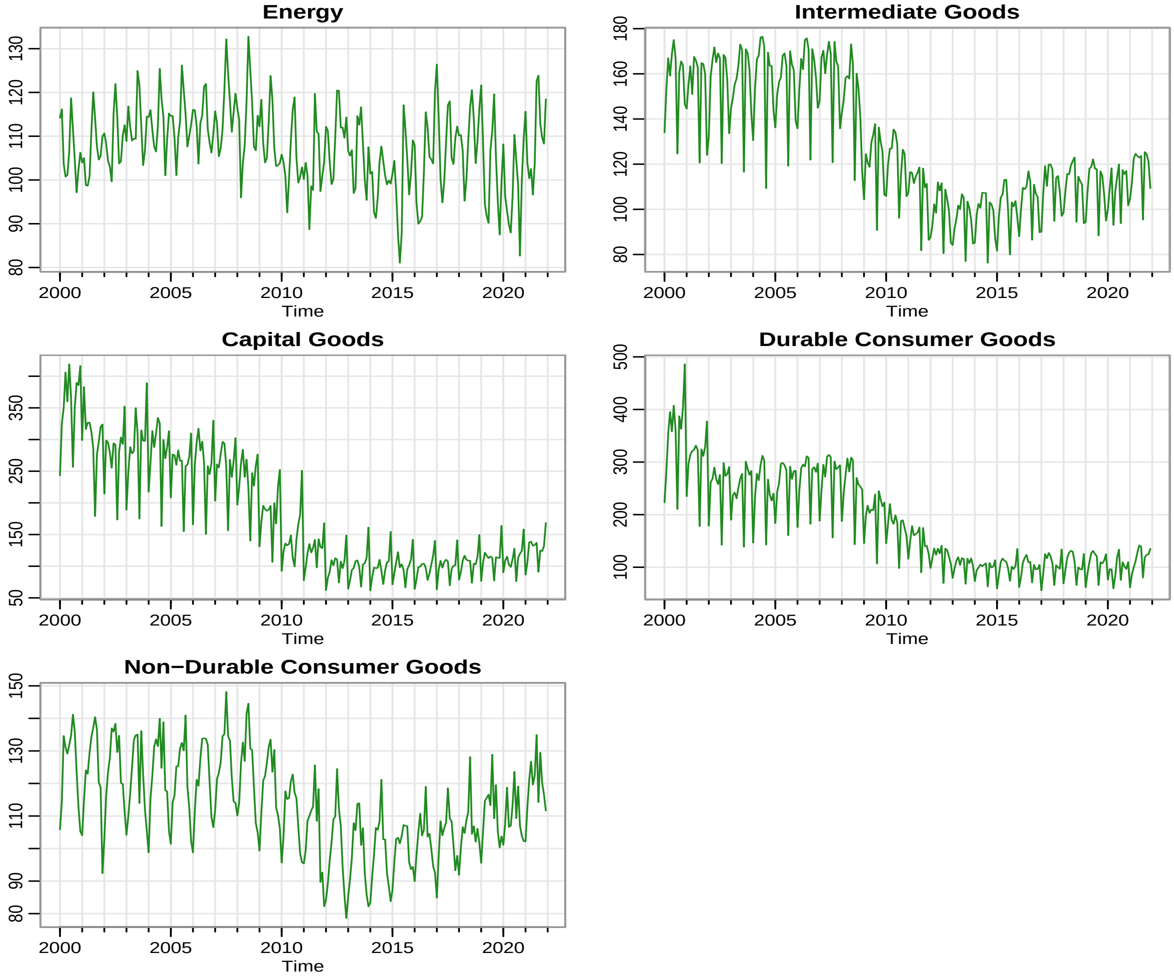

Figure 4.2: Original series of the Main Industrial Groupings Indices, January 2000 - December 2021.

4.2 METHODOLOGY

This section describes the methodology that will be used for our analysis. The analysis will follow 2 different models which are:

1. **Model 1 (M1)**: The analysis will be performed on the log transformed series - multiplicative model is considered.

2. **Model 2 (M2)**: There will be no transformation on the original data - additive model.

The procedure for the direct and indirect seasonal adjustment of the IPI, as well as for the seasonal adjustment of the Main Industrial Groupings, is divided into three parts: the pre-adjustment (TRAMO), the SEATS and the model diagnostics. The estimation span used for the analysis is from January 2000 to December 2021 which contains 264 observations (monthly data), with a base year of 2015.

TRAMO allows for a pre-adjustment of the series: detection of outliers, adjustment of calendar effects (Easter effect) and graphical illustration of the unadjusted and the linearized original series for the two models, using the same scale. The objective of pre-adjustment is to select an ARIMA model that best describes the characteristics of the original series for each of the two models. The pre-adjustment part consists of a summary table of the ARIMA model estimation, such as the estimated ARIMA model (automatic model identification), the calendar effects (Easter effect) and outliers. The outliers and the calendar effects that are displayed in the tables are statistically significant at 10% and 5% level respectively.

The second part (SEATS) performs the decomposition of the pre-adjusted linearized series into unobserved components: trend-cycle, seasonal and irregular, and it presents ARMA spectrum of the original and the seasonally adjusted linearized series for the two models, using the same scale (logarithmic). The spectral graphics allow the seasonally adjusted series to be checked for the presence of any seasonal effects. For the spectral analysis, the linearized series will be used, which are the original series corrected for outliers and calendar effects, because it is better not to be affected by these effects. Additionally, for all the spectra the following apply:

1. The spectral graphs have been estimated from the first differenced, log transformed data.

2. Intensity is presented on the decibel ($10\times \log_{10}$) scale.

The analysis of diagnostics for the TRAMO/SEATS process is fundamental to determine whether the seasonal adjustment results are of acceptable quality. Careful assessment of the seasonally adjusted data includes analysis of the stability of the seasonal component. Thus, we will report the results of some quality diagnostics, which include statistical tests and graphical diagnostics that depend on the chosen seasonal adjustment method.

The residuals of the TRAMO process provide a useful tool for verifying whether the seasonal adjustment is satisfactory or not and evaluate the quality of the ARIMA model estimated by TRAMO. The residuals should be independent, random and not include any seasonality. For testing the independence of the residuals, partial autocorrelation plots (PACF plots) will be used as they are beneficial for specifying Auto-Regressive Integrated Moving Average (ARIMA) models. In addition to the PACF plots, summary tables provide results of the Ljung-Box Q-Statistic computed for the 6, 12, 18, 24 lags. This test checks for the presence of autocorrelation between lags, which is a sign that the values of residuals are not independent. More specifically, the Ljung-Box test follows a $\chi^2_{(k-np)}$ distribution, where k depends on the frequency of the series (24 for a monthly series), and np the number of hyper-parameters of the model (number of parameters in the ARIMA model). For each test the corresponding p-value is reported.

The diagnostics also provide information about the standard deviation for the innovations of all theoretical model components obtained by SEATS. The innovation variance is the maximized variance of the model, while having the irregular component to derive the trend-cycle component and the seasonal component as stable as possible, meaning that no additional white noise could be removed from them. This assumption is also called "canonical decomposition".

The final table presents results derived from testing for the presence of residual seasonality in the detrended seasonally adjusted series using the Friedman test (F-test). For the detrended seasonally adjusted series the presence of residual seasonality is tested on the complete time span and on the last 3 years span. There is no residual seasonality when the corresponding p-value is greater than 0.1.

4.3 SEASONAL ADJUSTMENT OF THE IPI (DIRECT APPROACH)

Firstly, we wish to obtain a seasonal adjustment of the IPI using the direct approach, thus we sum the monthly data and seasonally adjust the aggregate series.

4.3.1 *Pre-adjustment (Tramo)*

A visual inspection of the unadjusted and the linearized series is the first step when conducting seasonal adjustment. A simple visualization of observations between the unadjusted and the linearized series highlights the most visible features of the series, such as outliers and calendar effects. Especially in the Figure 4.3, it appears that there are no visual differences between the two series for both models, except for April 2020 where there is a transitory change (outlier).

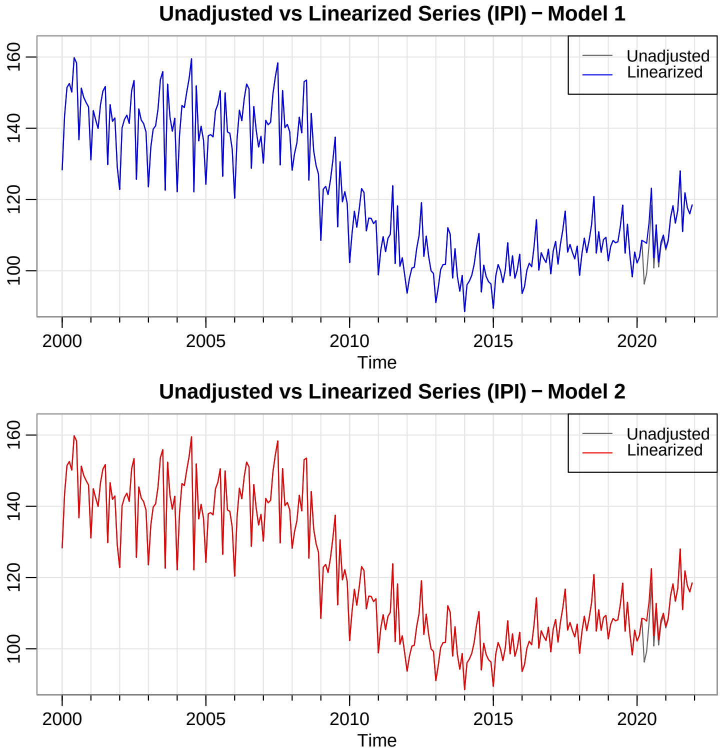

Figure 4.3: Unadjusted vs Linearized Series of the IPI for the two models (Direct Approach).

As a starting point, for the direct seasonal adjustment of the IPI we use the automatic procedure which yields the Airline model $(0,1,1)(0,1,1)$ and detects the April 2020 outlier as a Transitory Change for the two models (Table 4.1).

Outliers - Calendar Effects & ARIMA Model					
Models	**AO**	**TC**	**LS**	**Easter**	**ARIMA Model**
M1/M2	0	1	0	No	(0, 1, 1) (0, 1, 1)

Table 4.1: Outliers - calendar effects & the ARIMA model for the two models.

4.3.2 *The Seats procedure*

The next diagnosis is focused on verifying whether there is evidence of seasonality before and after seasonal adjustment, which can be achieved by spectral analysis. Figure 4.4 presents the ARMA spectrum of the original (black) and the seasonally adjusted linearized series of IPI for Model 1 (blue line) and Model 2 (red line). The original linearized series appear to have peaks at the seasonal frequencies (blue dotted lines). However, the SA linearized series do not exhibit seasonality, there are no peaks in seasonal frequencies.

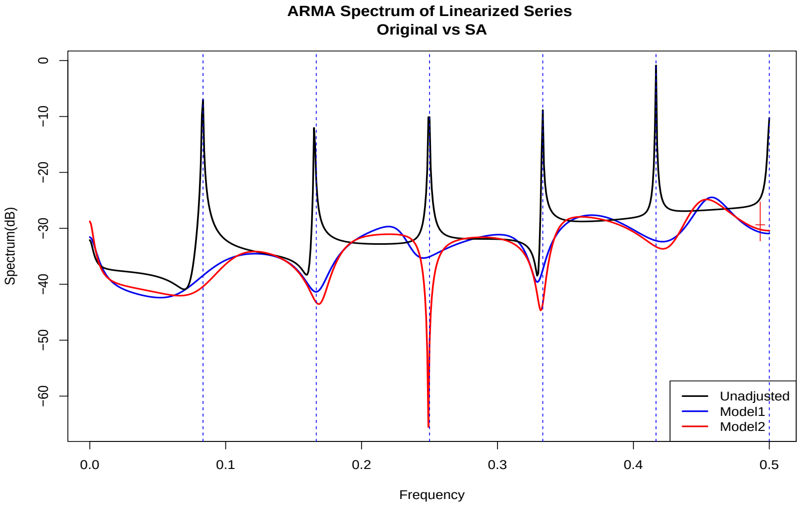

Figure 4.4: ARMA Spectrum of the Linearized Series (Original vs SA) of the IPI for the two models (Direct Approach).

4.3.3 *Model Diagnostics*

The final but most important step is the diagnostics for the ARIMA model which contain detailed information on the quality of the seasonal adjustment. The residuals of the ARIMA $(0,1,1)(0,1,1)$ model appear to display the characteristics of White Noise in the PACF plots (Figure 4.5) with only one lag of the 48 (or 2%) being significant. At a 95% confidence interval this is within probabilistic expectations. To assess the independence in detail, the Ljung-Box Q-statistics (Table 4.2) are computed for four different lags for Model 1 and Model 2 with 22 degrees of freedom for both models. The Ljung-Box test indicates that the residuals are not significantly different from white noise, since their corresponding p-values are over 0.05.

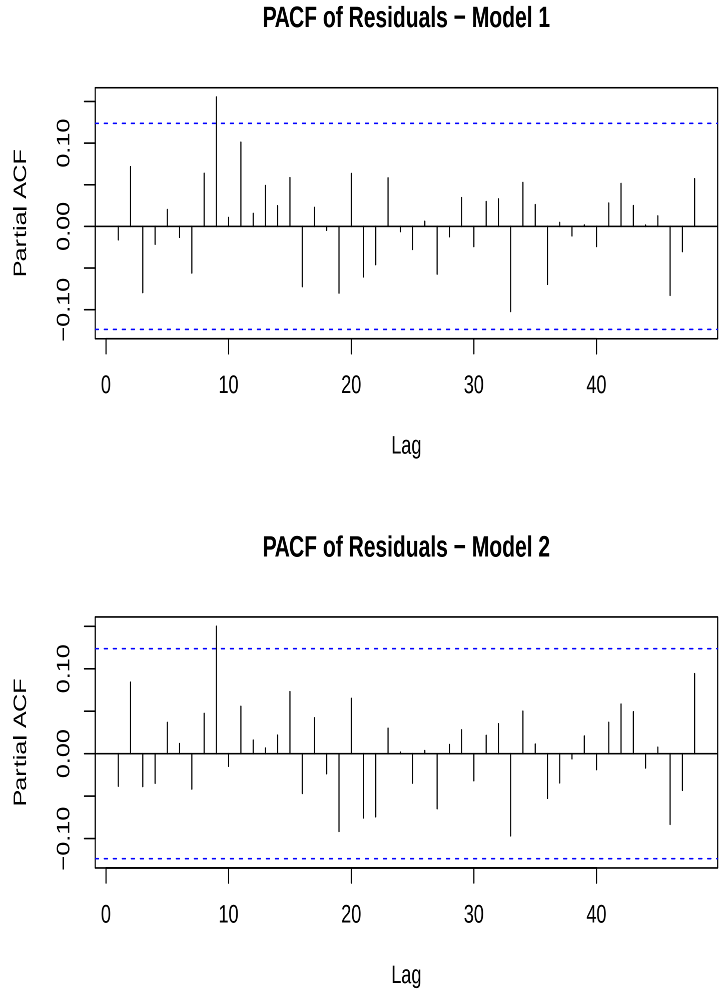

Figure 4.5: PACF plots for the TRAMO residuals of the Direct Method for the two models.

Autocorrelation Test for Residuals (Ljung-Box Test)

Lag	Model	Q-Statistic	P-value
6	M1	3.177	0.529
	M2	3.171	0.530
12	M1	13.786	0.183
	M2	10.599	0.389
18	M1	17.768	0.338
	M2	14.106	0.591
24	M1	22.267	0.444
	M2	20.387	0.559

Table 4.2: Ljung-Box test on residuals from the Tramo part for Model 1 and Model 2.

The following table (Table 4.3) presents some results from SEATS, and in particular the standard deviation for the innovations of the components. Interest centers on a more stable seasonal component, thus we seek to minimize the value of its standard deviation. Among the two models the differences are negligible. Moreover, the seasonal component for Model 1 is more stable than the corresponding component for Model 2, so Model 1 seems more preferable. Also the standard deviation for the innovations of the seasonal and trend-cycle component, for both models, are lower than that of the irregular component, which means that the assumption of canonical decomposition is satisfied.

Standard Deviation of Component Innovation

Model	Trend	SA	Seasonal	Irregular
M1	0.161	0.841	0.176	0.669
M2	0.152	0.817	0.207	0.653

Table 4.3: Standard deviation of the component innovations for the two models (Direct Approach).

https://doi.org/10.26219/heal.aueb.5891

The last information presented in Table 4.4 is the results of the F-test for the presence of residual seasonality in the seasonally adjusted series for the two models. SEATS shows no evidence of seasonality in the entire SA series and in the last 3 years for the direct approach, as the p-values are greater than 0.1.

F-test for the presence of residual seasonality			
Model	Time Period	F-Statistic	P-value
M1	Entire series	0.01	1.00
	Last 3 years	0.29	0.98
M2	Entire series	0.01	1.00
	Last 3 years	0.24	0.99

Table 4.4: F-test for the presence of residual seasonality in the SA series (Direct Approach).

4.4 SEASONAL ADJUSTMENT OF THE MIGS

In this section, the main features of the sub-indices (Energy, Intermediate, Capital, Durable Consumer and Non-Durable Consumer Goods) are reviewed. The seasonal adjustment of the MIGs helps us to examine the series at a more detailed level and it is a necessary step in the application of the indirect approach.

4.4.1 *Pre-adjustment (Tramo)*

In Figure 4.6 the original (unadjusted) and the linearized series for Model 1 are plotted. There are clearly differences for the Index of Energy, from the beginning of the analysis span (2000) until half of the 2015. It seems that the log transformation greatly affected the original series in contrast with the other industrial indices in which no important differences are noted between the unadjusted and linearized series.

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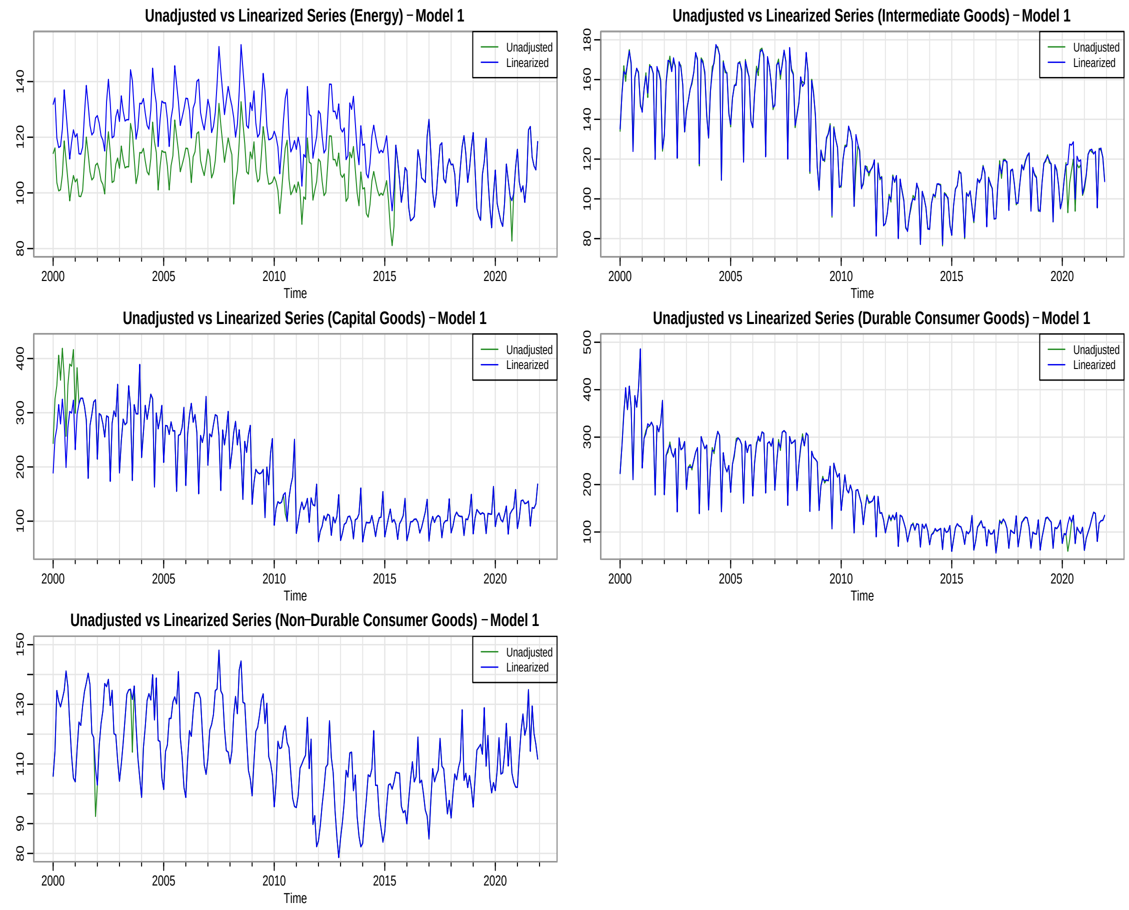


Figure 4.6: Unadjusted vs Linearized Series of the MIGs for Model 1.

The table (Table 4.5) below presents a summary of the TRAMO results. The Airline model is identified as the best model for all the MIGs, except for the Capital Goods. Additionally, the procedure detects Easter effect for the Intermediate and Durable Consumer Goods.

MODEL 1 : Outliers - Calendar Effects & ARIMA Model					
Main Industrial Grouping	**AO**	**TC**	**LS**	**Easter**	**ARIMA Model**
Energy	2	0	1	No	(0, 1, 1) (0, 1, 1)
Intermediate Goods	1	1	0	Yes	(0, 1, 1) (0, 1, 1)
Capital Goods	1	0	1	No	(1, 1, 1) (0, 1, 1)
Durable Consumer Goods	0	2	0	Yes	(0, 1, 1) (0, 1, 1)
Non-Durable Consumer Goods	2	0	0	No	(0, 1, 1) (0, 1, 1)

Table 4.5: Outliers - calendar effects & the ARIMA model for Model 1.

On the contrary, from the following figure (Figure 4.7) appears that there is no obvious discrimination between the unadjusted and the linearized series of the MIGs. The only exception is the Index of Capital Goods, and more specifically there are differences at the beginning of the series during 2000-2001, which is the result of the absence of outliers and especially one transitory change in April 2000 and the two level shifts in March and June of 2001, as reported in Table 4.6.

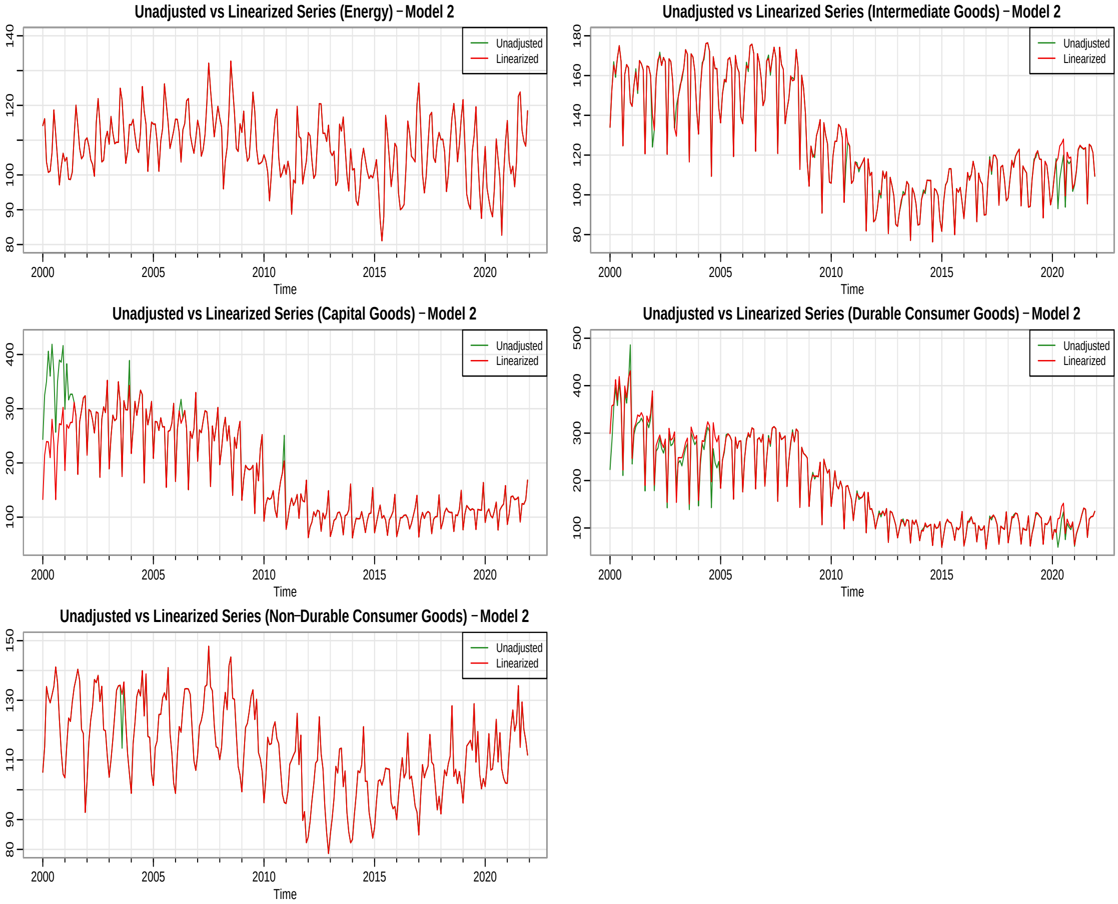


Figure 4.7: Unadjusted vs Linearized Series of the MIGs for Model 2.

As it appears from Table 4.6 the Airline model is the one chosen for the MIGs, except for the Durable Consumer Goods which has the ARIMA (0,1,1)(1,1,0) model. Moreover, the Easter effect is identified for the same Industrial Groupings as in Model 1.

MODEL 2 : Outliers - Calendar Effects & ARIMA Model					
Main Industrial Grouping	**AO**	**TC**	**LS**	**Easter**	**ARIMA Model**
Energy	0	0	0	No	(0, 1, 1) (0, 1, 1)
Intermediate Goods	3	1	0	Yes	(0, 1, 1) (0, 1, 1)
Capital Goods	3	1	2	No	(0, 1, 1) (0, 1, 1)
Durable Consumer Goods	2	1	3	Yes	(0, 1, 1) (1, 1, 0)
Non-Durable Consumer Goods	1	0	0	No	(0, 1, 1) (0, 1, 1)

Table 4.6: Outliers - calendar effects & the ARIMA model for Model 2.

4.4.2 *The Seats procedure*

After the detection and identification of the various effects, the next step is the seasonal adjustment. Judging by the peaks at the original linearized series (black lines), the ARMA spectra display clear seasonality for all the Main Industrial Groupings. However, the spectral graphs (Figure 4.8 and 4.9) show clearly that the procedure has successfully removed the seasonal peaks for the SA linearized series (blue and red lines) for both models. In some cases it also evident that it has removed "too much", creating dips at some seasonal frequencies.

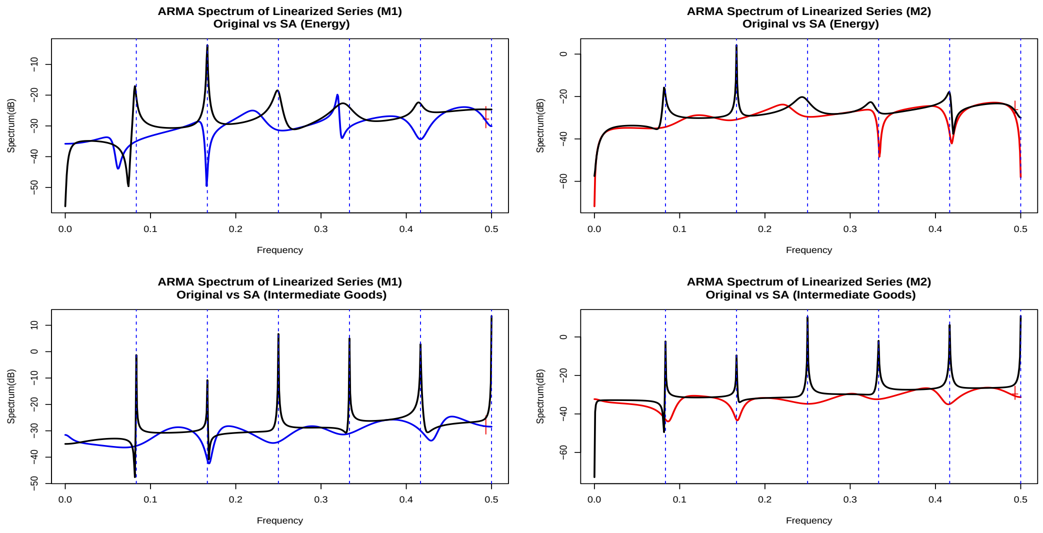


Figure 4.8: ARMA Spectrum of the Linearized Series (Original vs SA) of the Energy and Intermediate Goods, for Model 1 (blue) and Model 2 (red).

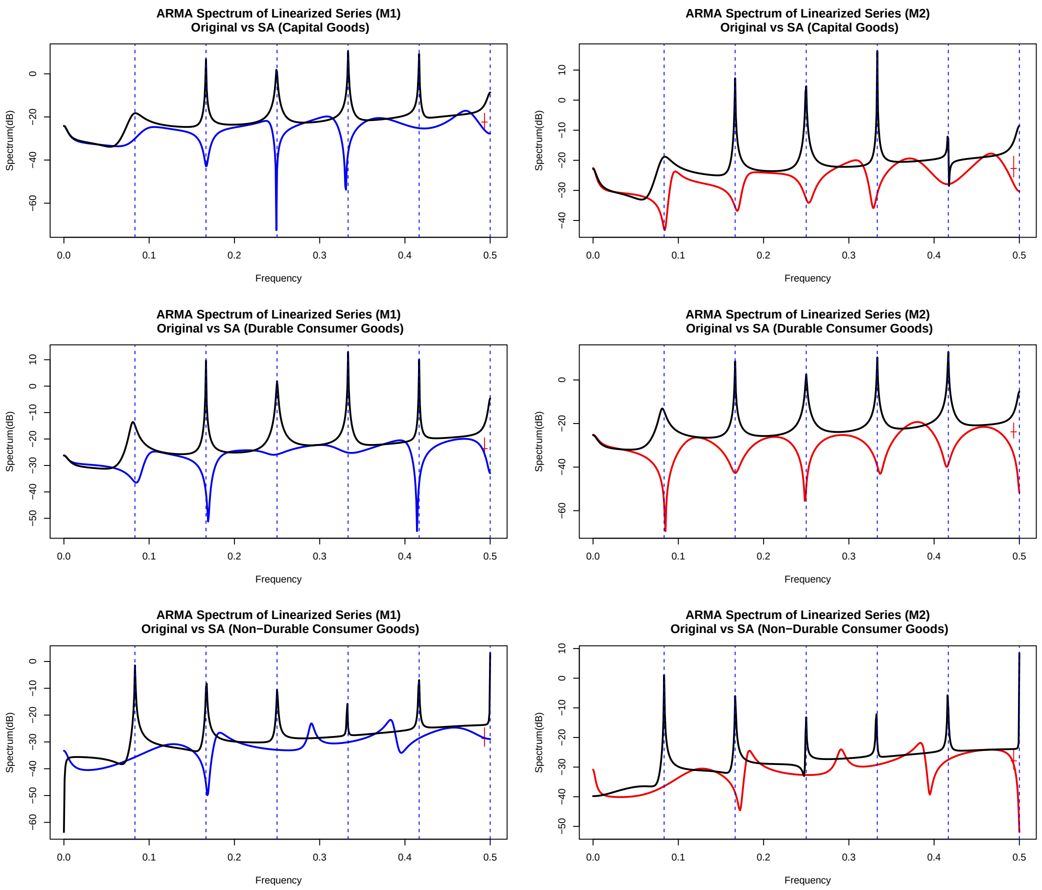
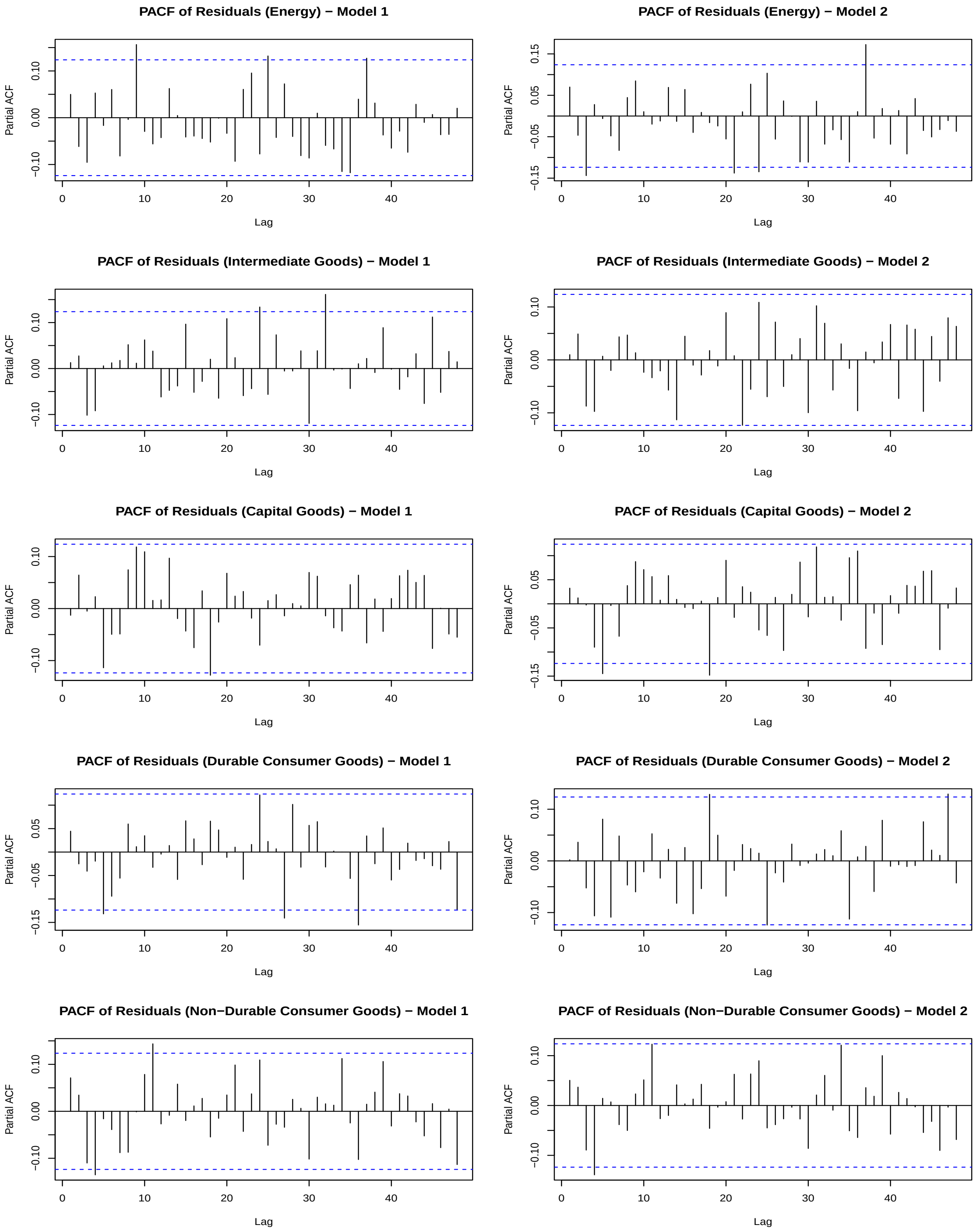


Figure 4.9: ARMA Spectrum of the Linearized Series (Original vs SA) of the Capital, Durable Consumer and Non-Durable Consumer Goods, for Model 1 (blue) and Model 2 (red).

4.4.3 *Model Diagnostics*

After seasonal adjustment, an immediate check on residuals should be performed to verify the independence of the ARIMA residuals. The PACF plots (Figure 4.10) and the Ljung-Box test (Table 4.7) on ARIMA residuals of the MIGs do not suggest any statistical problems for the two models. Note that the p-values of the Ljung-Box test are greater than 0.05 for the observed lags, which indicate that there is no significant residual autocorrelation. Therefore, the residuals are assumed to be independent.



PACF of Residuals (Energy) − Model 1

PACF of Residuals (Energy) − Model 2

PACF of Residuals (Intermediate Goods) − Model 1

PACF of Residuals (Intermediate Goods) − Model 2

PACF of Residuals (Capital Goods) − Model 1

PACF of Residuals (Capital Goods) − Model 2

PACF of Residuals (Durable Consumer Goods) − Model 1

PACF of Residuals (Durable Consumer Goods) − Model 2

PACF of Residuals (Non−Durable Consumer Goods) − Model 1

PACF of Residuals (Non−Durable Consumer Goods) − Model 2

Figure 4.10: PACF plots for the TRAMO residuals of the MIGs for Model 1 and Model 2.

Autocorrelation Test for Residuals (Ljung-Box Test)					
		Model 1		Model 2	
Lag	Main Industrial Grouping	Q-Statistic	P-value	Q-Statistic	P-value
6	Energy	5.686	0.224	7.581	0.108
	Intermediate Goods	5.113	0.274	5.041	0.283
	Capital Goods	5.173	0.159	8.197	0.085
	Durable Consumer Goods	8.288	0.082	8.562	0.073
	Non-Durable Consumer Goods	10.916	0.027	8.302	0.081
12	Energy	16.202	0.094	14.196	0.164
	Intermediate Goods	8.6607	0.565	7.915	0.637
	Capital Goods	14.786	0.096	17	0.074
	Durable Consumer Goods	11.508	0.319	11.286	0.335
	Non-Durable Consumer Goods	24.757	0.010	14.356	0.157
18	Energy	20.267	0.208	17.269	0.368
	Intermediate Goods	13.3	0.651	12.590	0.702
	Capital Goods	25.939	0.039	24.040	0.089
	Durable Consumer Goods	14.716	0.545	21.922	0.146
	Non-Durable Consumer Goods	27.44	0.037	16.072	0.448
24	Energy	30.711	0.102	28.983	0.145
	Intermediate Goods	21.483	0.491	21.287	0.503
	Capital Goods	30.972	0.074	31.662	0.083
	Durable Consumer Goods	19.806	0.595	23.584	0.369
	Non-Durable Consumer Goods	34.763	0.041	19.921	0.588

Table 4.7: Ljung-Box test on residuals from the Tramo part for Model 1 and Model 2.

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Comparing the standard deviation of the component innovations, Table 4.8 shows that the trend-cycle component of Capital Goods in Model 1, appears to be more stable than in Model 2. The trend-cycle components for the rest of the MIGs are more stable in Model 2 than Model 1. Additional, the seasonal components for Energy and Capital Goods are more stable in Model 2 than in Model 1, while the seasonal component for the rest of the MIGs is more stable in Model 1.

The standard deviation and therefore the innovation variance of the seasonal and trend-cycle components, for both models, are lower than that of the irregular component meaning that the assumption of canonical decomposition holds. The decomposition performed by SEATS also identified and estimated the innovation variance of the transitory component for the Capital Goods with value 0.062 in Model 1, and for the Durable Consumer Goods with value 0.029 in Model 2 .

Standard Deviation of Component Innovation				
		Model 1		
Main Industrial Grouping	Trend	SA	Seasonal	Irregular[1]
Energy	0.221	0.903	0.105	0.676
Intermediate Goods	0.251	0.886	0.126	0.628
Capital Goods	0.109	0.749	0.303	0.521
Durable Consumer Goods	0.161	0.754	0.251	0.573
Non-Durable Consumer Goods	0.134	0.832	0.202	0.684
		Model 2		
Energy	0.200	0.913	0.089	0.706
Intermediate Goods	0.228	0.794	0.228	0.554
Capital Goods	0.138	0.728	0.295	0.572
Durable Consumer Goods	0.105	0.588	0.389	0.387
Non-Durable Consumer Goods	0.118	0.834	0.205	0.709

Table 4.8: Standard deviation of the component innovations of the MIGs, for Model 1 and Model 2.

[1] The irregular component does not include the standard deviation of the transitory component.

Finally, Table 4.9 presents the results of the F-test for the presence of residual seasonality in the SA series of the MIGs for the two models. It appears that there is no residual seasonality present in the SA series for both models, for the entire series and the last 3 years, as the corresponding p-values are greater than 0.1.

F-test for the presence of residual seasonality					
		Model 1		Model 2	
Main Industrial Grouping	Time Period	F-Statistic	P-value	F-Statistic	P-value
Energy	Entire series	0.01	1.00	0.004	1.00
	Last 3 years	0.41	0.94	0.50	0.88
Intermediate Goods	Entire series	0.01	1.00	0.002	1.00
	Last 3 years	0.15	0.99	0.15	0.99
Capital Goods	Entire series	0.05	0.99	0.005	1.00
	Last 3 years	0.08	0.99	0.04	0.99
Durable Consumer Goods	Entire series	0.04	0.99	0.01	1.00
	Last 3 years	0.17	0.99	0.03	0.99
Non-Durable Consumer Goods	Entire series	0.02	0.99	0.01	0.99
	Last 3 years	0.39	0.95	0.37	0.95

Table 4.9: F-test for the presence of residual seasonality in the SA series of the MIGs, for Model 1 and Model 2.

4.5 SEASONAL ADJUSTMENT OF THE IPI (INDIRECT APPROACH)

The alternative seasonal adjustment is the indirect approach. Under the indirect adjustment method, we seasonally adjust each of the component series (Main Industrial Groupings) separately, and then aggregate the series that we are interested in (e.g. original (unadjusted), seasonally adjusted linearized series, etc.).

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4.5.1 *Pre-adjustment (Tramo)*

Same as before, the first step is the pre-adjustment, but here we do not perform detection for outliers and calendar effects, since we work directly with the adjusted series.

From the Figure 4.11 we can detect differences between the unadjusted and the linearized series of the IPI. Especially for the Model 1, it appears that the effect of logarithm creates noticeable differences between the two series, in contrast to Model 2 where the series appear to almost coincide.

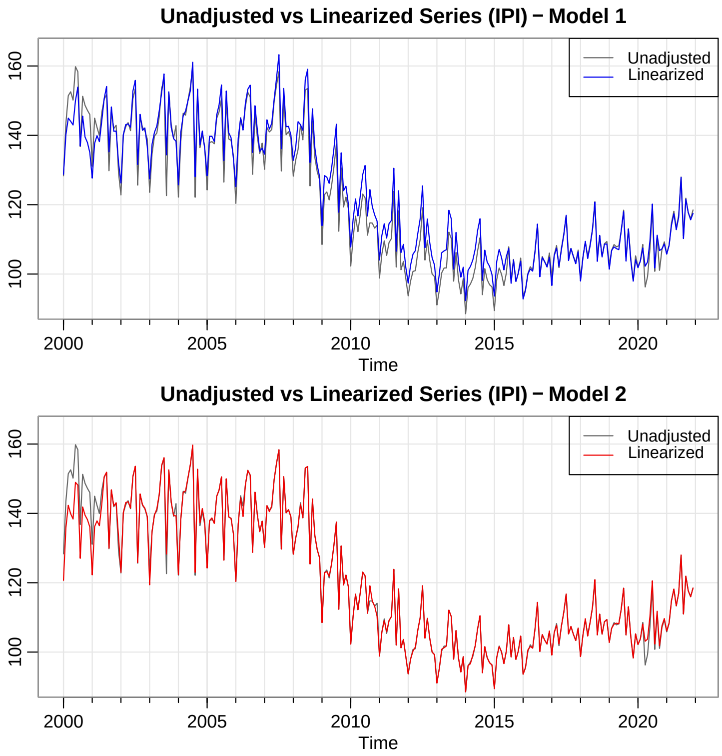

Figure 4.11: Unadjusted vs Linearized Series of the IPI for the two models (Indirect Approach).

4.5.2 *The Seats procedure*

An assessment of how good the performance of a seasonal adjustment method is, it can be given by the use of spectral graphs as we mentioned before. Figure 4.12 shows the ARMA spectrum of the original (black) and the seasonally adjusted (blue and red lines) linearized series for the two models. As it is reasonable the original series have peaks at the seasonal frequencies. On the other hand, the SA series of IPI do not show any indication of seasonality, for both models. In other words, Figure 4.12 depicts no spectral peaks at the seasonal frequencies for the seasonally adjusted series.

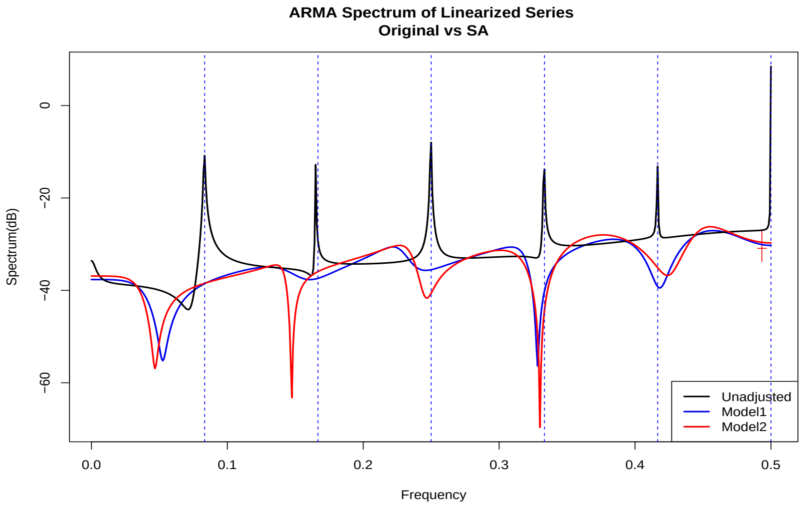

Figure 4.12: ARMA Spectrum of the Linearized Series (Original vs SA) of the IPI for the two models (Indirect Approach).

4.5.3 *Model Diagnostics*

The indirect SA series should also be tested for residual seasonality, because seasonal adjustment at the disaggregate level might be more prone to leave residual seasonality in the aggregate data. In other words, there may be components series that each exhibit minor seasonality where that seasonality is however positively correlated across them. The omitted

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seasonality may therefore be quite consequential in the aggregate, even if it was not at the component level.

The results of the F-test (Table 4.10) for the two models show that there is no residual seasonality left in the SA series for both models.

F-test for the presence of residual seasonality			
Model	Time Period	F-Statistic	P-value
M1	Entire series	0.10	0.99
	Last 3 years	0.37	0.96
M2	Entire series	0.17	0.99
	Last 3 years	0.45	0.92

Table 4.10: F-test for the presence of residual seasonality in the SA series (Indirect Approach).

4.6 COMPARISON OF DIRECT AND INDIRECT ADJUSTMENT OF THE IPI

In this section we present the main results obtained by comparing the direct seasonal adjustment of the IPI with the indirect adjustment, including the outliers, based on the utilisation of the same adjustment methods for all Main Industrial Groupings. As mentioned in the previous sections, the seasonal adjustment of the IPI can be achieved indirectly by summing up the previously seasonally adjusted components series (MIGs) or by directly seasonally adjusting the aggregate series.

Figure 4.13 presents the original series and the two seasonal adjusted ones for each model (on the same scale), for the time period January 2000 - December 2021. The data in the top graph of the figure show some differences between the direct and indirect approach for Model 1. On the other hand, the two approaches appear to be almost equivalent for Model 2. The Airline model chosen for four of the five Main Industrial Groupings is the main reason that the two approaches do not show much difference.

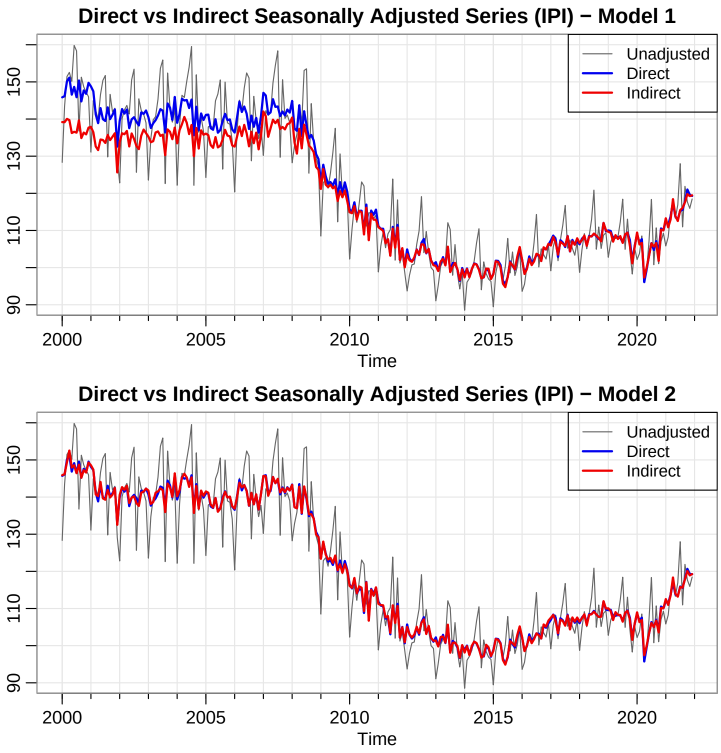

Figure 4.13: Direct vs Indirect Seasonally Adjusted Series for Model 1 and Model 2.

As shown in both graphs, the comparative graphical analysis is not able to provide useful information to discriminate between the two approaches. Therefore, a more analytical investigation is required. Many empirical works have touched this aspect, such as the seasonal adjustment of euro area GDP (Astolfi, Ladiray and Mazzi ([8]), Planas and Campolongo ([4]), and Gómez ([17])).

For the two models, four dimensions of seasonal adjustment quality were used to compare the direct and indirect approach. These dimensions are:

- Residual seasonality
- Concordance analysis of growth rates
- Analysis of smoothness
- Revision Analysis

4.6.1 *Residual Seasonality*

The ARMA spectra analyse the original and the SA series for remaining seasonality for the two seasonal adjustments. They check for the presence of peaks at the seasonal frequencies. Figure 4.14 illustrates the estimated ARMA spectra for the original, directly and indirectly seasonally adjusted series of the IPI.

The spectral graphs are interpreted as follows: the original series (black lines) presents "visually significant peaks" over seasonal frequencies, thus there is evidence of seasonal effects in the series. However, for the SA series (blue and red lines) derived from the direct and indirect approach the spectra do not indicate any residual seasonality for the two models.

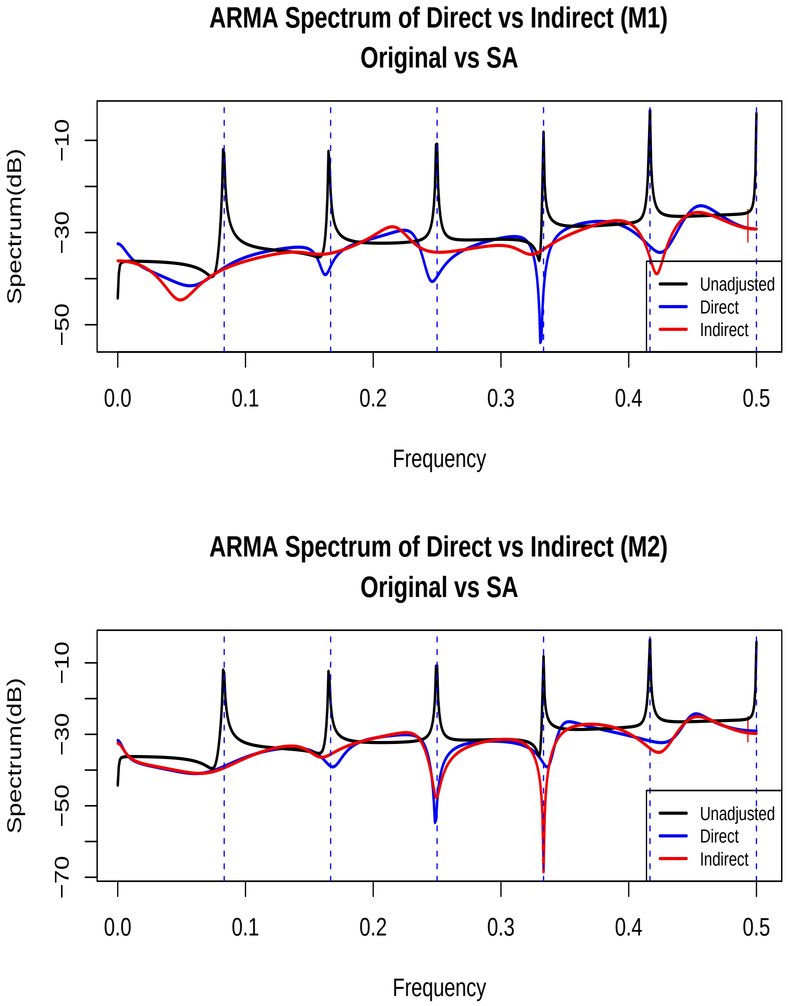

Figure 4.14: ARMA Spectrum of Direct vs Indirect (Original vs SA Series) of the IPI for the two models.

Notes:

1. The spectral graphs have been estimated from the first differenced, log transformed data.
2. Intensity is presented on the decibel ($10 \times \log_{10}$) scale.

4.6.2 *Concordance analysis of growth rates*

A further step in the comparison of our results is represented by the analysis of the sign concordance of the annual growth rates (Astolfi, Ladiray and Mazzi [13]), using the formulas mentioned in Section 3.2. A key point to be considered in the seasonal adjustment is to control if there is any big inconsistency in signs of the annual growth rate calculated on SA series with the direct and the indirect adjustment. We can measure the concordance as the ratio of annual growth rates having the same sign on the total of observation minus twelve. As shown in Table 4.11, the level of sign concordance is quite high (92.5% for Model 1 and 97.2% for Model 2). Model 1 shows almost three times as many inconsistencies as Model 2.

Moreover the mean, variance, minimum and maximum value and the variation range of the differences between the annual growth rates of the two approaches have been computed (same scale). From the results in Table 4.12 it is clear that there are differences between the two approaches.

Model	Direct	Indirect	Number of observations	C1
Model 1	Concordance		233	92.5%
	Inconsistency		19	7.5%
Model 2	Concordance		245	97.2%
	Inconsistency		7	2.8%

Table 4.11: Sign concordance analysis of the annual growth rates (SA) for the two models.

Difference in annual growth rates (SA) between the two approaches					
Model	Mean	Minimum	Maximum	Variance	Range
Model 1	-0.33	-4.40	2.93	1.01	7.33
Model 2	0.004	-1.29	1.43	0.15	2.73

Table 4.12: Differences in annual growth rates (SA) between direct and indirect approach for the two models.

Figure 4.15 shows the annual growth rates of the SA series derived with the two approaches for the two models. As it appears the differences in the annual growth rates between the two adjustments are more distinct for Model 1 than in Model 2. Moreover, as emerges from the graphical analysis (Figure 4.16) the difference between direct and indirect approach in the annual growth rates for Model 1 and the corresponding difference between the two approaches for Model 2 appear to be quite far apart.

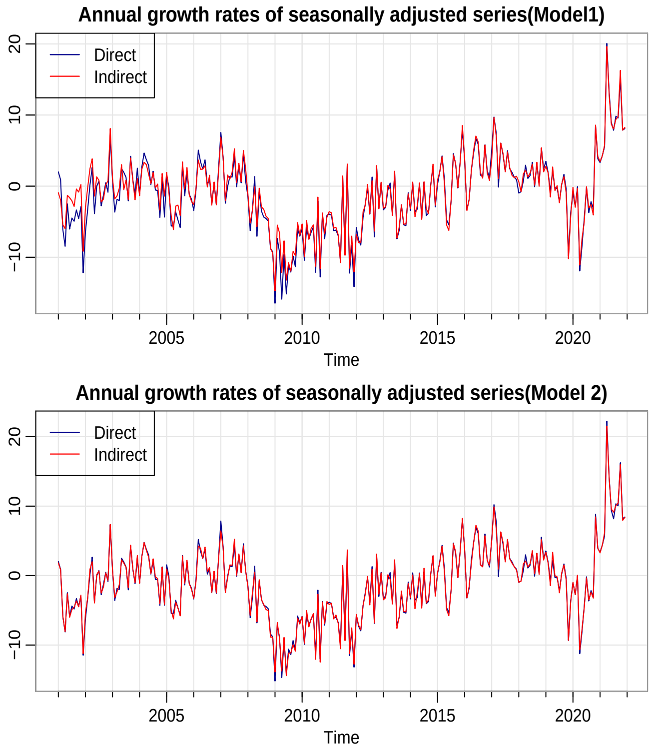

Figure 4.15: Annual growth rates (in percentage) of seasonally adjusted series for Model 1 and Model 2, obtained with the two approaches.

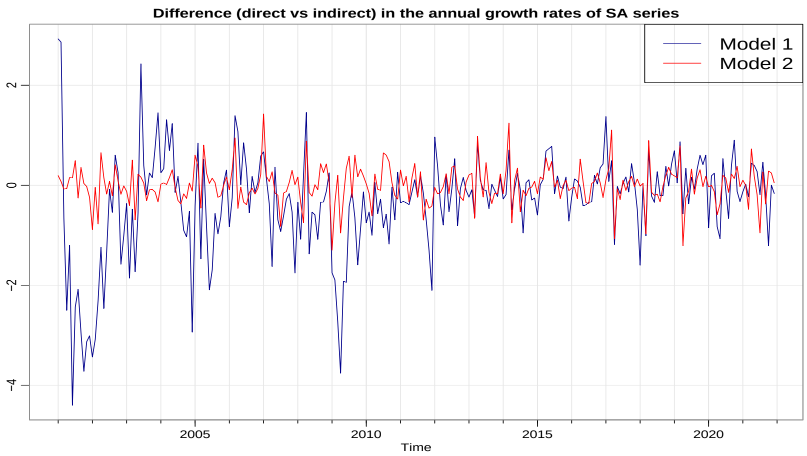

Figure 4.16: Difference (between direct and indirect) in annual growth rates (in percentage) of seasonally adjusted series for Model 1 and Model 2.

4.6.3 *Analysis of smoothness*

In order to assess the degree of smoothness of the series, we are using three different roughness measures (R1, R3, MAR), that refer to the seasonally adjusted series, the trend-cycle and the seasonal component. The smoothness of seasonally adjusted data is often considered as one of the most important criteria. However, it must be stressed, as mentioned in Section 3.2, that this criterion has to be used carefully because the irregular component is an integral part of the series and it seems quite strange to prefer the series that presents the smallest irregular (Ladiray and Mazzi [14]).

The measures were calculated (on the same scale) in both models for the entire series and for the last three years. The results of which are presented in Table 4.13, show that there is no clear evidence in favor of one of the approaches. More specifically the following conclusions can be drawn :

- From the results of the R1 and R3 measures, appear that the indirect approach is more favourable than the direct one.

- The MAR measures (preferred by Gómez and Maravall [11]) for the trend component indicate that the direct approach is smoother than the indirect for both models.

	Model 1		Model 2		Direct
Indicator	Direct	Indirect	Direct	Indirect	vs Indirect
R1(SA)	2965.201	2605.291	2816.791	2788.973	I
R1(SA), Last 3 years	375.923	401.278	355.364	342.383	D(M1)/I(M2)
R3(SA)	1316.261	1068.72	1262.170	1120.006	I
R3(SA), Last 3 years	372.728	269.469	363.315	227.906	I
MAR(S)	36439.79	36194.9	97.798	150.358	I(M1)/D(M2)
MAR(S), Last 3 Years	3596.69	3573.80	1.929	1.678	I
MAR(TC,1)	73.522	100.415	69.583	114.521	D
MAR(TC,1), Last 3 Years	9.501	12.653	8.904	12.059	D
MAR(TC,2)	280.856	313.645	267.559	355.344	D
MAR(TC,2), Last 3 Years	36.269	47.032	34.244	45.384	D

Table 4.13: Measures of roughness for seasonally adjusted series.

4.6.4 *Revision Analysis*

An analysis of revisions history, using the measures described in Section 3.2, was performed for each adjustment for both models, in order to assess the stability of the directly and indirectly seasonally adjusted estimates. The process is summarized as follow:

1. November of 2017 was selected as the start date

2. the series was seasonally adjusted up to and including the start date, forecasting the value of the IPI for the following time period (e.g. December 2017)

3. the start date was moved forward one time period (month) and the series was seasonally adjusted again, forecasting the next value of the IPI; this process continued until the end of the series

The direct and indirect estimates, initial and final, are shown in Figure 4.17, where the initial estimates are the forecast estimates and the final estimates are the SA series. As stressed by Maravall ([16]) large revisions are associated with highly stochastic components and converge quickly, while smaller revisions are implied by very stable components and converge slowly. Generally, the slow convergence of the SA series estimator to the final estimator suggests that very little would be gained from moving from a current adjustment to a concurrent one. It is also useful to point out that in the case of the indirect approach we are working with a sort of linear combination of different filters (different ARIMA models) which may not be the same, so it is difficult to talk about the revision properties of the filter. In the case of the direct approach, only one filter is applied (Astolfi, Ladiray and Mazzi [13]).

Thus, seasonal adjustment with the smallest revisions, i.e. with initial estimates closer to the final estimates would be preferable. Both the direct and indirect adjustments have some months at which there are large revisions — January and April of 2019 are two examples for direct, and January and August of 2018 for indirect. However, there are other months with large revisions for the direct and indirect approach — for example April 2020 (for both models) and January 2019 (for both models) respectively.

Furthermore, the revision history analysis plot is accompanied by the information provided by Table 4.14. From the following table, the mean absolute revision (MAR), the mean squared revision (MSR) and the standard deviation of revision (SDR) for the SA series and the trend-cycle estimates are lower in the direct approach compared to the indirect one. Therefore, the direct approach is preferable, for both models, due to the smaller revisions, so it is considered more stable than the indirect. In addition, since the Airline model is the main ARIMA model of the component series, there is not issue with the indirect approach and the revision analysis can be considered reliable.

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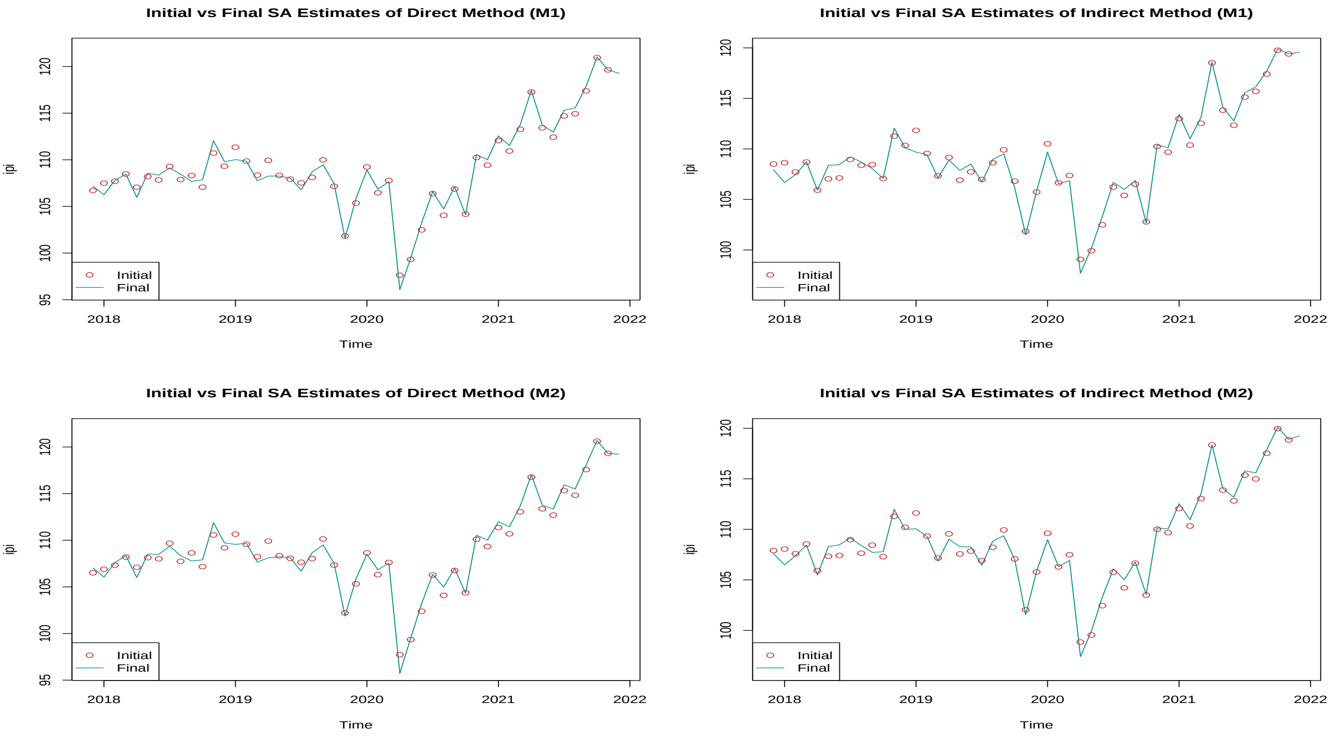

Figure 4.17: Revisions, Initial vs Final, for the Direct and Indirect Adjustment for the two models.

	Model 1		Model 2		Direct
Indicator	Direct	Indirect	Direct	Indirect	vs Indirect
Mean AR (SA)	0.505	0.792	0.551	0.816	D
SDR (SA)	0.402	0.647	0.425	0.641	D
MSR (SA)	0.413	1.224	0.481	1.293	D
Mean AR (TC)	0.849	1.303	0.861	1.304	D
SDR (TC)	0.622	1.057	0.642	1.107	D
MSR (TC)	1.099	2.989	1.143	3.244	D

Table 4.14: Measures for the revisions (mean, standard deviation and mean squared).

https://doi.org/10.26219/heal.aueb.5891

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5

CONCLUSIONS

This thesis applies the seasonal adjustment program TRAMO/SEATS to the Greek Industrial Production Index (monthly series), and it shows how the programs output can be used to discriminate among two seasonal adjustment approaches, the direct and the indirect, for two models, one with log-transformed data and the other without transformation. First, a brief review of the method was presented as well as some useful criteria for choosing between direct and indirect adjustment, and then we carried out the seasonal adjustment of the IPI.

In particular, we have seen the usefulness of the pre-adjustment phase (TRAMO), which allowed us to detect significant outliers and calendar effects, as well as to determine the most appropriate ARIMA model for the IPI and the Main Industrial Groupings. Thereafter, the use of the ARMA spectra for the SA linearized series have shown that the IPI as well as the Main Industrial Groupings do not exhibit seasonality. Additionally, the SEATS output was used to check for the stability of the trend-cycle component and the seasonal component, but also to test for the presence of residual seasonality in the SA series. In conjunction with the diagnostics for the SEATS output, autocorrelation tests were also performed for the ARIMA residuals.

Moreover, the two approaches of seasonal adjustment have been investigated, direct and indirect approach, and have been shown to produce almost similar results for the model without data transformation. On the other hand, they appeared to have some differences for the log-transformed model. The choice of the ARIMA Airline model is the main reason that the two approaches do not present considerable differences.

The two adjustments have been compared in terms of four dimensions of seasonal adjustment quality: residual seasonality, consistency, roughness and revisions. On balance, neither of the approaches is obviously superior; there is no evidence of residual seasonality in the aggregate series for either adjustment (for both models), and the results for the roughness dimension are mixed. Nevertheless, the revision analysis indicated a preference in favour of the direct approach for both models.

In conclusion, Maravall ([18]) states that "Because aggregation has a strong effect on the spectral shape of the series, and because seasonal adjustment is a non linear transformation of the original series, direct adjustment is preferable, even at the cost of destroying identities between the original series. The absence of a definitive solution has fostered a pragmatic approach among users: choose the solution that yields the SA series with the more desirable properties."

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