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ABSTRACT

Tourist demand is subject to considerable variations, a fact which aggravates the development of forecast models of sufficiently adequate accuracy. This study develops models that permit including most if not all factors of influence. To this end, due consideration was given to calendar effects as well as unknown special effect in time series models and econometric approaches in an attempt to improve the quality of the forecast. Results showed that for the data set used, a combination of complex data adjustment procedures and adequate model structures substantially improved the accuracy of the forecast or simple approaches lose out to more complex ones. Accordingly, the central issue of this study, i.e. whether complexity matters, can certainly be answered quite simply by "yes, it does."

Key words: *calendar effects, econometric indicator approach, multivariate time series model, outlier detection, transfer function*

INTRODUCTION

The methodology to handle the short-term forecast problem in tourism time series (e.g. arrivals) has risen to a high standard over recent years. Examples found in recent literature are univariate ARIMA approaches as well as multivariate methods based on time series or causal econometrically focussed, such as structural time-series models, error correction models or transfer function models (Kulendran and Witt 2001 and 2003; Turner, Kulendran, and Fernando 1997; Turner and Witt 2001). Whereas known special effects such as mega-events and terrorist attacks have been included by way of intervention analysis (Coshall 2003; Enders 2004; Smeral and Wüger 2000) in designing short-term forecast models, little attention has been given to considerations that variations in tourism demand may be critically influenced by calendar effects such as the number of weekends per month, the concrete date of national, Easter and Whitsuntide holidays, or unknown special effects such as the impact of shocks, discretionary marketing measures, media reports and demand data errors. Non-consideration of calendar effects, unknown special events and “outliers” will produce biased parameters in the design of a model.

In this paper, we will attempt to add further dimensions to the state-of-the-art in designing short-time tourism forecast models: we will demonstrate that the forecast quality of the models tested is relatively high when methods to detect outliers and adjust for calendar effects are used. For this purpose, both time-series-based and causal multivariate econometric forecast models were estimated for the period of 1992 to 2002. In this effort, multivariate time-series models were used which include both deterministic and stochastic components, as were transfer function models which take into account business cycle indicators as an explanatory variable. In addition, an econometric model was estimated which tested an option mostly ignored in the literature on tourism forecasts: the additional use as determining variables of flexible trends of dependent variables as well as demand and business cycle indicators adjusted in terms of their contribution to explain the dependent variables. The flexible (long-term) trends in the dependent variables were determined using Hodrick-Prescott (HP) filters (Hodrick and Prescott 1997). By applying dynamic factor models, selected business cycle indicators for arrivals were adjusted by extracting components relevant for explaining arrivals (Forni et al. 1999 and 2000; Fiorentini and Planas 2003). A joint element in all these approaches is that seasonal and calendar adjustment, outlier

detection plus parameter identification are performed simultaneously because it is only through this procedure that the true links can be captured.

The estimation and evaluation of the forecast quality were based on data of monthly tourist arrivals in Austria, with a distinction made between total arrivals and arrivals of Austrians, German¹⁾ guests and total foreign visitors.

The forecast quality of the models thus developed was measured on the basis of the “mean absolute percentage error” (MAPE) and the “out of sample” principle, i.e. the forecast was extended beyond the estimation period of 1992–2002 and the values forecast for January 2003 through December 2003 were compared to actual values.

As a basis for comparing the forecast quality of the three main models, univariate ARIMA models and causal multivariate econometric models were used, with the seasonal, calendar and special effects excluded only by simple smoothing methods, i.e. neither outlier detection methods, calendar adjustments nor complex seasonal adjustment methods were applied. The causal multivariate econometric model did not have any flexible trends filtered out of the dependent variables and neither were explanatory components extracted from the demand or business cycle indicators. Another basis for comparing the forecast quality was the “Absolute-No-Change” model.

As this paper concentrates chiefly on measuring the forecast quality of model approaches, no in-depth description is given here of the range of estimation methods and the variety of explanatory models of tourism demand, but reference is made to the large literature (Archer 1976; Crouch 1992; Enders 2004; Frechtling 2001; Green 2003; Lim 1997; Lim and McAleer 2001a, Makridakis, Wheelwright, and Hyndman 1998; Sinclair and Stabler 1998; Smeral and Witt 1996; Smeral 2003a and 2003b; Song and Witt 2000; Song, Witt, and Jensen 2003; Witt and Witt 1992). Similarly, no attempt is made to compare parameters or determination coefficients, especially since the forecast focus of this paper makes it clear that a restriction of comparisons to the MAPE (Mean Absolute Percentage Error) of the out-of-sample period is efficient.

¹⁾ In Austria, German guests make up about 50% of the total number, so that they carry a large weight in total arrivals and thus substantially affect overall development.

MAIN FEATURES OF THE MODELS USED

As a rule, an attempt is made to develop approaches that incorporate a maximum of relevant factors influencing the explanation of tourist arrivals. As a benchmark for the forecast accuracy offered by the three central models, univariate time-series models and multivariate causal models were developed, which were estimated on the basis of a rough adjustment (moving twelve-month averages = $movav_{12}$) of the seasonal and special effects. Another basis for comparison was the “Absolute No Change Model”, i.e. the absolute monthly values of 2002 were used as forecast values for 2003.

Benchmark Models

For modelling monthly tourist arrivals (Y_t) using ARIMA approaches, the original values were logarithmed and smoothed. Next, a suitable ARIMA model was identified, which has a regular (p,d,q) and a quasi²-seasonal part (P,D,Q). In formal terms, we thus get the following model:

$$movav_{12}(\ln Y_t) \hat{=} ARIMA(p,d,q)(P,D,Q)_{12}$$

The estimate produced an ARIMA model of (1,2,1)(0,1,0)₁₂. For domestic and international arrivals, as well as arrivals of German tourists and total arrivals, models could be found for the observation period based on the transformed time series that had a relatively high explanatory power and significant coefficients.

With regard to developing causal econometric models, unfortunately no internationally comparable monthly data on the relevant source markets are available for most explanatory factors, so that a number of overall economic indicators had to be used instead.

As indicators ($INDX_t$) for explaining the monthly development of total guest arrivals, guest arrivals from Austria and abroad and from Germany specifically, variables used included the relevant domestic and international production and retail sales indices and the touristically weighted, real-effective exchange rate index of Austria (i.e. the relative price in a single currency). Underlying this was the thesis that such indicators constituted proxies for short-term income and purchasing power development trends and/or the consumption and

²) By transforming the data into moving 12-month averages, the season was excluded. The 12th difference thus has only a quasi-seasonal character (even though it is theoretically accurate) and needs to be viewed rather as a tool of adjusting trends and levels.

business climate as well as economic expectations. For the real-effective exchange rate index as a direct “price indicator” (whether Austria has become cheaper or more expensive than its competitors) this also applies indirectly through the impact of the trade in goods, other services than tourism and FDI and their effects on the overall economic development. Further it was assumed that the indicators have a lead effect for tourism development and can thus be described as “leading indicators”.

For the estimated regressions, autocorrelation was found in the residuals. To eliminate this autocorrelation from the error variables, it is modelled based on an autoregressive process of an order p . In the cases examined here, the REGARIMA models with autoregressive error models of the 2nd order ($p = 2$) were found to be optimal. In formal terms:

$$movav_{12}(\ln Y_t) \hat{=} f(INDX_{t-n}, u_t)$$

$$u_t = AR(p)$$

u_t = error term, t = time index, n = number of lags

Y_t and $INDX_t$ are absolute previous-year differences of the moving 12-month averages of the logarithmised original values. The parameter estimates for the REGARIMA models and ARIMA models were computed using the EViews program (Quantitative Micro Software 1994–2000). After adjusting the autocorrelation in the residuals, significant regression results and high determination coefficients were found. With the exception of international arrivals, significant equations could be determined for all aggregates.

Multivariate Time Series Models

In order to forecast arrivals using complex time-series models, a multivariate approach was chosen. In the determinist part of this approach, calendar effects (C_i) such as the number of weekends (D_i) and holidays (H_i) per month plus Easter holiday effects (E_i) were considered. Special effects (O_i) were included by way of an outlier detection method. Using such a method, the effect of special events on the data generation process is highlighted (Chen, Liu, and Hudak 1990; Thury and Wüger 1992; Brandner and Schuberth 2000). Simultaneously, the model parameters of the data generation processes and outlier effects were estimated in an iterative approach. Here, each iteration step tests the observation value of a given time series whether it constitutes an “additive

outlier” (A_j , i.e. events that affect a time series at a single date), a “level shift” (L_j , permanent change in the data generation process), an “innovational outlier” (IO_j effects the innovation in the data generation process) or a “temporary change” (T_j , i.e. an event having an inintial impact that decays exponentially with some dampening factor). Once the type of outlier is identified, an adequate adjustment is carried out. The three steps (detecting the outlier, adjusting it and estimating the parameters, based on the corrected series) are repeated until all outliers have been eliminated.³⁾

Once the deterministic components were removed, the rest was modelled using an ARIMA approach that comprised both a regular (p,d,q) and a seasonal (P,D,Q) part. The regular term reflects the longer-term (trend, business cycle) influences, whereas the seasonal part shows the effects on the data generation process in the course of the year. The chosen multivariate time-series model thus explains the monthly tourist arrivals by:

- calendar and Easter holiday effects: $C_{it}(D_i, H_i, E_i)$,
- special effects and outliers (e.g. exchange rate effects, events, temporary marketing measures, price shocks, terrorist attacks, wars, etc.): $O_{jt}(A_j, L_j, IO_j, T_j)$,
- trend and business cycle influences: (p, d, q) , and
- seasonal influences: $(P, D, Q)_{12}$.

In formal terms:

$$\ln Y_t \hat{=} g\{C_{it}(D_i, H_i, E_i), O_{jt}(A_j, L_j, IO_j, T_j), ARIMA(p, d, q)(P, D, Q)_{12}\}$$

For the estimation, two software packages were used: TRAMO developed by Maravall and Gomez (1997) and X12-REGARIMA⁴⁾ developed by Findley et al. (1997). These programs provide for efficient modelling of the single components (calendar effects, outliers) and for identifying ARIMA models.

³⁾ The major difference between the outlier detection method and the intervention approach is in the fact that the date of the special influence must be known for intervention models.

⁴⁾ Alternatively we also used SCA-EXPERT (Liu 1997), which produced very similar results so that we do not show them separately.

Econometric Indicator Models

The complex econometric indicator approach chosen by us for this exercise attempts to control all major influence factors – calendar effects, seasonal influences, outliers and so-called habit effects, flexible trends in demand development and business cycle influences.

Calendar and seasonal adjustments were performed with the TRAMO/SEATS software package (Maravall and Gomez 1997), which builds on the estimation of an adequate time-series model of arrivals considering calendar effects, deriving from this a consistent model for the seasonal component. In addition, the X12 program (Findley et al. 1997) was used for calendar and seasonal adjustment. X12 uses moving averages for determining the components (season, trend) and applies multivariate time-series models only to account for calendar effects, to filter out special effects using outlier detection methods and to cope with the information loss at each end of a time series caused by calculation of the symmetric moving average.

Figure 1 shows the values, calendar- and seasonally adjusted, obtained by both methods. Accordingly, the series, seasonally adjusted by TRAMO/SEATS, with the exception of domestic arrivals, are in part much smoother than those adjusted by X12 which show a much larger stochastic element due to the moving average procedure. Thus, for arrivals from Germany, the variation co-efficient of the time series calendar- and seasonally adjusted by X12 is 73.9 percent higher than that of the series seasonally adjusted by TRAMO/SEATS (Table 1).

Habit effects were covered by levels once reached in the past. A satisfactory holiday stay may cause people to return and will thus impact positively on future demand. Any negative experience, on the other hand, may make people avoid the destination (holiday location) in the next year; repeated returns may produce a saturation effect which engenders a negative effect on future holiday stays. The sign of the coefficient for the lagged endogenous variable indicates whether positive or negative habit effects will prevail on balance.

Visits to holiday places are subject to trends that will change over time for a variety of reasons. An attempt was made to capture such flexible trends in arrivals by so-called HP filters (Hodrick and Prescott 1997; Enders 2004). This smoothing procedure is used in macroeconomics in order to obtain an estimation of the (long-term) trend of a time series. Hodrick and Prescott (1997) first used this method to examine the post-war business cycle

in the US. This method splits a given time series into a trend and a stationary component, using a double linear filter.

The trend series is determined by minimising the variance of time series Y_t around the trend s_t , with due regard to the second-order differences of the trend. The point thus is to choose the trend so that the following expression is minimised:

$$\sum_{t=1}^T (y_t - s_t)^2 + \lambda \sum_{t=2}^{T-1} \{(s_{t+1} - s_t) - (s_t - s_{t-1})\}^2$$

λ is an arbitrary constant reflecting the “costs” of trend fluctuations (expressed by the second-order differences), variations are thus subject to a penalty. Accordingly: the greater the penalty parameter, the smoother the trend series.

As shown in Figure 2, the arrival trends thus obtained were not linear, but no major differences were found in the filter-eliminated flexible trends between series calendar and seasonally adjusted by X12 and TRAMO/SEATS. Both international and German arrivals tended to fall until about 1996/1997, after which they tended to rise again. This was linked to the net real income losses suffered by German households in the “old” *Länder* in the wake of German reunification which dampened tourism demand up to 1997. The change to the positive received a further impetus from improvements in quality and structure.

Domestic arrivals were rising, although at different degrees of intensity: the trend was relatively flat between 1992 and 1996/97, picked up over the following years and then levelled off again towards the millennium. The trend of total arrivals was U-shaped but not symmetric during the observation period.

Beside habits and trends a suitable business cycle indicator should deliver information not just on turning points and – even more important – information on forecasts of total arrivals (Lahiri and Moore 1991; Kulendran and Witt 2001 and 2003; Rosello-Nadal 2001).

Economic activities in market economies are characterised by a constant stream of up- and downturns that are manifested by the cyclical behavior and co-movement of many economic time series. Consequently it is possible to describe the state of an economy by an index (the reference cycle) which captures the joint behaviour of these variables.

A heuristic approach for implementing this concept is found in the so-called NBER method (Burns and Mitchell 1946; Zarnowitz 1992) which analyses a data set in terms of a reference series (arrivals). Based on descriptive statistics and a turning point analysis, the time series are broken down into leading, coincident and lagging time series, and those time series that belong to the same category may then be combined into an overall index.

An alternative to the heuristic NBER approach is offered by the so-called factor models. These assume that a common force drives the dynamics of the time series observed. This joint force, known as common factor, nevertheless cannot be observed directly because economic variables frequently are disturbed by random noise and other influences. Factor models (Sargent and Sims 1977; Stock and Watson 1993) eliminate these disturbances and estimate common components in each time series, whether by static (Stock and Watson 2002) or dynamic (Forni et al. 1999 and 2000) approaches.

By using a dynamic factor model, we have attempted to extract from the demand and business cycle indicators (in our case the relevant domestic and international retail trade sales indices) the component relevant for explaining arrivals, based on the BUSY software package (Fiorentini and Planas 2003). Figure 3 shows the course of the reference series, the flexible trend and the extracted indicator. Results suggest estimating an adequate econometric equation, in which seasonally and outlier-adjusted arrivals (SOY_t) are explained by a habit term (an endogenous variable lagged by n periods), a flexible trend (HPY_t) and an extracted business cycle indicator ($EXINDX_t$). If the error terms in this econometric approach still showed “conspicuousnesses” (that means is not “white noise”⁵), they were modelled with a suitable ARIMA approach, with MA terms have been approximated by AR terms, especially since the point is in developing forecasts and since no information is available on future errors. The estimations were performed using the EViews program.

Based on this approach, we get an estimation of adjusted arrivals (see Figure 3) from which non-adjusted (actual) arrivals were derived by multiplication with the seasonal factors (SFY_t).

In formal terms, the econometric indicator approach can be shown as follows:

$$SOY_t \hat{=} f(SOY_{t-n}, HPY_t, EXINDX_{t-m}, u_t)$$

⁵) “White noise” means that errors in the estimating equations are independent and show totally random variations.

$$u_t = AR(p)$$

$$Y_t = SFY_t * SOY_t$$

$n, m = \text{no. of lags}$

Transfer Function Models

Transfer function models are essentially an extension of ARIMA models and a theoretically clear generalisation of multiple regressions with dependent errors. The extension made by us involves a suitable business cycle indicator. In this, we suggest a one-directional causal relationship between the endogenous variable (arrivals) and these business cycle indicators. Transfer function models certainly require a relatively high estimation input, but they help to exclude spurious correlation and they are suitable to model complex relationships. For the estimation we used the “linear transfer function” (LTF) approach because it simplifies identification and can be generalised to the multi-dimensional case (Liu and Hudak 1994; Makridakis, Wheelwright, and Hyndman 1998). An important element of this iterative method is the initial estimation of a set of transfer weights $\omega(B)$, which indicate how a change in the business cycle indicators ($INDX_t$) will impact on the output variables (arrivals) at any time throughout the relevant period of their effect. Another important point in this iterative procedure (LTF) is a first calculation of an approximation of the so called residual component. The residual component consists of the combined influence of all other factors such as calendar effects (C_{it}), special effects (O_{it}) as well as trend and seasonal influences (shown by an ARIMA model) on arrivals. A model was developed for this residual component which allows conclusions to be drawn for the original transfer function.

The transfer function approach used here and estimated with the SCA software package (Liu 1997) models the arrivals in a time series approach that also contains deterministic elements (calendar and outlier effects) and additionally considers information from suitable indicators (e.g. retail trade sales, etc.). The indicator information flows into the estimated equation not just for a given point in time but throughout the relevant time interval for which the total influence is calculated.

In purely formal terms, the transfer function models used can be shown as follows:

$$\ln Y_t \hat{=} h \left\{ \omega(B) \text{INDX}_t, C_{it}(D_i, H_i, E_i), O_{jt}(A_j, L_j, IO_j, T_j), \text{ARIMA}(p, d, q)(P, D, Q)_{12} \right\}$$

$$\omega(B) = \omega_0 - \omega_1 B - \omega_2 B^2 - \dots - \omega_s B^s$$

s is a constant that reflects the polynomial order of transfer weights, i.e. the lag structure of the input variables (i.e. the time lag at which the business cycle indicator impacts on the output variable, in this case arrivals). B is the back-shift operator.

FORECAST ACCURACY

Correlation between the forecast values of the multivariate time series model and reality is excellent, and indeed markedly better than for the ARIMA reference models with a simple adjustment method (Figure 4, Tables 2 and 3). While the simple ARIMA model showed a mean absolute percentage error (MAPE) of 6.01 for domestic arrivals in 2003, the complex approaches had a MAPE between 2.15 and 2.42 (Table 2). For international arrivals, the ARIMA model produced a MAPE of 13.20, whereas the complex models achieved MAPEs of 5.77–6.58. For German arrivals, the MAPE from the ARIMA model was 18.92, whereas the complex models had MAPEs between 7.47 and 8.50. With regard to total arrivals, the simple approach delivered a MAPE of 10.26, and the more complex models showed values between 4.41 and 4.48.

A comparison of multivariate time series models with the Absolute-No-Change model shows that forecast accuracy is distinctly better when more complex methods are used than with the Absolute-No-Change model (Table 3). Similar to the findings of Kulendran and Witt (2001), we found that simpler ARIMA approaches that lack special adjustment procedures have substantially higher forecast errors than the corresponding No-Change models.

For forecasting arrivals on the basis of econometric indicator models, exogenous variables need to be provided for the forecast period. The necessary extrapolation was done by the Holt-Winters method, for which we chose a non-seasonal approach because the flexible trend and the business cycle indicator by their very definition lack any seasonal effects (Lim and McAleer 2001b; Makridakis, Wheelwright, and Hyndman 1998). Holt (1957) and Winters (1960) so generalised exponential smoothing, which allows developing forecasts as

exponentially weighted sums of past values, that forecasts can be calculated analogously when the time series observed are not stationary but show a trend.

Obviously the need to forecast the trend and business cycle indicator on one's own for the purposes of an ex-ante forecast involves an additional error potential, but this may be kept to a minimum because there are adequate procedures available to forecast such longer-term variables with sufficient accuracy for at least one year.

An analysis of the results found that models using explanatory indicators extracted through the use of factor models, when based on MAPE, typically produced better results than the NBER method.

When we compare the results of complex econometric indicator approaches (Table 4) and the simple REGARIMA indicator approach (Figure 5, Table 3), we find the former to be clearly superior to the latter when measured by the MAPE, in spite of the need for a trend forecast. With regard to domestic arrivals, the measure was 4.80 for the simple REGARIMA approach, and between 2.06 and 2.43 for the complex approaches. With regard to German arrivals, the MAPE is 19.88 for the simple approach and 7.98–8.58 for the complex one. And lastly, the MAPE for total arrivals was much higher for the simple econometric indicator approach (12,02) than for the complex approach (3.62–4.99). As was shown with regard to the multivariate time series models, greater complexity cuts the MAPE by at least half.

Measured by the MAPE, a comparison of complex time series approaches and complex econometric indicator models finds relatively small differences only. This result agrees, at least in part, with findings by other studies (Kulendran and Witt 2003).

Same as with regard to the evaluation of complex multivariate time series models, complex econometric indicator models furnished clearly better forecast results than the Absolute-No-Change models, although the latter are mostly more accurate than the simple REGARIMA approaches.

In order to obtain better comparisons between the results of the transfer function approach and the econometric models, forecast values (rather than actually observed values provided, due to the lead time, they had been available at the time of forecast) were used for the indicator (in this case the EU retail trade sales) for the entire forecast period.

In view of the high volatility of the non-extracted indicator and the obvious difficulties in forecasting this indicator, only the forecast quality for total arrivals was improved vis-à-vis the multivariate time series model (MAPE = 4.18; Figure 6). Compared to the complex indicator approaches the transfer functions achieved, at least in part, better results, which (measured in terms of the MAPE) were between the forecast results calculated on the basis of TRAMO/SEATS and X12.

CONCLUSION

Tourist demand shows uncommonly strong variations in the course of time, business cycles and seasons – this is the consequence of the fact that tourist consumption is able to respond promptly and easily to any kind of influence, with the result that the data are highly “dirty”, i.e. show an above-average degree of randomness. Accordingly and obviously this will greatly aggravate the detection of true relationships such as is attempted in constructing models. The current study therefore sets out to construct models that allow including many if not all factors of influence. To this end, calendar effects and unknown special effects were specifically and adequately considered in time series models and econometric approaches with a view to improving the forecast quality.

The results thus obtained confirmed us in our view that, given the data set used, the combination of complex data adjustment methods and adequate model structures will significantly improve forecast results and that simpler approaches are decidedly outperformed by complex methods. In other words and to answer the central issue of this paper: complexity clearly does matter.

Considering that the economic reality appears to be affected to an ever greater extent by exogenous shocks and special events, it is important to gain control over the underlying factors, by turning into key issues questions such as “Does the increase of the potential terrorist risk affect the trend of long-distance travelling or does it rather boost short-distance trips?”; or “Does the proliferation of festivals affect demand?”

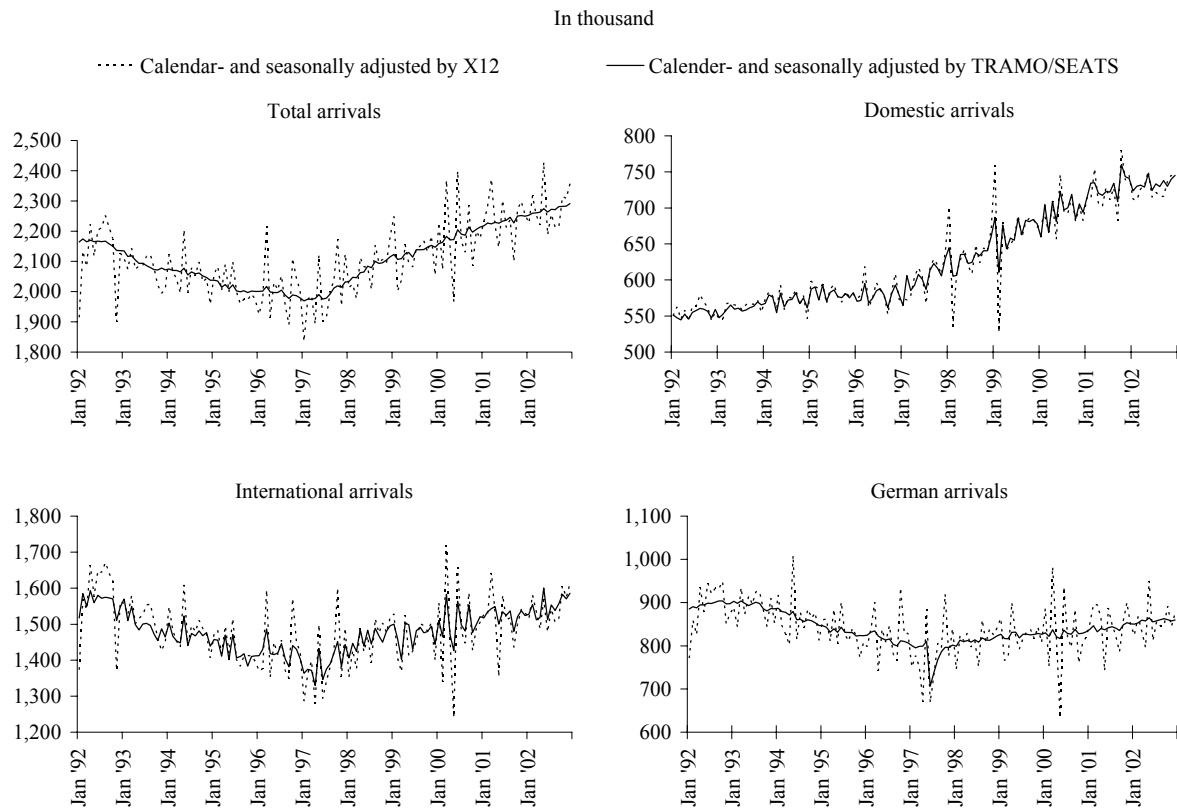
It is, however, interesting and amazing to note that, for the current data set, it took complex methods to clearly improve on the Absolute-No-Change model in terms of the forecast accuracy. In other words and to formulate it cautiously for the current data set: the application of simpler standard approaches apparently does not suffice to achieve an adequate forecast accuracy when compared to the benchmark of the Absolute-No-Change model.

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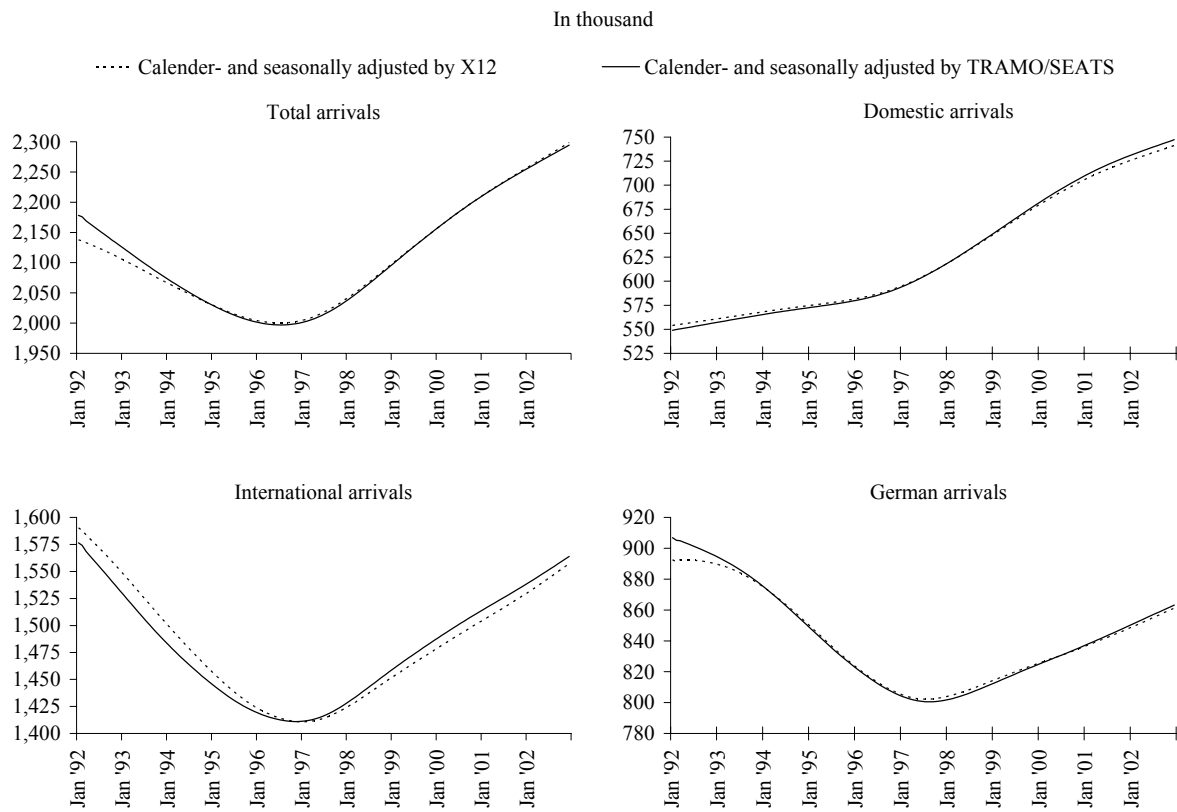
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FIGURE 1
COMPARISON OF TOURIST ARRIVALS,
CALENDER- AND SEASONALLY ADJUSTED BY X12 AND TRAMO/SEATS



Source: Own calculations.

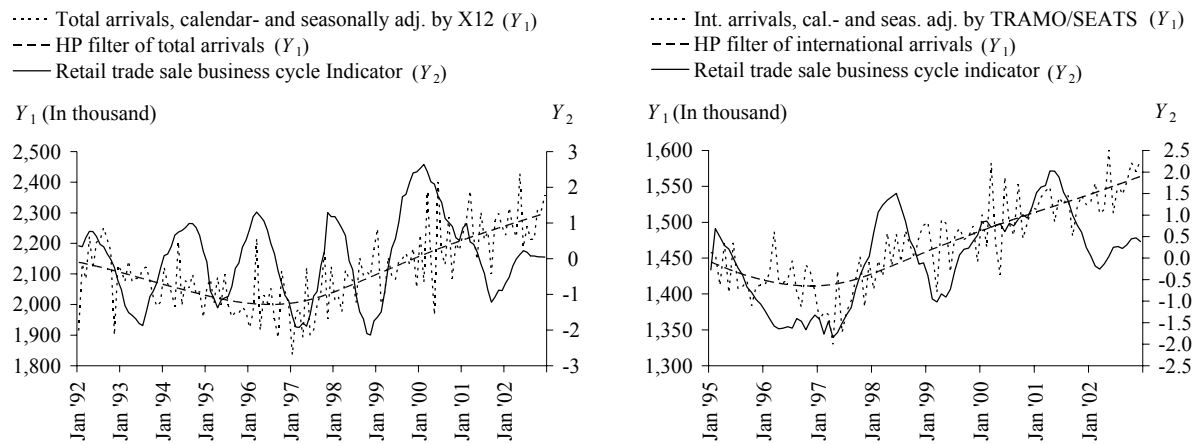
FIGURE 2
FLEXIBLE TRENDS OF THE ARRIVALS DETERMINED BY USING AN HP FILTER



Source: Own calculations.

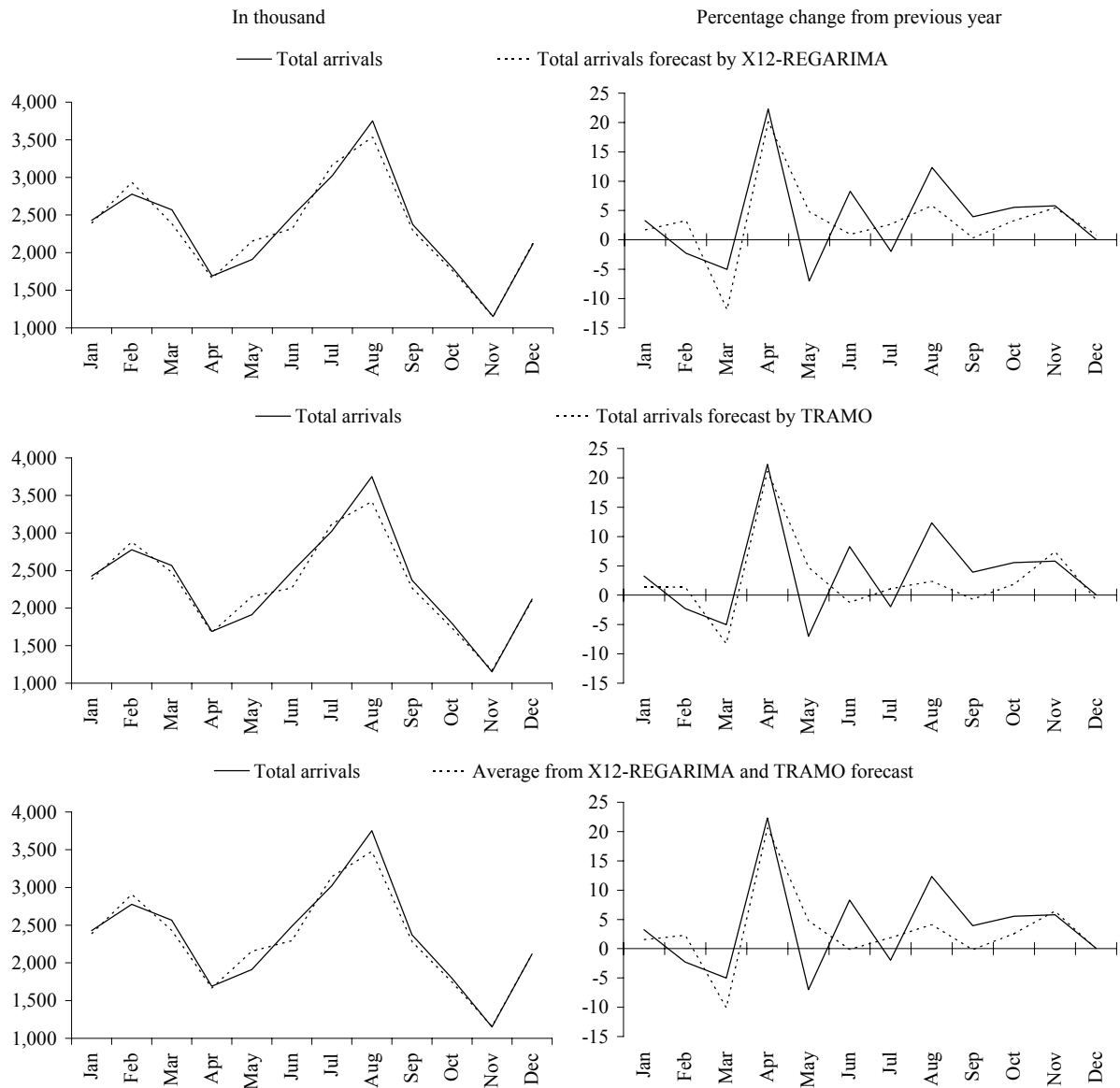
FIGURE 3

**DEVELOPMENT OF CALENDAR- AND SEASONALLY ADJUSTED ARRIVALS,
THE FLEXIBLE TREND (HP FILTER) AND THE BUSINESS CYCLE INDICATOR**



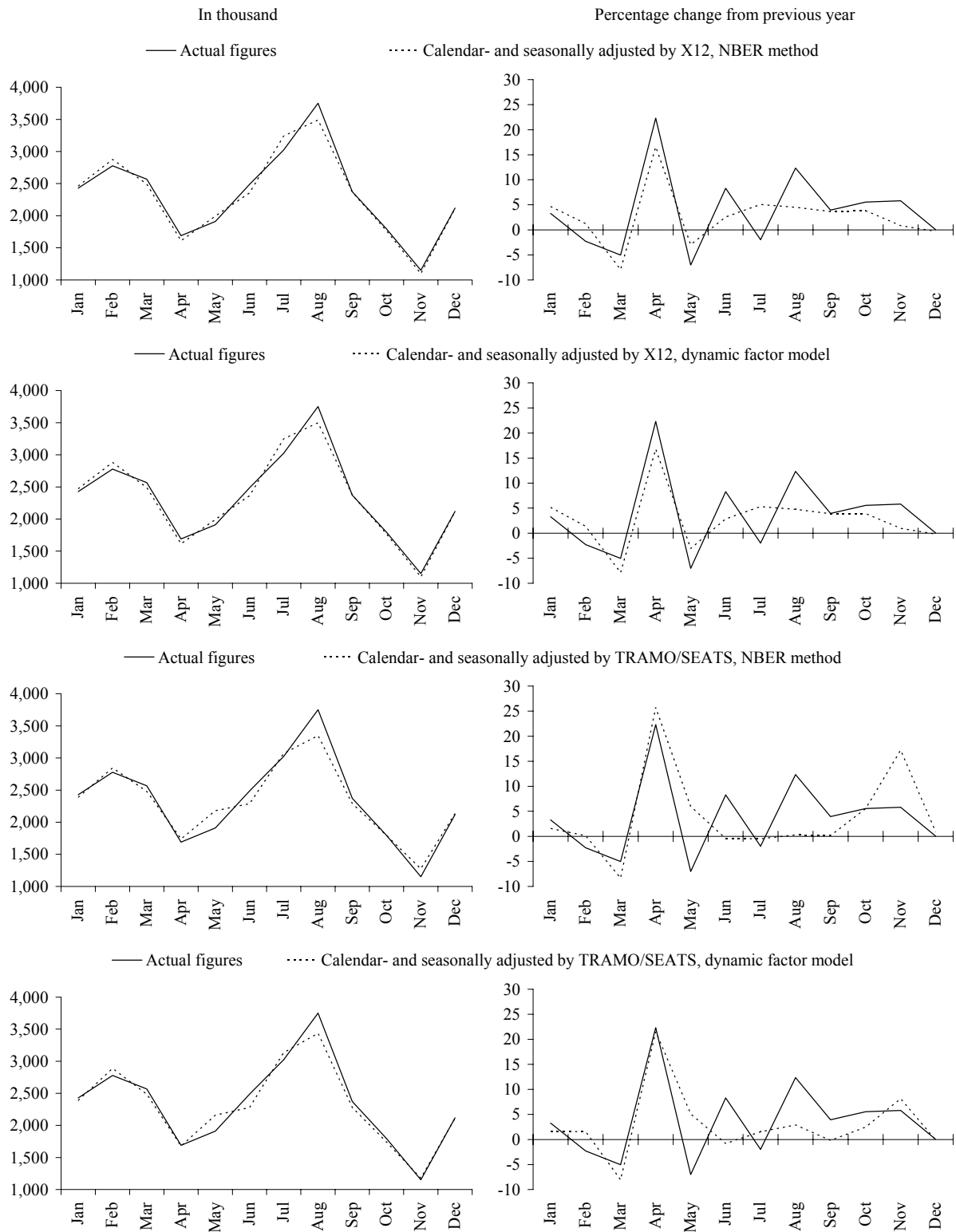
Source: Own calculations. Left scale (Y_1): arrivals and HP filter; right scale (Y_2): real extracted retail trade sales index.

FIGURE 4
FORECAST OF TOTAL ARRIVALS USING COMPLEX TIME SERIES MODELS
(X12-REGARIMA AND TRAMO), 2003



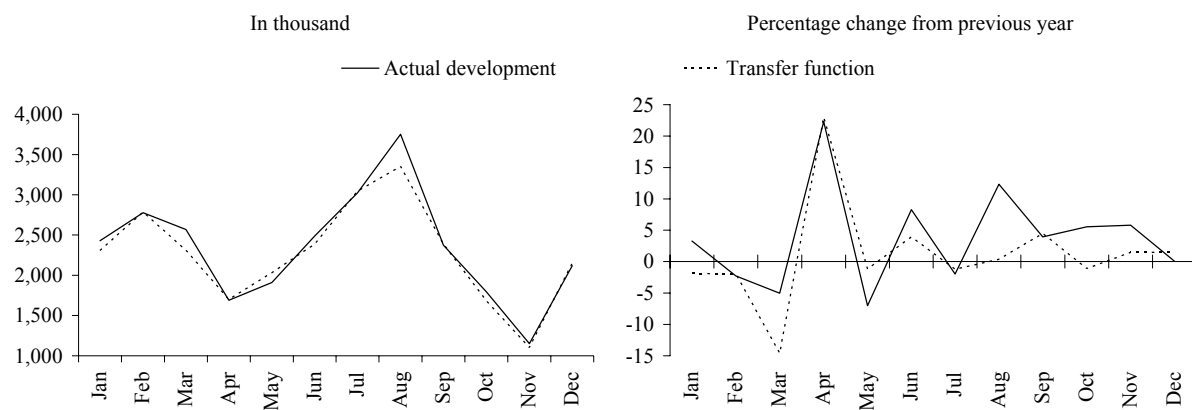
Source: Own calculations.

FIGURE 5
COMPARISON OF THE FORECAST USING COMPLEX INDICATOR APPROACHES (NBER METHOD AND DYNAMIC FACTOR MODEL) AND TOTAL ACTUAL ARRIVAL FIGURES, 2003



Q: Own calculations.

FIGURE 6
COMPARISON OF THE FORECAST USING A TRANSFER FUNCTION APPROACH¹⁾
AND ACTUAL TOTAL ARRIVALS, 2003



Source: Own calculations. – ¹⁾ In the deterministic part, the EU retail trade sales were used as indicator in addition to adjustment for outliers and calendar effects.

TABLE 1
COMPARISON OF VARIATION COEFFICIENTS¹⁾ OF TOURIST ARRIVALS,
CALENDAR- AND SEASONALLY ADJUSTED BY X12 AND TRAMO/SEATS, 1992 TO 2002

Arrivals	X12	TRAMO/SEATS
Total	5.71	4.40
Domestic	10.62	10.58
International	6.04	4.04
German	7.25	4.17

Source: Own calculations. – ¹⁾ Standard deviation in percent of the mean value.

TABLE 2
MULTIVARIATE TIME SERIES MODELS¹⁾ AND THEIR FORECAST ACCURACY FOR 2003

		Model ²⁾ (p,d,q)(P,D,Q) ₁₂	MAPE ³⁾
Total arrivals	X12-REGARIMA	(2,1,2)(0,1,1)	4.41
	TRAMO/SEATS	(0,1,1)(0,1,1)	4.48
Domestic arrivals	X12-REGARIMA	(0,1,1)(0,1,1)	2.15
	TRAMO/SEATS	(1,1,1)(0,1,1)	2.42
International arrivals	X12-REGARIMA	(2,1,0)(0,1,1)	5.77
	TRAMO/SEATS	(0,1,1)(0,1,1)	6.58
German arrivals	X12-REGARIMA	(2,1,0)(0,1,1)	7.47
	TRAMO/SEATS	(1,0,0)(0,1,0)	8.50

Source: Own calculations. – ¹⁾ Modelling considers calendar and outlier effects in the deterministic part. – ²⁾ The models consist of a regular (p,d,q) and seasonal part (P,D,Q), where p = order of the regular AR term, d = regular integration order, q = order of the regular MA term, P = order of the seasonal AR term, D = seasonal integration order, and Q = order of the seasonal MA term. – ³⁾ Mean Absolute Percentage Error.

TABLE 3
BENCHMARK MODELS AND THEIR FORECAST ACCURACY FOR 2003

		MAPE ¹⁾
Total arrivals	REGARIMA	12.02
	ARIMA(1,2,1)(0,1,0) ₁₂	10.26
	Absolute-No-Change	5.98
Domestic arrivals	REGARIMA	4.80
	ARIMA(1,2,1)(0,1,0) ₁₂	6.01
	Absolute-No-Change	4.03
International arrivals	ARIMA(1,2,1)(0,1,0) ₁₂	13.20
	Absolute-No-Change	8.05
German arrivals	REGARIMA	19.88
	ARIMA(1,2,1)(0,1,0) ₁₂	18.92
	Absolute-No-Change	10.73

Source: Own calculations. ¹⁾ Mean Absolute Percentage Error.

TABLE 4
COMPLEX ECONOMETRIC INDICATOR APPROACHES USED¹⁾
AND THEIR FORECAST ACCURACY, 2003

Arrivals	Seasonal adjustment method	Indicator calculation method	MAPE ²⁾
Total	X12	NBER method	3.62
		Dynamic factor model	3.58
	TRAMO/SEATS	NBER method	4.99
		Dynamic factor model	4.34
Domestic	X12	NBER method	2.06
		Dynamic factor model	2.25
	TRAMO/SEATS	Dynamic factor model	2.43
		International	X12
Dynamic factor model	5.64		
TRAMO/SEATS	NBER method		6.31
	Dynamic factor model		6.13
German	X12	NBER method	7.98
		TRAMO/SEATS	NBER method
	Dynamic factor model		8.58

Source: Own calculations. – ¹⁾ A REGARIMA approach was used, with due consideration of habit effects, a flexible trend and a business cycle indicator to explain the time series adjusted for calendar, seasonal and outlier effects by X12 and TRAMO/SEATS. The values thus obtained were multiplied with suitable seasonal factors in order to obtain the estimated value for arrivals in 2003. – ²⁾ Mean Absolute Percentage Error.

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