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The nature of the relationship between international tourism and international trade: The case of German imports of Spanish wine

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ABSTRACT

This paper deals with the relationship between international trade and tourism. In particular, we focus on the effect that German tourism to Spain has on German imports of Spanish wine. Due to the different stochastic properties of the series under analysis, which display different orders of integration, we use a methodology based on long memory regression models, where tourism is supposed to be exogenous. The results show that at the aggregate level, tourism has an effect on wine imports that lasts between two and nine months. Disaggregating the imports across the different types of wine it is observed that only for red wines from Navarra, Penedús and Valdepeñas, and to a certain extent for sparkling wine, tourism produces an effect on its future demand. From a policy-making perspective our results imply that the impact of tourism on the host economy is not only direct and short-term but also oblique and delayed, thus reinforcing the case for tourism as a means for economic development.

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1. Introduction

International tourism has grown strongly during the last decades. Worldwide tourist trips reached almost 700 million in 2000, as compared to about 25 million in 1950. Measured in relative terms, at 120 trips per thousand of world population in 2000, tourism activity has increased more than ten-fold during this period (World Tourism Organisation, various issues). At the same time, international merchandise trade has also grown significantly. According to figures of the World Trade Organisation, world exports per head of world population have increased from 44 current US dollars in 1961 to almost 1,200 USD in 2003. Thus, because there seems to be correlation between the international flows of people and goods a growing body of studies has emerged, which, using different methodologies, have investigated the possibility of a causal relationship between these two phenomena.

From a policy perspective, the topic of possible significant and positive interdependencies between tourism inflows and exports of manufactures is important in at least two ways. First, industrial development officers and trade association officials may find it useful to better understand the dynamics and determinants of industrial export success. While, in practice, it may be difficult to actively influence tourism arrivals, the knowledge about confirmed tourism-trade interdependencies may make it easier to predict exports on the basis of tourism data. Second, tourism development agencies could demonstrate that the positive impacts of international travel on a national economy may not only be direct and immediate but also oblique and delayed. If tourists can be shown that they not only generate income and jobs while they are in the country, but also create significant economic impulses by means of resulting exports to their source countries later on, the attention given to tourism development may surely be raised.

Easton (1998) analysed whether Canadian aggregate exports are complementary or substitutive to tourist arrivals, using pooled data regressions. The study finds "some

evidence of substitution of Canadian exports for tourist excursions to Canada" (p. 542) by showing that when the relative price of exports goes up, the number of tourists visiting Canada increases. Kulendran and Wilson (2000) analysed the direction of causality between different travel and (aggregate) trade categories for Australia and its four main trading partners, using time series data. Their results show that travel Granger causes international trade in some cases and vice versa in others. Shan and Wilson (2001) replicate this latter approach and also find two-way Granger causality using aggregate data for the case of China. Aradhyula and Tronstad (2003) used cross-section data and a simultaneous bivariate qualitative choice model to show that cross-border business trips have a significant and positive effect on US agribusinesses' propensity to trade. Fischer (2004) explored the connection between bilateral aggregate imports and imports of individual products and bilateral tourist flows, using an error-correction model. The results show that trade/tourism elasticities are consistently higher for individual products. Table 1 summarises the previous research on the topic.

(Insert Table 1 about here)

One of the aspects which has not yet been explored according to our knowledge is the temporal nature of the relationship between tourism and trade. As Kulendran and Wilson (2000) put it when recommending further research directions: "… the lag structures between the travel and trade flows … may require further attention" (p. 1007).

This paper deals with the case of the relationship between the German wine imports from Spain and the number of German travellers to that country. It aims at analysing empirically whether German tourism to Spain has any effect on the future imports of products from that country. We concentrate on the case of wine due to several reasons. First, wine has become a truly globalised industry with about 40% of production (in value terms) being exported worldwide in 2001 (Anderson, 2004). Spain is a particularly well suited case

because of its strong increase in wine exports (from USD 663 million in 1990 to 1.3 billion in 2001) (Albisu, 2004).[1] Second, in industrialised nations wine is a commonly available commodity offered in a large variety mostly differentiated by production origin. Given that objective wine quality is hard to assess for non-expert consumers, the origin of a wine is often used as a short-cut quality indicator in cases where the country of origin is associated with a preferred holiday destination (Felzenstein et al., 2004). Last, wine imports have been shown to display the most significant connection with tourism activities among a range of investigated products in previous studies (Fischer, 2004).

The organisation of this paper is as follows: in Section 2, we briefly describe the methodology employed in the paper and present the econometric model used in the empirical work. In Section 3 we describe the time series used in the analysis and examine their statistical properties. Section 4 contains the empirical application relating German wine imports from Spain with the number of German travellers to Spain. In Section 5 we disaggregate the import wine series according to the different products, while Section 6 concludes.

2. The econometric model

As mentioned in Section 1, most of the time series work examining the relationship between international trade and tourism is based on cointegration techniques. However, that methodology imposes a priori the assumption that all the individual series must share the same degree of integration, usually 1. In other words, the series must be individually I(1),

[1] In Spain the largest incoming tourist group were Germans from 1997 (7.8 million stays) to 2002 (11.3m), according to Eurostat data. Only in 2003, British tourists (12.2m) outnumbered the German ones (10.4m).

and they will be cointegrated if there exists a linear combination of them that is I(0) stationary.[2]

In the context of the series analysed in the present paper (which are aggregate wine imports and total tourism), we face however with various problems. First the two series do not posses the same order of integration. In fact, as explained later in Section 3, the wine imports data is I(0), while tourism is clearly nonstationary I(1). Moreover, the latter series presents a clear seasonal pattern, while the former does not. If the two series were in fact seasonally integrated, cointegration could still be the methodology used, along the lines of the procedure suggested by Hylleberg, Engle, Granger and Yoo (HEGY, 1990). (See, e.g., Kulendran and Wilson, 2000). However, a simple inspection at Figure 1 shows that the aggregate wine import series is not seasonally integrated.

For many years, seasonality was considered as a component that obscured the time series properties of the data, and seasonal adjustment procedures were implemented to sort this problem out. However, these methods have been strongly criticised in recent years on the basis that seasonal data contains some statistical relevant information by themselves. Contributors to this view include Ghysels (1988), Barsky and Miron (1989), Braun and Evans (1995) and others. The first two articles point out that seasonal adjustment procedures lead to mistaken inferences about economic relationships between time series data. In this paper we deal with the seasonal problem in tourism by using two approaches. First we deseasonalise the series by using seasonal dummy variables. As a second approach, we take first seasonal differences (on the logged series), such that the series becomes then the growth monthly rates. Looking at the orders of integration of the two deseasonalised series, we still

[2] For the purpose of the present paper we define an I(0) process $\{u_t, t = 0, \pm 1, \ldots\}$ as a covariance stationary process with a spectral density function that is positive and finite at the zero frequency. An I(1) process is then defined as a process that requires first differences to get I(0) stationarity.

face with the problem that both series are now I(1), while wine import is I(0), invalidating thus the analysis based on cointegration.

What we propose in this paper is to look at the relationship between the two variables (aggregate wine imports and tourism) by using a new methodology based on fractional integration.

We say that a time series $\{x_t, t = 0, \pm 1, \ldots\}$ is integrated of order d (and denoted by $x_t \sim I(d)$) if:

$$(1 - L)^d \, x_t = u_t, \qquad t = 1, 2, \ldots, \qquad (1)$$

$$x_t = 0, \qquad t \leq 0,$$ [3]

where u_t is I(0) and L is the lag operator ($Lx_t = x_{t-1}$). The polynomial above can be expressed in terms of its binomial expansion, such that for all real d,

$$(1 - L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \ldots.$$

The macroeconomic literature has usually stressed the cases of d = 0 and 1. However, d can be any real number. Clearly, if d = 0 in (1), $x_t = u_t$, and a "weakly autocorrelated" x_t (e.g., ARMA) is allowed for. However, if d > 0, x_t is said to be a long memory process, also called "strongly autocorrelated" because of the strong association between observations that are widely separated in time. As d increases beyond 0.5 and through 1, x_t can be viewed as becoming "more nonstationary", for example, in the sense that the variance of partial sums increases in magnitude. These processes were initially introduced by Granger (1980, 1981), Granger and Joyeux (1980) and Hosking (1981), (though earlier work by Adenstedt (1974) and Taqqu (1975) shows an awareness of its representation). They were theoretically justified in terms of aggregation of ARMA processes with randomly varying coefficients by

[3] This equation is a standard assumption in the context of fractional integration. For an alternative definition of fractionally integrated processes (type I class), see Marinucci and Robinson (2001).

Robinson (1978) and Granger (1980). Cioczek-Georges and Mandelbrot (1995), Taqqu et al. (1997), and Chambers (1998) also use aggregation to motivate long memory processes, while Parke (1999) uses a closely related discrete time error duration model. More recently, Diebold and Inoue (2001) propose another source of long memory based on regime-switching models. Empirical applications based on fractional models like (1) are among others Diebold and Rudebusch (1989), Baillie and Bollerslev (1994), Gil-Alana and Robinson (1997), and Gil-Alana (2000).[4]

To determine the appropriate degree of integration in a given time series is important from both economic and statistical viewpoints. If d = 0, the series is covariance stationary and possesses "short memory", with the autocorrelations decaying fairly rapidly. If d belongs to the interval **(**0, 0.5**)**, x_t is still covariance stationary. However, the autocorrelations take a much longer time to disappear than in the previous case. If $d \in [0.5, 1)$, the series is no longer covariance stationary, but it is still mean reverting, with the effect of the shocks dying away in the long run. Finally, if $d \geq 1$, x_t is nonstationary and non-mean reverting. Thus, the fractional differencing parameter d plays a crucial role in describing the persistence in the time series behavior: the higher the d, the higher the level of association between the observations.[5]

We now consider the following model,

$$y_t = \beta' z_t + x_t, \qquad t = 1, 2, \ldots, \tag{2}$$

where y_t is a raw time series; β is a (kx1) vector of unknown parameters; z_t is a (kx1) vector of deterministic (or weakly exogenous) variables, and x_t is given by (1).

Robinson (1994) proposed a Lagrange Multiplier (LM) test of the null hypothesis:

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[4] See also Baillie (1996) for an interesting review of I(d) models.

[5] At the other end, if d < 0, x_t is said to be "anti-persistent", because the spectral density function is dominated by high frequency components. See Mandelbrot (1977).

$$H_o : \; d = d_o, \qquad (3)$$

in a model given by (1) and (2) for any real value d_o. Under H_o (3), the residuals are

$$\hat{u}_t = (1 - L)^{d_o} y_t - \hat{\beta}' w_t, \qquad t = 1, 2, \ldots$$

where

$$\hat{\beta} = \left(\sum_{t=1}^{T} w_t w_t' \right)^{-1} \sum_{t=1}^{T} w_t (1 - L)^{d_o} y_t; \qquad w_t = (1 - L)^{d_o} z_t,$$

where T means the sample size. Thus, if $d_o = 1$, we are testing for a unit root, though other fractional values of d are also testable. The functional form of the test statistic (denoted by $\hat{r}$) is described in Appendix A.

Based on the null hypothesis (3), Robinson (1994) established that under some regularity conditions:[6]

$$\hat{r} \rightarrow_d N(0,1) \quad as \quad T \rightarrow \infty,$$

and also the Pitman efficiency of the test against local departures from the null.[7] Thus, we are in a classical large sample-testing situation by reasons described in Robinson (1994): An approximate one-sided 100α% level test of H_o (3) against the alternative: H_a: $d > d_o$ ($d < d_o$) will be given by the rule "Reject H_o (3) if $\hat{r} > z_\alpha$ ($\hat{r} < - z_\alpha$)", where the probability that a standard normal variate exceeds z_α is α. This version of the tests of Robinson (1994) was used in empirical applications in Gil-Alana and Robinson (1997) and Gil-Alana (2000) and, other versions of his tests, based on seasonal, (quarterly and monthly), and cyclical data can be respectively found in Gil-Alana and Robinson (2001) and Gil-Alana (1999, 2001). There exist other procedures for estimating and testing the fractionally differenced parameter in a

[6] These conditions are very mild, and concern technical assumptions to be satisfied by the model in (1) and (2).

[7] This means that the test is the most efficient one when directed against local alternatives. In other words, if we direct the tests against the alternative: H_a: $d = d_o + \delta T^{-1/2}$, the limit distribution is normal, with variance 1 and mean that cannot be exceeded in absolute value by any rival regular statistic.

parametric way, some of them also based on the likelihood function. As in other standard large-sample testing situations, Wald and LR test statistics against fractional alternatives will have the same null and local limit theory as the LM tests of Robinson (1994). Sowell (1992) employed essentially such a Wald testing procedure but it requires an efficient estimate of d, and while such estimates can be obtained, the LM procedure of Robinson (1994) seems computationally more attractive.

3. The time series data

The series (German imports of Spanish wine in euro) were obtained from two different Eurostat databases. First, aggregate imports (AWI) were taken from "DS-016894 – EU trade since 1995 by HS2-HS4". The source of the disaggregated data is the "DS-016890 – EU trade since 1995 by CN8" database. The latter database contains about two dozens of different wine categories. From these we have chosen the eight most important ones (referred to as products A to H in our analysis). These together represent about 62% of total German wine imports on average over the period of investigation (1998m1-2004m11). All products are quality wines which are produced in certain Spanish areas and are sold with a controlled denomination of origin label. The different wine types are described in more detail in Table 2.

(Insert Table 2 about here)

Figure 1 displays plots of the aggregate wine imports and its first differences, along with their corresponding correlograms and periodograms. Starting with the original series, we observe that though there are some peaks at some probably seasonal values, it seems that there is no a strong seasonal component. The correlogram and the periodogram of the original data seem to indicate that the series is I(0). In fact, if we take first differences both

the correlogram and the periodogram show that the series is then overdifferenced with respect to the zero frequency.[8]

(Insert Figures 1 and 2 about here)

For the tourism time series we use the number of German people travelling to Spain, monthly, for the same time period as before, obtained from the Instituto Nacional de Estadística (INE). Plots of the data, the first differences and their correlograms and periodograms are displayed in Figure 2. Contrary to the previous figure, the values here show a strong seasonal pattern and this becomes even clearer by looking at the correlograms and periodograms.[9]

Since we are mainly interested in the relationship between the two variables, the first thing we do is to analyze the statistical properties of each of the variables individually. For this purpose, we first implemented some classic methods to investigate if the series are stationary I(0) or nonstationary I(1). In particular, we use the tests proposed by Dickey and Fuller (ADF, 1979), Phillips and Perron (PP, 1988) and Kiatwkowski, Phillips, Schmidt and Shin (KPSS, 1992).[10]

The results of the above procedures for the Aggregate Wine Imports are displayed in Table 3. We observe that using no regressors, the tests cannot reject the hypothesis of a unit root. However, including an intercept and/or a linear trend, this hypothesis is rejected in all cases in favour of stationarity.

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[8] The periodogram is an asymptotic unbiased estimate of the spectral density function $f(\lambda)$. If a series is I(0), $0 < f(0) < \infty$, and if it is overdifferenced, $f(0) = 0$. Thus, the periodogram should mimick that behaviour.

[9] As an alternative definition of German tourism in Spain we also employed the number of nights spent in Spanish hotels by German travellers. However, the series presents a similar pattern as the one used in the present article.

[10] The first two methods (ADF, PP) test the null hypothesis of a unit root (I(1)) against the alternative of stationarity, while KPSS tests the null of stationarity against the alternative of a unit root.

(Insert Table 3 about here)

Anyway, the use of these procedures for testing the order of integration of the series is too restrictive in the sense that they only consider integer values for the degree of differentiation. Moreover, it is a well-known stylized fact that the above unit-root procedures have very low power if the alternatives are of a fractional form (Diebold and Rudebusch, 1991, Hassler and Wolters, 1994, etc.) Across Table 4 and Figure 3 we display the results for the AWI series based on two approaches for estimating and testing the order of integration of the series from a fractional point of view.

The results in Table 4 refers to the parametric approach of Robinson (1994) described in Section 2, assuming that z_t in (2) is a deterministic component that might include a constant (i.e. $z_t = 1$) or a linear time trend (i.e. $z_t = (1, t)'$). In other words, we test the null hypothesis (3): $d = d_o$, for any real value d_o in the model given by:

$$y_t = \alpha + \beta t + x_t, \tag{4}$$

$$(1 - L)^d x_t = u_t, \tag{5}$$

assuming that u_t is white noise and also autocorrelated. In the latter case, we use the Bloomfield (1973) exponential spectral model. This is a non-parametric approach of modelling the I(0) disturbances, in which the spectral density function of u_t is given by:

$$f(\lambda;\tau) = \frac{\sigma^2}{2\pi} \exp\left(2 \sum_{r=1}^{p} \tau_r \cos(\lambda r) \right),$$

where p refers to the number of parameters required to describe the short run dynamics. Like the stationary AR(p) model, the Bloomfield (1973) model has exponentially decaying autocorrelations and thus, we can use a model like this for u_t in (5). Formulae for Newton-type iteration for estimating the τ_r are very simple (involving no matrix inversion) and updating formulae when p is increased are also simple. Moreover, this model accommodates

very well to the functional form of the test statistic $\hat{r}$, and we can replace $\hat{A}$ in Appendix A by the population quantity:

$$\sum_{l=p+1}^{\infty} l^{-2} = \frac{\pi^2}{6} - \sum_{l=1}^{p} l^{-2},$$

which indeed is constant with respect to the τ_r (unlike the AR case).

Table 4 displays the 95% confidence intervals of those values of d_o where H_o (3) cannot be rejected for the three cases of no regressors (in the undifferenced regression (4)), an intercept, and an intercept and a linear time trend. These confidence intervals were built up according to the following strategy. First, we choose a value of d_o from a grid. Then, we form the test statistic testing the null for this value. If the null is rejected at the 5% level, we discard this value of d_o. Otherwise, we keep it. An interval is then obtained after considering all the values of d_o in the grid. We also report in the tables, (in parenthesis within the brackets), the value of d_o (d_o^*) which produces the lowest statistic in absolute value across d_o. That value should be an approximation to the maximum likelihood estimate.[11] We observe that the intervals include the I(0) null in all cases, the values of d ranging from -0.37 (Bloomfield u_t with an intercept and/or a linear time trend) and 0.39 (Bloomfield with no regressors). Moreover, the values of d producing the lowest statistics are in all cases negative, implying thus anti-persistent behaviour.

(Insert Table 4 and Figure 3 about here)

As an alternative approach to estimate d, we also use a semiparametric method proposed by Robinson (1995). It is semiparametric in the sense that we do not have to specify any particular model for the I(0) disturbances u_t. It is basically a local "Whittle estimate" in the frequency domain, based on a band of frequencies that degenerates to zero.

[11] Note that the LM procedure of Robinson (1994) is based on the Whittle function, which is an approximation to the likelihood function.

The proper form of the estimate ($\hat{d}$) is described in Appendix B. Under finiteness of the fourth moment and other mild conditions, Robinson (1995) proved that:

$$\sqrt{m}\,(\hat{d} - d_o) \rightarrow_d N(0, 1/4) \quad as\ T \rightarrow \infty,$$

where m is a bandwidth parameter number, d_o is the true value of d and with the only additional requirement that $m \rightarrow \infty$ slower than T.[12] Robinson (1995) showed that m must be smaller than T/2 to avoid aliasing effects. We have decided to use in this article the Whittle estimator, firstly because of its computational simplicity. In fact, we do not need to employ any additional user-chosen numbers in the estimation (as is the case with other procedures). Moreover, we do not have to assume Gaussianity in order to obtain an asymptotic normal distribution, Robinson's (1995) estimate being more efficient than other methods.

Figure 3 displays the estimates of d for values of m from 1 to T/2.[13] We also include in the figure the 95%-confidence intervals corresponding to the I(0) case. It is observed that practically all values of d are within the I(0) interval, which is consistent with the results based on the parametric approach above.

As a conclusion, the results presented across Tables 3 and 4 and Figure 3 suggest that the aggregate wine imports series is stationary I(0).

(Insert Figures 4 and 5 about here)

Next, we concentrate on tourism, and the first thing we do is to remove the seasonal component. Here we take two approaches. First, we assume that seasonality is deterministic

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[12] The exact requirement is that $(1/m) + ((m^{1+2\alpha}(\log m)^2)/(T^{2\alpha})) \rightarrow 0$ as $T \rightarrow \infty$, where α is determined by the smoothness of the spectral density of the short run component. In the event of a stationary and invertible ARMA, α may be set equal to 2 and the condition is $(1/m) + ((m^5(\log m)^2)/(T^4)) \rightarrow 0$ as $T \rightarrow \infty$.

[13] Some attempts to calculate the optimal bandwidth numbers have been examined in Delgado and Robinson (1996) and Robinson and Henry (1996). However, in the case of the Whittle estimator, the use of optimal

and use seasonal dummies to remove that component. The plots of the deseasonalised series are given in Figure 4 and we observe that the series may be nonstationary due to the high persistence observed across the plots. As a second approach we assume that the seasonality in tourism has a stochastic nature, and use seasonal first differences on the logged series, creating thus a new series, which is the growth monthly rate. Plots are now displayed in Figure 5, and, similarly to the previous case, nonstationarity is found in this series.[14]

(Insert Tables 5 – 8 and Figures 6 and 7 about here)

Across Tables 5 - 8 and Figures 6 and 7 we display the same type of analysis as the one performed before for the wine import series. The results are very similar in both series: using classic methods (Tables 5 and 7) evidence of a unit root is found in all cases when using the test statistic with most realistic assumptions. Using the fractional framework, the unit root is almost never rejected though fractional orders of integration, with values of d slightly below 1 are also plausible in most of the cases.

To conclude, we can summarize the results presented across this section by saying that the aggregate wine imports seem to be stationary I(0), while tourism, once the seasonal component has been removed, is nonstationary I(1).

4. An empirical application based on a long memory regression model

Denoting Aggregate Wine Imports by AWI_t and Deseasonalised Tourism as DT_t, we employ through the model given by (1) and (2), testing H_o (3) for given values d_o = 0, 0.01, …, 2,

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values has not yet been theoretically justified. Other authors, such as Lobato and Savin (1998) use an interval of values for m but we have preferred to report the results for the whole range of values of m.

[14] Note that in the two series the periodograms presents peaks at the zero frequency, while the periodograms of the first differences have positive and finite values at such a frequency. Therefore, the two series seem to be I(1).

assuming that u_t is white noise and Bloomfield (with p = 1).[15] However, in order to examine the dynamic structure underlying the two series, we use as a regressor lagged values of the tourism series.[16] In other words, we test the null model,

$$AWI_t = \alpha + \beta DT_{t-k} + x_t, \qquad (6)$$

$$(1 - L)^d x_t = u_t, \qquad (7)$$

with k in (6) equal to 1, 2, …, and 12. First, we employ the deseasonalised tourism series based on the seasonal dummies. As an alternative approach, we could have employed a dynamic lag-structure for DT in (6) in line with the literature on dynamic regressions in standard models. However, that approach would impose the same degree of integration across the lags, while here we permit different values of d for each lag. Table 9 reports the results for the case of white noise disturbances, while Table 10 refers to the Bloomfield model. In both cases, we report, for each k, the estimates for the coefficients (and their corresponding t-ratios), the value of d_o producing the lowest statistic, its confidence interval (at the 95% level) and the value of the test statistic.

(Insert Tables 9 and 10 about here)

Starting with the case of white noise u_t, (Table 9), we see that β appears significant for k = 1, 2, 3 and 4, implying that tourism has an effect on wine imports that lasts at least the following four months. We also see that the interval of non-rejection values of d is relatively wide in all cases, ranging from -0.41 (k = 8) to 0.05 (k = 6). The case of d = 0 is included in all intervals but lowest statistics are obtained for negative d. Note that the

[15] Other values of p were also employed and the results were very similar to those reported in the paper with p = 1.

[16] We conducted some tests for exogeneity of tourism in the wine imports equation. To establish evidence for non-causality, an unrestricted VAR was used. Weak exogeneity appeared to be satisfied in the dynamic equation because when entering the current value of DT in the equation it proved to be insignificantly different from zero. This finding supports the view that DT is weakly exogenous for the model.

estimates of α and β are based on the value of d producing the lowest statistic, which seems to be more appropriate from a statistical viewpoint. Imposing a weak dependence structure on the disturbances throughout the model of Bloomfield (1973), (Table 10), the intervals are now wider, the values of d with the lowest statistics being still negative, and the slope coefficient is now significant for the first seven periods, implying a longer dynamic effect of tourism than in the previous case.

(Insert Tables 11 and 12 about here)

Tables 11 and 12 are similar to Tables 9 and 10 above but using the monthly growth rates as the deseasonalised series. If u_t is white noise, only the first two lags appear statistically significant, however, using the model of Bloomfield (1973), the significant coefficients reach the lag 9.

We can therefore conclude this section by saying that there is some kind of dynamic behaviour in the effect that German tourism has on German imports of Spanish wines. This significant effect lasts less than a year though varies substantially depending on the model considered and the type of series used for measuring tourism.

5. Disaggregation by products

In this section we examine separately the different wine products and perform the same type of analysis as the one employed in Section 4. That is, we consider the same model as in (6) and (7), using specific types of wine rather than the aggregate flow.

(Insert Tables 13 and 14 about here)

In Tables 13 and 14 we use the DT_t series (with seasonal dummies), for the two cases of white noise (in Table 13) and Bloomfield disturbances (in Table 14). We observe that the results are very similar in both cases, implying that the short run dependence (i.e., the type of modelling approach) is not very important when describing the behaviour of these two

series. In general, we observe that only for two wine types (reds from Navarra and those from Valdepeñas) the coefficients are significant across the whole period of analysis. For sparkling wine and reds from Penedús, the significant coefficients start five periods after, and the effect of tourism lasts three periods for the former and 8 months for the latter wine type. Very similar results were obtained when using the growth monthly rate of tourism as a regressor.

6. Concluding comments

In this paper we have examined the relationship between German imports of Spanish wines and German tourism to Spain. For this purpose, we first analysed each of the series separately, and it was found that wine imports was I(0) stationary, while tourism (once the seasonal component was removed) was nonstationary I(1). Due to the different orders of integration observed in the two series, we examine the relationship between the two variables by means of a long memory linear regression model, using tourism retarded k periods (k = 1, …, 12) as a weakly exogenous variable.

(Insert Table 15 about here)

The obtained results are summarised in Table 15. The first row gives the total effect as the sum of the monthly effects in euro per one percent increase of tourists.[17] On average, total monthly wine imports of Spanish wine into Germany have increased by about EUR 2 per every increase of roughly 5,000 tourists over the analysed period. For individual wine types, the impact has been mixed. While for sparkling wine the positive effect (about EUR 1.8) is lower than for the overall wine category, three wine types, all quality reds (from

[17] The numbers are the simple mean from the estimates given in Table 13 and 14. The interpretation of the estimates for the monthly growth rates series (Tables 11 and 12) are not directly comparable to the former ones, therefore they have not been included in the summary calculation of Table 15.

Navarra, Penedús and Valdepeñas), have experienced import-promoting effects of about EUR 12-14. Taken together, these three wine types accounted for about 7% of total wine imports during the analysed period.

We find that the connection between tourism and trade seems only to hold for red wines and sparkling wine but not for white wine. Moreover, there seems to be a possible connection between wine quality (as expressed by price) and the magnitude and length of the tourism effect. Table 15 lists unit values (import value / import quantity) as a proxy for import prices of the analysed wine types. The two most-expensive red wine types (Penedús and Valdepeñas) also display the strongest import-promoting effects. However, quality reds from Rioja seem to be an exception. Although the average import unit value at EUR 2.3 per litre is higher than the one for quality reds from Navarra (EUR 1.6), no significant relationship with the tourism series have been found. A possible explanation for this exception may be the fact that Rioja reds comprise both some of the best, most expensive and internationally-appreciated Spanish quality wines and lots of lowly-priced bulk wine (mainly produced in the 'Baja' region) (Albisu, 2004). Given their long tradition, Rioja wines may thus be internationally received as the 'typical' Spanish wine, similar to Bordeaux wines in France or Chianti reds in Italy. Hence, Rioja wine exports may reflect both demand by quality-oriented international wine collectors and price-conscious mass retailers, both types of demand probably being little affected by international tourism flows.

The average lengths of the import-promoting effects is about 5.5 months for total wine imports, three months for sparkling wine and 9-10 months for the just mentioned quality reds. This result clearly shows that, at least in the analysed case, tourism has a positive impact on the travel destination economy, which lasts for many months after the tourists have already left the country.

From a methodology point of view, the approach employed in this paper solves at least partially the strong dichotomy produced by the I(0)/I(1) specifications by using fractional values for the orders of integration, and given the different stochastic nature of the two series considered here, the use of a long memory regression model where one of the variables is weakly exogenous allows us to examine the dynamic behaviour of the series in a much more flexible way. The frequency domain formulation of the test statistic used here seems to be very unpopular with many econometricians and, though there exist time domain versions of the tests (Robinson, 1991, Tanaka, 1999), the preference here for the frequency domain approach is motivated by the somewhat greater elegance of formulae it affords, especially when the Bloomfield model is used.

Overall, this analysis has clearly shown that the export- (and thus economy-) promoting effects of international tourism, in some cases at least, are statistically significant, positive, relatively long-lasting and considerable in magnitude. Policy makers and industry as well as tourism development officials are therefore well-advised to consider these interactions in their planning and budget allocation decisions. Apart from the identification work to be done of which manufactured goods and tourist groups display significant connections, industrial and tourism development officer should work hand-in-hand to implement effective foreign marketing programmes and strategies to optimally exploit existing tourism-trade interaction effects.

Further research should focus on the identification of those goods and tourism groups (i.e., countries) which display the strongest links. In addition, more knowledge is needed on the causes of and determinants for these relationships.

Appendix A

The test statistic proposed by Robinson (1994) is based on the Lagrange Multiplier (LM) principle, and is given by:

$$\hat{r} = \frac{T^{1/2}}{\hat{\sigma}^2} \hat{A}^{-1/2} \hat{a},$$

where T is the sample size and

$$\hat{a} = \frac{-2\pi}{T} \sum_{j=1}^{T-1} \psi(\lambda_j) g(\lambda_j;\hat{\tau})^{-1} I(\lambda_j); \qquad \hat{\sigma}^2 = \sigma^2(\hat{\tau}) = \frac{2\pi}{T} \sum_{j=1}^{T-1} g(\lambda_j;\hat{\tau})^{-1} I(\lambda_j);$$

$$\hat{A} = \frac{2}{T}\left(\sum_{j=1}^{T-1} \psi(\lambda_j)^2 - \sum_{j=1}^{T-1} \psi(\lambda_j)\hat{\varepsilon}(\lambda_j)' \times \left(\sum_{j=1}^{T-1} \hat{\varepsilon}(\lambda_j)\hat{\varepsilon}(\lambda_j)' \right)^{-1} \times \sum_{j=1}^{T-1} \hat{\varepsilon}(\lambda_j)\psi(\lambda_j) \right)$$

$$\psi(\lambda_j) = \log\left|2\sin\frac{\lambda_j}{2}\right|; \quad \hat{\varepsilon}(\lambda_j) = \frac{\partial}{\partial\tau}\log g(\lambda_j;\hat{\tau}); \quad \lambda_j = \frac{2\pi j}{T}; \quad \hat{\tau} = \arg\min_{\tau\in T^*} \sigma^2(\tau),$$

where T^* is a compact subset of the R^q Euclidean space. $I(\lambda_j)$ is the periodogram of u_t evaluated under the null,

$$\hat{u}_t = (1-L)^{d_o} y_t - \hat{\beta}' w_t; \; \hat{\beta} = \left(\sum_{t=1}^{T} w_t w_t' \right)^{-1} \sum_{t=1}^{T} w_t (1-L)^{d_o} y_t; \quad w_t = (1-L)^{d_o} z_t,$$

and g above is a known function coming from the spectral density of u_t, $f = (\sigma^2/2\pi)g$. Note that these tests are purely parametric and therefore, they require specific modelling assumptions regarding the short memory specification of u_t. Thus, if u_t is white noise, then, $g \equiv 1$, (and thus, $\hat{\varepsilon}(\lambda_j) = 0$), and if u_t is an AR process of form $\phi(L)u_t = \varepsilon_t$, $g = |\phi(e^{i\lambda})|^{-2}$, with $\sigma^2 = V(\varepsilon_t)$, so that the AR coefficients are a function of τ.

Appendix B

The estimate of Robinson (1995) is implicitly defined by:

$$\hat{d} = \arg\min_d \left(\log \overline{C(d)} - 2\,d\,\frac{1}{m}\sum_{j=1}^{m} \log \lambda_j \right),$$

$$for\ \ d \in (-1/2\,,\,1/2)\,;\ \ \overline{C(d)} = \frac{1}{m}\sum_{j=1}^{m} I(\lambda_j)\,\lambda_j^{2d},\quad \lambda_j = \frac{2\,\pi\,j}{T},\ \ \frac{m}{T} \to 0.$$

where m is a bandwidth parameter number. Velasco (1999a, b) has recently showed that the fractionally differencing parameter d can also be consistently semiparametrically estimated in nonstationary contexts by means of tapering. See also Phillips and Shimotsu (2004, 2005) for recent refinements of this procedure.

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Tables and Figures

TABLE 1		
Overview of previous studies analysing the relationship between international tourism and trade		
Research focus	**Categories**	**Studies**
Country	• Bilateral trade flows • Country-world/region	Easton (1998); Kulendran & Wilson (2000); Fischer (2004) Shan & Wilson (2001)
Product	• Aggregate (e.g., total country exports) • Specific products	Easton (1998); Kulendran & Wilson (2000); Shan & Wilson (2001); Fischer (2004) Fischer (2004);
Trade categories	• Exports (X) • Imports (M) • Total trade (X + M)	Easton (1998); Kulendran & Wilson (2000) Kulendran & Wilson (2000); Fischer (2004) Kulendran & Wilson (2000); Aradhyula & Tronstad (2003)
Travel categories	• Total travel • Business travel • Holiday travel • Visiting friends and relatives • Other travel	Easton (1998); Kulendran & Wilson (2000); Fischer (2004) Kulendran & Wilson (2000); Aradhyula & Tronstad (2003) Kulendran & Wilson (2000); Aradhyula & Tronstad (2003) Kulendran & Wilson (2000) –
Direction of causality	• TOUR ☐ TRADE • TOUR ☐ TRADE	Kulendran & Wilson (2000); Shan & Wilson (2001) Kulendran & Wilson (2000); Shan & Wilson (2001)
Nature of relationship	• Substitutive • Complementary	Easton (1998) –
Type of data	• Time series • Cross section • Panel data	Kulendran & Wilson (2000); Fischer (2004) Aradhyula & Tronstad (2003) Easton (1998)

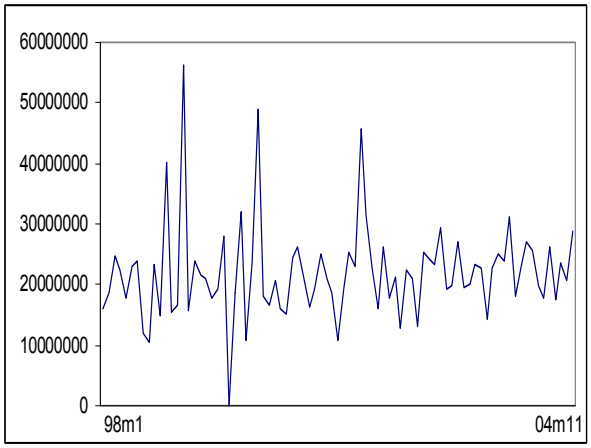
TABLE 2		
Overview of products (German imports of Spanish wines) used in the empirical analysis		
Abbreviation	**Product code**	**Product description**
AWI	HS4 2204	**Wine of fresh grapes**, incl. fortified wines; grape must, partly fermented and of an actual alcoholic strength of > 0.5% vol or grape must with added alcohol of an actual alcoholic strength of > 0.5% vol
A	CN8 22041019	**Sparkling wine** of fresh grapes of actual alcoholic strength of >= 8.5% vol (excl. champagne)
B	CN8 22042134	Quality **white** wines produced in **Penedús**, in containers holding <= 2l and of an actual alcoholic strength by volume of <= 13% vol (excl. sparkling wine and semi-sparkling wine)
C	CN8 22042136	Quality **white** wines produced in **Rioja**, in containers holding <= 2l and of an actual alcoholic strength by volume of <= 13% vol (excl. sparkling wine and semi-sparkling wine)
D	CN8 22042171	Quality wines produced in **Navarra**, in containers holding <= 2l and of an actual alcoholic strength by volume of <= 13% vol (other than sparkling wine, semi-sparkling wine and general white wine)
E	CN8 22042174	Quality wines produced in **Penedús**, in containers holding <= 2l and of an actual alcoholic strength by volume of <= 13% vol (other than sparkling wine, semi-sparkling wine and general white wine)
F	CN8 22042176	Quality wines produced in **Rioja**, in containers holding <= 2l and of an actual alcoholic strength by volume of <= 13% vol (other than sparkling wine, semi-sparkling wine and general white wine)
G	CN8 22042177	Quality wines produced in **Valdepeñas**, in containers holding <= 2l and of an actual alcoholic strength by volume of <= 13% vol (other than sparkling wine, semi-sparkling wine and general white wine)
H	CN8 22042192	**Sherry**, in containers holding <= 2l and of an actual alcoholic strength by volume of > 15% vol to 18% vol

Source: Eurostat

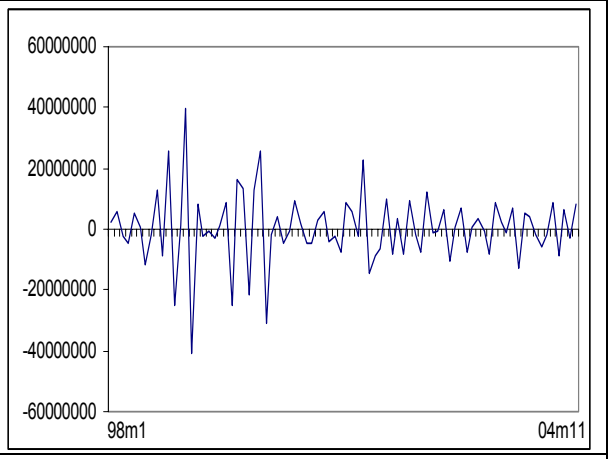
FIGURE 1

German aggregate wine imports from Spain

Original time series

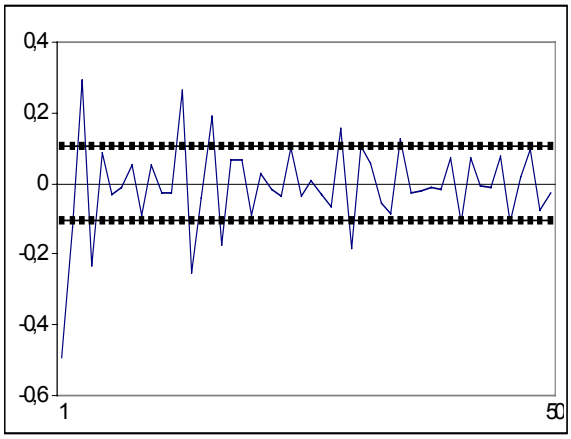


First differences



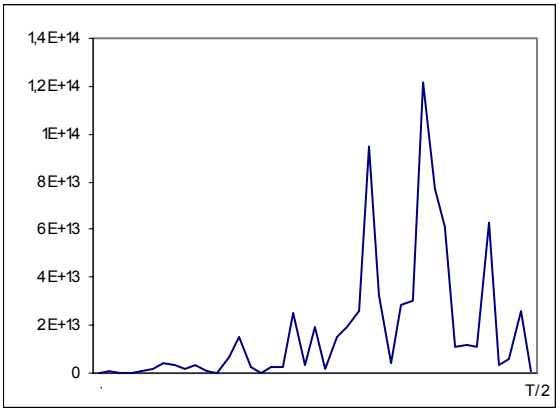
Correlogram original series*

Correlogram first differences*



Periodogram original series

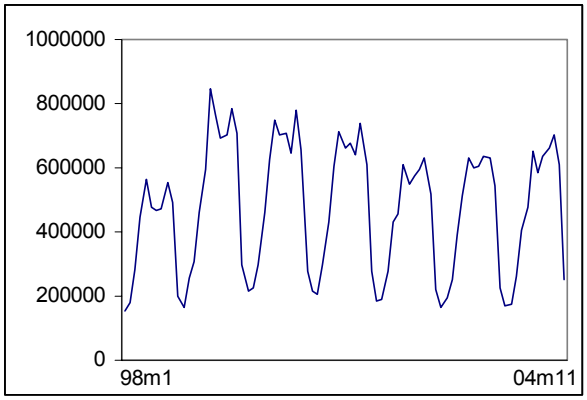
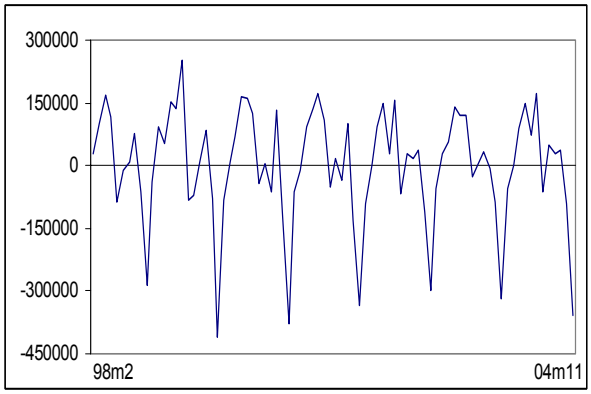
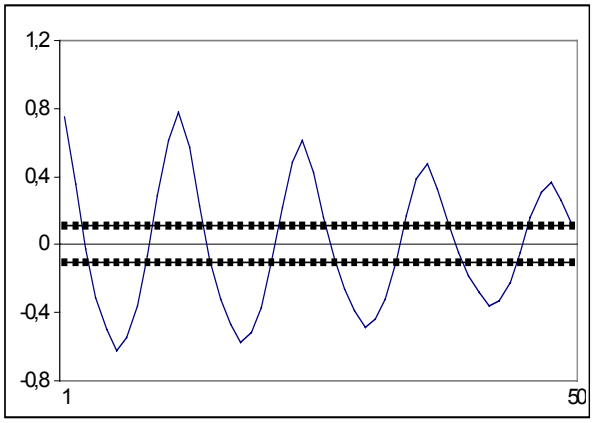
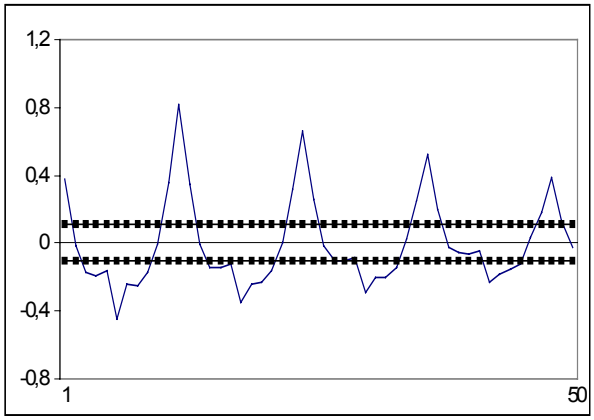
Periodogram first differences

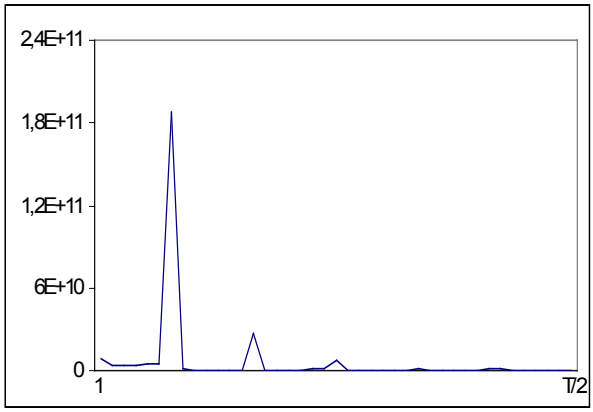


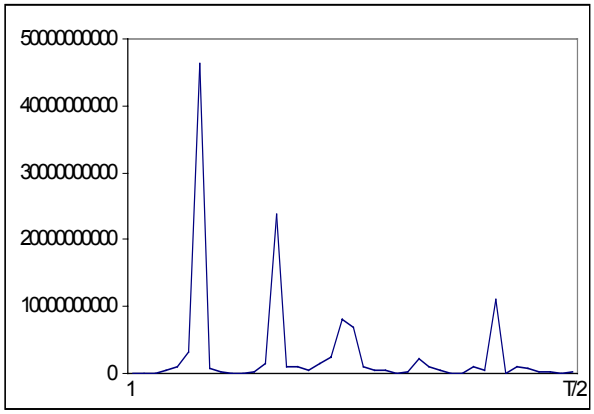
The large sample standard error under the null hypothesis of no autocorrelation is $1/\sqrt{T}$ or roughly 0.038.

FIGURE 2

German travellers to Spain

Original time series	First differences
	
Correlogram original series*	**Correlogram first differences***
	
Periodogram original series	**Periodogram first differences**





The large sample standard error under the null hypothesis of no autocorrelation is $1/\sqrt{T}$ or roughly 0.038.

TABLE 3			
Test statistics for the null hypothesis of a unit root (and 5% critical values) for Aggregate Wine Imports			
	No regressors	With an intercept	With a linear trend
ADF	-0.39 (-1.94)	-4.59 (-2.90)	-4.56 (-3.47)
PP	-1.42 (-1.94)	-10.0 (-2.90)	-9.99 (-3.47)
KPSS	---	0.076 (0.46)	0.075 (0.14)

The original series seems to displays no trend but has a non-zero mean. Therefore one would tend to use the 'intercept' test results, clearly implying AWI is I(0), i.e., stationary.

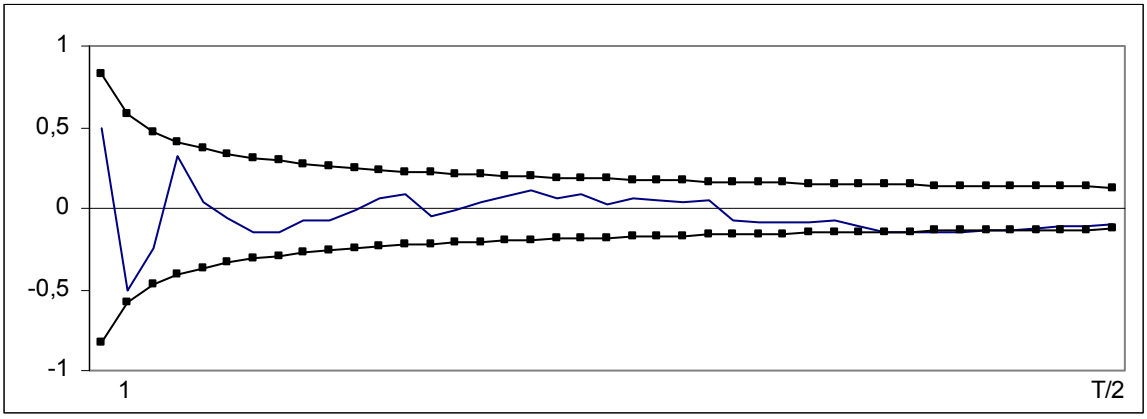
TABLE 4			
95% confidence intervals of the non-rejection values of d for Aggregate Wine Imports			
	No regressors	With an intercept	With a linear trend
White noise	[-0.15 (-0.11) 0.06]	[-0.26 (-0.14) 0.02]	[-0.34 (-0.21) 0.02]
Bloomfield (p = 1)	[-0.16 (-0.09) 0.32]	[-0.33 (-0.08) 0.31]	[-0.35 (-0.26) 0.28]

Bloomfield (p = 2)	[-0.17 (-0.13) 0.39]	[-0.37 (-0.18) 0.36]	[-0.37 (-0.19) 0.34]

The values in parenthesis within the brackets refers to the value of d producing the lowest statistic. It is supposed to be an approximation to the MLE.

FIGURE 3

Estimates of d based on Gaussian semiparametric estimate for AWI

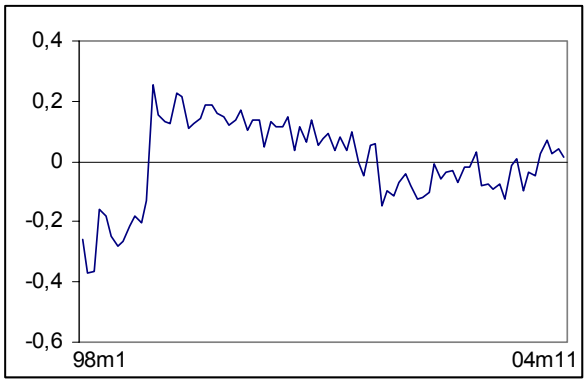


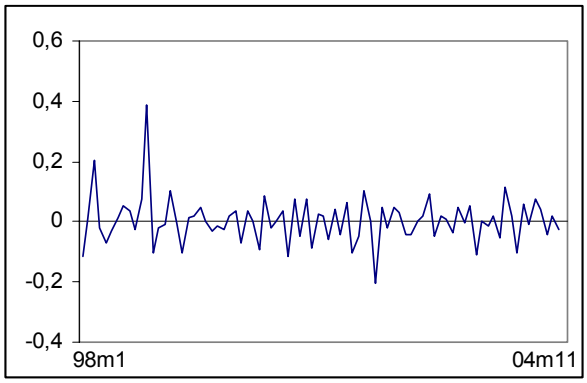
The horizontal axe refers to the bandwidth parameter number while the vertical one corresponds to the estimated values of d. The dotted line refers to the 95% confidence interval for the I(0) hypothesis.

FIGURE 4

German travellers to Spain detrended by seasonal dummies

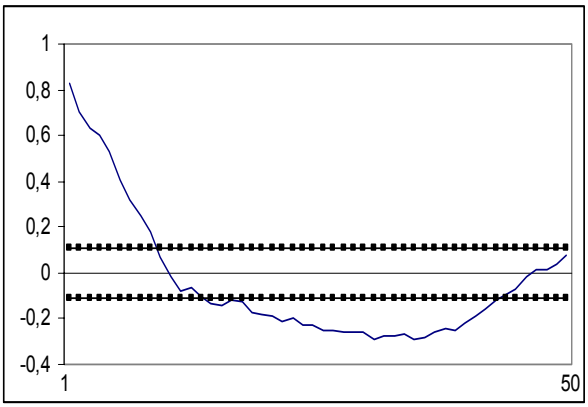
Original time series	First differences

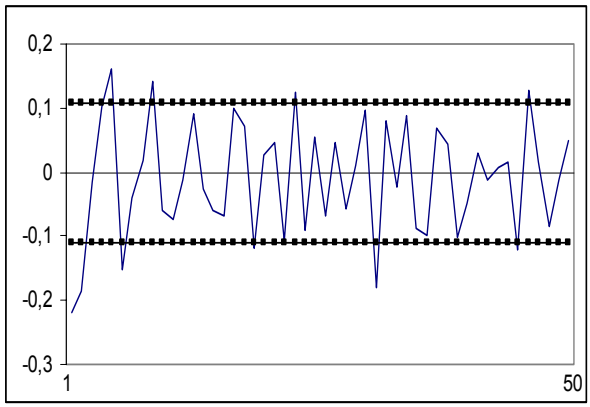




Correlogram original series*

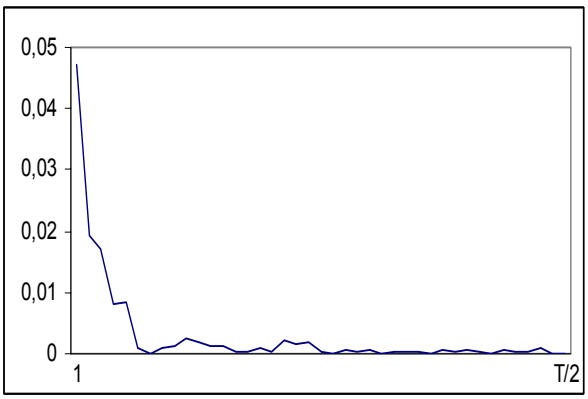
Correlogram first differences*

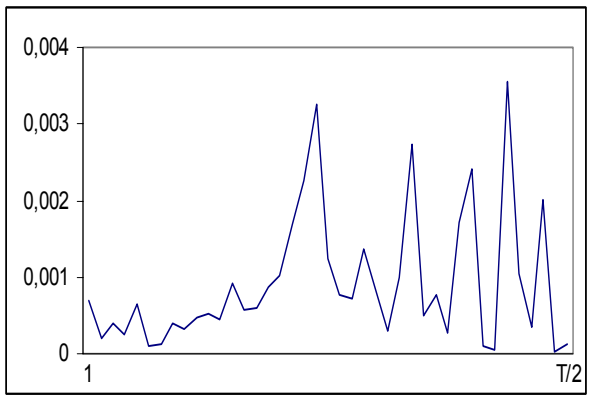




Periodogram original series

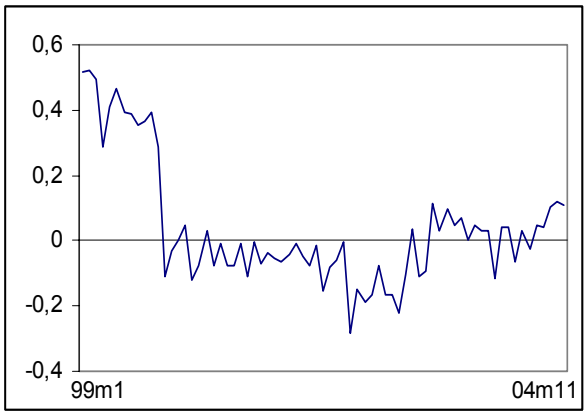
Periodogram first differences



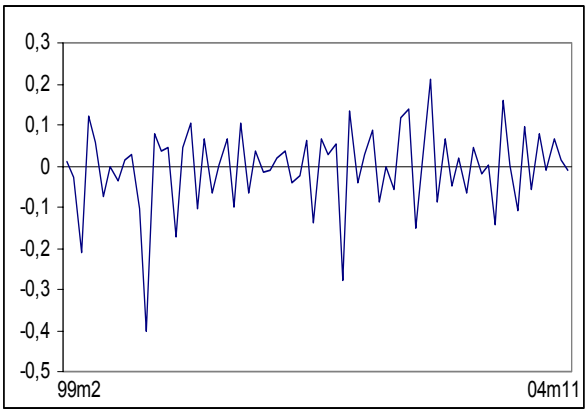


The large sample standard error under the null hypothesis of no autocorrelation is $1/\sqrt{T}$ or roughly 0.109.

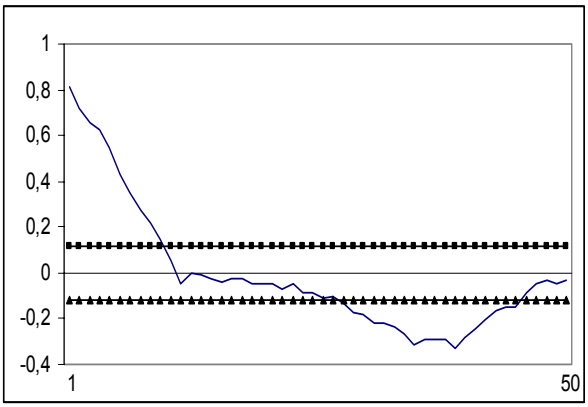
FIGURE 5	
Monthly growth rates in the German travellers to Spain	
Original time series	**First differences**



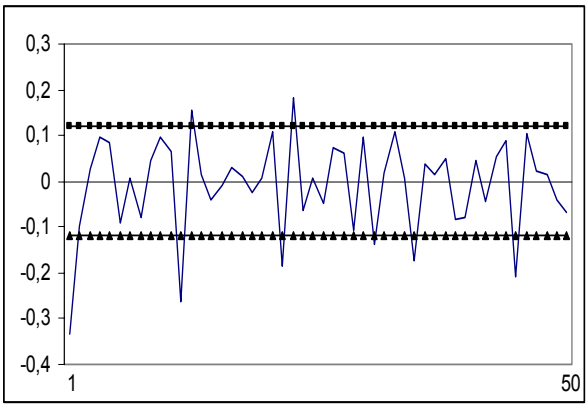
Correlogram original series*



Correlogram first differences*



Periodogram original series



Periodogram first differences

The large sample standard error under the null hypothesis of no autocorrelation is $1/\sqrt{T}$ or roughly 0.109.

TABLE 5
Test statistics for the null hypothesis of a unit root (and 5% critical values) for the

deseasonalised travellers (DT) series (detrended by seasonal dummies)			
	No regressors	With an intercept	With a linear trend
ADF	-2.13 (-1.94)	-2.19 (-2.90)	-2.38 (-3.47)
PP	-2.68 (-1.94)	-2.65 (-2.90)	-2.59 (-3.47)
KPSS	---	0.98 (0.46)	0.44 (0.146)

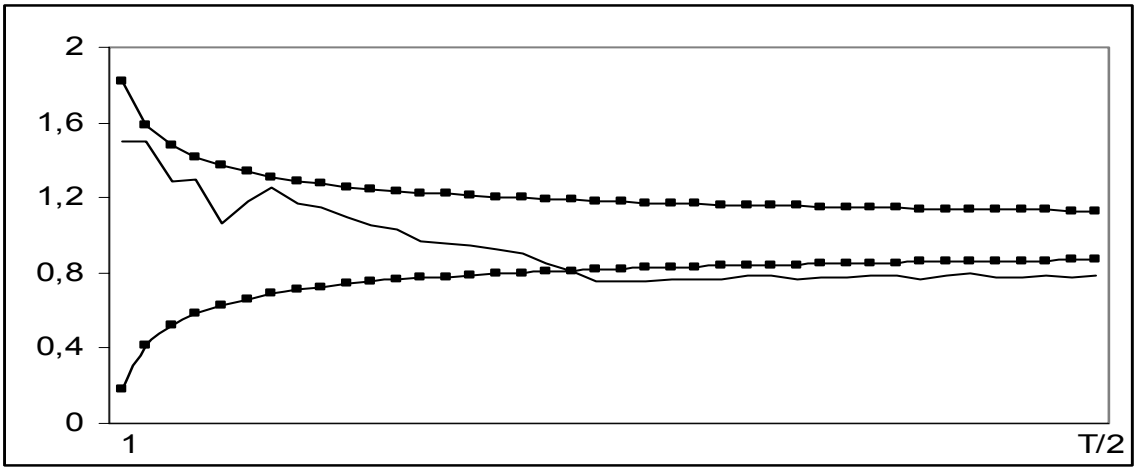
In this series there does not seem to be a trend but the series fluctuates around zero. One would therefore tend to accept the 'no regressors' test results, implying the series is I(1), i.e., non-stationary.

TABLE 6			
95% confidence intervals of the non-rejection values of d for the DT series			
	No regressors	With an intercept	With a linear trend
White noise	[0.62 (0.75) 0.95]	[0.62 (0.73) 0.89]	[0.65 (0.74) 0.89]
Bloomfield (p = 1)	[0.40 (0.59) 0.91]	[0.45 (0.76) 1.02]	[0.61 (0.80) 1.03]
Bloomfield (p = 2)	[0.30 (0.61) 1.14]	[0.32 (0.98) 1.31]	[0.58 (0.99) 1.39]

The values in parenthesis within the brackets refers to the value of d producing the lowest statistic.
It is supposed to be an approximation to the MLE.

FIGURE 6

Estimates of d based on Gaussian semiparametric estimate for DT series



The horizontal axe refers to the bandwidth parameter number while the vertical one corresponds to the estimated values of d. The dotted line refers to the 95% confidence interval for the I(!) hypothesis.

TABLE 7			
Test statistics for the null hypothesis of a unit root (and 5% critical values) for Monthly Growth Rate of the travellers series			
	No regressors	With an intercept	With a linear trend
ADF	-2.50 (-1.94)	-2.43 (-2.90)	-1.64 (-3.47)
PP	-3.02 (-1.94)	-2.91 (-2.90)	-2.44 (-3.47)
KPSS	---	0.99 (0.46)	0.23 (0.146)

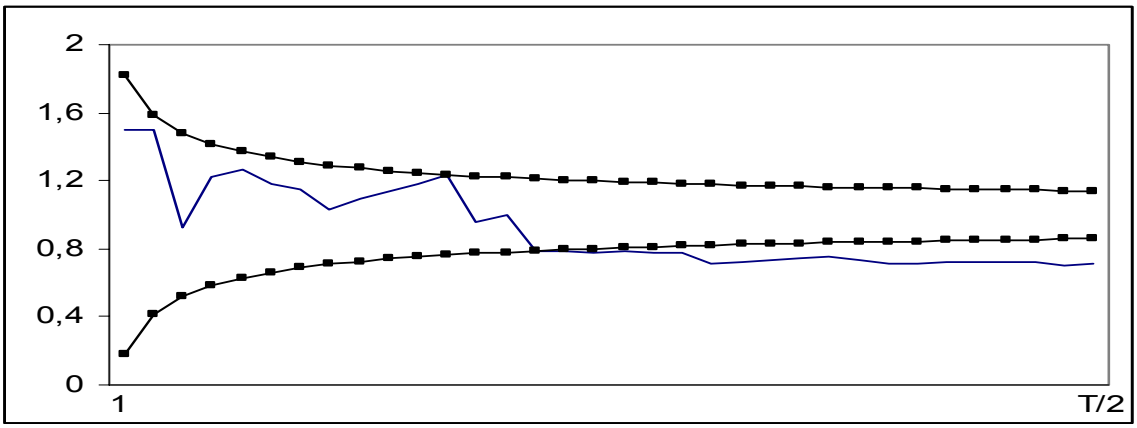
In this series there is no tend but the series fluctuates around zero. Therefore, one would use 'no regressors' test results, implying clearly the series is I(1), i.e. non-stationary.

TABLE 8			
95% confidence intervals of the non-rejection values of d for Monthly Growth Rate series			
	No regressors	With an intercept	With a linear trend
White noise	[0.62 (0.73) 0.90]	[0.56 (0.79) 1.11]	[0.51 (0.77) 1.19
Bloomfield (p = 1)	[0.56 (0.66) 0.80]	[0.57 (0.83) 1.11]	[0.52 (1.06) 1.39]
Bloomfield (p = 2)	[0.60 (0.69) 0.82]	[0.66 (0.87) 1.10]	[0.63 (1.07) 1.41]

The values in parenthesis within the brackets refers to the value of d producing the lowest statistic.
It is supposed to be an approximation to the MLE.

FIGURE 7

Estimates of d for the Monthly Growth Rate of travellers series



The horizontal axe refers to the bandwidth parameter number while the vertical one corresponds to the estimated values of d. The dotted line refers to the 95% confidence interval for the I(!) hypothesis.

TABLE 9

Estimates of parameters in AWI_t and $TRAV_{t-k}$ relationship, using deseasonalised data

$$AWI_t = \alpha + \beta DT_{t-k} + x_t; \quad (1-L)^d x_t = u_t$$

With white noise disturbances (in parenthesis t-ratios)

k	Alpha	Beta	d-95% confidence interval	d	Stat.
1	16.738 (1152.21)	**0.507 (2.951)**	[-0.37 0.01]	-0.22	-0.0245
2	16.751 (1126.75)	**0.467 (2.713)**	[-0.39 0.03]	-0.22	0.0445
3	16.751 (1056.77)	**0.358 (1.996)**	[-0.39 0.04]	-0.21	-0.0445

4	16.733 (1003.17)	**0.352 (1.911)**	[-0.37 0.04]	-0.20	0.0505
5	16.736 (992.33)	0.293 (1.592)	[-0.39 0.04]	-0.20	-0.035
6	16.755 (971.13)	0.268 (1.440)	[-0.36 0.05]	-0.20	0.0255
7	16.761 (910.11)	0.217 (1.147)	[-0.36 0.04]	-0.19	0.0053
8	16.770 (1190.02)	0.059 (0.345)	[-0.41 0.04]	-0.25	-0.0157
9	16.781 (1178.78)	-0.112 (-0.035)	[-0.38 -0.03]	-0.24	-0.0065
10	16.779 (1198.88)	-0.070 (-0.445)	[-0.40 -0.03]	-0.23	-0.0367
11	16.784 (1137.70)	-0.159 (-0.963)	[-0.39 0.02]	-0.24	0.0243
12	16.773 (1153.71)	-0.128 (-0.798)	[-0.41 0.01]	-0.22	0.0451

In bold, significant values at the 5% significance level.

TABLE 10					
Estimates of parameters in AWI_t and $TRAV_{t-k}$ relationship, using deseasonalised data					
With Bloomfield (p = 1) disturbances (in parenthesis, t-ratios)					
k	Alpha	Beta	d-95% confidence interval	d	Stat
1	16.734 (2645.81)	**0.486 (4.363)**	[-0.62 0.03]	-0.37	0.0065
2	16.713 (3555.17)	**0.433 (4.650)**	[-0.75 0.02]	-0.46	-0.0004
3	16.712 (3837.67)	**0.396 (4.445)**	[-0.77 0.02]	-0.44	0.0566
4	16.752 (3640.92)	**0.368 (4.016)**	[-0.85 0.01]	-0.43	-0.0987
5	16.754 (4838.55)	**0.302 (3.911)**	[-0.95 0.05]	-0.41	-0.0425
6	16.753 (4411.51)	**0.260 (3.219)**	[-0.97 0.05]	-0.49	0.0044
7	16.754 (2930.76)	**0.219 (2.136)**	[-0.94 0.05]	-0.49	0.0140
8	16.766 (2381.66)	0.053 (0.444)	[-0.75 0.08]	-0.47	-0.0447
9	16.787 (2519.90)	-0.105 (-1.111)	[-0.70 0.05]	-0.45	-0.0154
10	16.781 (2565.64)	-0.109 (-0.947)	[-0.75 0.04]	-0.45	-0.0156
11	16.790 (3225.34)	-0.198 (-1.150)	[-0.81 0.10]	-0.49	-0.0655
12	16.777 (3561.03)	-0.113 (-1.345)	[-0.82 0.11]	-0.44	-0.0165

In bold, significant values at the 5% significance level.

TABLE 11					
Estimates of parameters in AWI_t and $TRAV_{t-k}$ relationship using Monthly Growth Rates					
$AWI_t = \alpha + \beta DT_{t-k} + x_t; \quad (1-L)^d x_t = u_t$					
With white noise disturbances (in parenthesis, t-ratios)					
k	Alpha	Beta	d-95% confidence interval	d	Stat
1	16.771 (1227.33)	**0.234 (2.031)**	[-0.45 0.04]	-0.25	-0.0242
2	16.769 (1150.38)	**0.223 (1.838)**	[-0.44 0.09]	-0.25	-0.0354
3	16.761 (1058.18)	0.045 (0.342)	[-0.43 0.12]	-0.22	0.0254
4	16.764 (939.35)	0.135 (1.382)	[-0.41 0.14]	-0.17	-0.0235
5	16.765 (959.99)	0.131 (1.081)	[-0.44 0.13]	-0.19	-0.0235

6	16.766 (967.77)	0.070 (0.577)	[-0.43 0.12]	-0.20	-0.0153
7	16.769 (957.17)	0.067 (0.617)	[-0.42 0.11]	-0.19	0.0611
8	16.766 (904.16)	0.059 (0.863)	[-0.42 0.15]	-0.19	0.0783
9	16.769 (881.81)	0.035 (0.256)	[-0.44 0.18]	-0.19	0.0145
10	16.763 (940.87)	0.013 (0.045)	[-0.44 0.15]	-0.21	0.0246
11	16.763 (928.85)	-0.051 (-0.467)	[-0.45 0.11]	-0.22	-0.0265
12	16.763 (878.28)	-0.043 (-0.376)	[-0.44 0.15]	-0.21	0.0556

In bold, significant values at the 5% significance level.

TABLE 12

Estimates of parameters in AWI_t and $TRAV_{t-k}$ relationship, using growth monthly rates

With Bloomfield (p = 1) disturbances (in parenthesis, t-ratios)

k	Alpha	Beta	d-95% confidence interval	d	Stat
1	16.777 (6113.28)	**0.212 (6.134)**	[-1.33 0.17]	-0.53	0.0129
2	16.780 (8934.05)	**0.255 (11.041)**	[-1.31 0.28]	-0.55	-0.0545
3	16.766 (8500.14)	**0.055 (2.400)**	[-1.46 0.22]	-0.53	-0.0365
4	16.773 (10816.4)	**0.106 (6.152)**	[-1.47 0.15]	-0.58	-0.0654
5	16.773 (11433.3)	**0.077 (4.688)**	[-1.66 0.17]	-0.56	0.0655
6	16.772 (11261.3)	**0.073 (4.344)**	[-1.62 0.21]	-0.67	-0.0276
7	16.770 (9670.66)	**0.057 (3.151)**	[-1.62 0.21]	-0.66	0.0065
8	16.773 (10341.6)	**0.087 (5.137)**	[-1.55 0.24]	-0.66	0.0067
9	16.771 (14991.8)	**0.090 (8.744)**	[-1.64 0.23]	-0.71	-0.0869
10	16.773 (10229.8)	0.021 (1.911)	[-1.63 0.24]	-0.69	-0.0317
11	16.771 (12723.2)	-0.021 (-1.156)	[-1.71 0.19]	-0.67	0.0055
12	16.765 (12960.2)	0.005 (1.056)	[-1.72 0.15]	-0.63	0.0156

In bold, significant values at the 5% significance level.

TABLE 13

Slope coefficients in the regression using the DT (dummy variables) series and white noise u_t.

k	A	B	C	D	E	F	G	H
1	0.275	-1.682	-1.264	**1.497**	0.001	-0.327	**1.432**	-0.354
2	0.307	-0.821	-0.835	**1.458**	0.204	0.100	**1.174**	-0.736
3	0.287	-0.403	-0.311	**1.229**	0.529	-0.404	**1.279**	-1.049
4	0.519	-0.887	-1.048	**1.073**	0.651	-1.050	**0.861**	-1.520
5	**0.608**	-0.022	0.024	**1.000**	**1.226**	-0.548	**1.567**	-1.101
6	**0.612**	0.087	-0.694	**1.101**	**1.614**	-0.900	**1.227**	-1.120
7	**0.617**	1.234	-1.059	**1.248**	**1.521**	-0.829	**1.532**	-1.445

8	0.279	-0.673	-0.525	**0.895**	**1.249**	-0.560	**1.332**	-0.900
9	0.019	-1.980	-0.897	0.612	**1.447**	-1.074	**1.100**	-0.864
10	0.098	-1.560	-0.336	**0.799**	**1.483**	-1.335	**1.008**	-0.875
11	-0.045	0.293	-1.177	**1.257**	**2.177**	-1.198	**1.256**	-0.399
12	0.149	0.890	-0.782	0.482	**2.287**	-1.206	**1.437**	-0.273

A: Sparkling wine; B: White from Penedes; C: White from Rioja; D: Wines from Navarra; E: Wines from Penedes: F: Wines from Rioja; G:Wines from Valdepeñas; H: Sherry. In bold, significant coefficients at the 5% significance level.

TABLE 14

Slope coefficients in the regression using the DT (dummy variables) series and Bloomfield (p = 1) u_t.

k	A	B	C	D	E	F	G	H
1	0.274	-1.697	-1.112	**1.674**	-0.291	-0.033	**1.226**	-0.135
2	0.304	-1.583	-0.379	**1.552**	0.018	0.867	0.894	-0.701
3	0.308	-1.574	1.111	**1.429**	0.387	-0.008	**1.250**	-1.015
4	0.518	-1.470	-1.221	**1.361**	0.368	-1.074	0.602	-1.522
5	**0.604**	-1.225	**1.953**	**1.028**	**1.157**	0.344	**1.534**	-1.062
6	**0.612**	-1.188	-0.403	**1.144**	**1.605**	-0.739	**1.119**	-1.103
7	**0.615**	-1.073	-1.212	**1.310**	**1.537**	-0.480	**1.539**	-1.474
8	0.279	-1.326	0.284	**0.924**	**1.455**	0.622	**1.265**	-0.905
9	0.039	-1.398	-0.876	0.544	**1.873**	-0.547	**1.034**	-0.869
10	0.121	-1.194	0.690	**0.805**	**2.012**	1.206	**0.947**	-0.885
11	-0.011	-0.803	-1.485	**1.263**	**2.309**	-1.547	**1.275**	-0.404
12	0.196	-0.622	-0.698	0.468	**2.353**	-1.437	**1.464**	-0.310

A: Sparkling wine; B: White from Penedes; C: White from Rioja; D: Wines from Navarra; E: Wines from Penedes: F: Wines from Rioja; G:Wines from Valdepeñas; H: Sherry. In bold, significant coefficients at the 5% significance level.

TABLE 15

Summary results from estimated regressions: relationship between German tourists to Spain and German imports of Spanish wine

	Product				
	Total aggregate wine	Sparkling wine	Red wine from Navarra	Red wine from Penedús	Red wine from Valdepeñas
Average sum of effects (euro per one percent increase of tourists)	2.07	1.83	12.02	13.65	13.93
Average lengths of effect (months)	5.5	3	10	8	11
Unit value (euro per litre), 2003	1.34	2.72	1.64	3.11	2.70

Unit values are calculated from Eurostat data. The 2003 unit values for the other analysed products are: white wine from Penedús (B): 2.78 euro per litre; white wine from Rioja (C): 1.89; red wine from Rioja (F): 2.31; Sherry (H): 2.32.