The Nature of the Relationship Between International Tourism and International Trade: the Case of German Imports of Spanish Wine

Fischer, Christian; Gil-Alana, Luis Alberiko

The Nature of the Relationship Between International Tourism and International Trade: the Case of German Imports of Spanish Wine

Journal:	*Applied Economics*
Manuscript ID:	APE-06-0345
Journal Selection:	Applied Economics
JEL Code:	F14 - Country and Industry Studies of Trade < F1 - Trade < F - International Economics, C22 - Time-Series Models < C2 - Econometric Methods: Single Equation Models < C - Mathematical and Quantitative Methods, Q13 - Agricultural Markets and Marketing|Cooperatives|Agribusiness < Q1 - Agriculture < Q - Agricultural and Natural Resource Economics, L83 - Sports|Gambling|Recreation|Tourism < L8 - Industry Studies: Services < L - Industrial Organization
Keywords:	international trade, tourism, long memory, Spanish wine

The Nature of the Relationship Between International Tourism and International Trade: the Case of German Imports of Spanish Wine

Christian Fischer, University of Bonn, Institute for Food and Resource Economics, 53115 Bonn, Germany
Luis A. Gil-Alana, Universidad de Navarra, Faculty of Economics, 31080 Pamplona, Spain

Running title:
Relationship Between International Tourism and International Trade

Abstract:
This article deals with the relationship between international trade and tourism. 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, a methodology is used based on long memory regression models, where tourism is supposed to be exogenous. The period covered is January 1998 to November 2004. The results show that 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 future import 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.

Corresponding author:
Dr. Christian Fischer, University of Bonn, Institute for Food and Resource Economics, Nussallee 21, D-53115 Bonn, Germany. Ph.: +49-228-73-3582, Fax: +49-228-73-3374, christian.fischer@ilr.uni-bonn.de

The second named author acknowledges financial support from a PIUNA Project at the University of Navarra, Pamplona, Spain.

The Nature of the Relationship Between International Tourism and International Trade: the Case of German Imports of Spanish Wine

This article deals with the relationship between international trade and tourism. 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, a methodology is used based on long memory regression models, where tourism is supposed to be exogenous. The period covered is January 1998 to November 2004. The results show that 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 future import 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.

Keywords: international trade, tourism, long memory, Spanish wine.

JEL classification: F14, C22, Q13, L83

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 tenfold during this period (World Tourism Organization, WTO, various issues). At the same time, international merchandise trade has also grown significantly. According to figures of the WTO, world exports per head of world population have increased from 44 current USD in 1961 to almost 1,200 in 2003. Thus, because there seems to be correlation between the international flows of people and goods a growing literature 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 enhance the ability to predict exports by taking into consideration tourism data. Second, tourism development agencies could demonstrate that the positive impacts of international travel on a national economy may be multiple and lasting. If tourists can be shown of not only generating income and jobs while they are in the country, but also of creating significant economic impulses by means of resulting exports to their source countries, the attention given to tourism development may perhaps be raised.

Although a microeconomic model has not yet been developed to establish theoretically the link between trade and tourism, there is a host of empirical work which shows the connection between the two. Easton (1998) analyzed whether Canadian total 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) analyzed the direction of causality between different travel and (aggregate) trade categories for Australia and its four main trading partners. 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 China. Aradhyula and Tronstad (2003) used 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 aggregate imports and imports of individual products and bilateral tourist flows, using an error-correction model. His results show that trade-tourism elasticities are consistently higher for individual products.

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 described by Kulendran and Wilson (2000) when recommending further research directions: "… the lag structures between the travel and trade flows … may require further attention" (p. 1007).

This article deals with the relationship between the German wine imports from Spain and the number of German travellers to that country. It aims to empirically analyze whether tourism has an effect on future imports and, if yes, determine the length of this effect. Thus we expand current scientific knowledge about the temporal structure of the tourism-trade link. For several reasons we concentrate on the case of wine. First, wine has become a truly globalised industry with about 40% of production (in value terms) being exported worldwide in 2001 (Anderson, 2004). Second, in industrialized 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, Hibbert and Vong, 2004). Last, wine imports have been shown to display a significant connection with tourism activities among a range of previously investigated products (Fischer, 2004).

Investigating Spain and Germany seems particularly interesting given that Spain is both a significant exporter of wine and an important tourist destination, while Germany is an important importer of wine and a main tourism source country. In 2001, Spain was the world's third biggest wine exporter (in value terms) while Germany was its third most important wine import market, behind the UK and the US (Anderson, 2004). In 2000, Spanish wine accounted for 14.8% of total German import value and imports were up 12% on the year earlier (Storchmann and Schamel, 2004). Between 1997 and 2004, this share rose more or less steadily from 11.9% to 15.5%. In Spain, the largest incoming tourist group from 1997 (7.8 million stays) to 2002 (11.3m) were Germans, according to Eurostat data. Only in 2003, did British tourists

(12.2m) outnumber Germany (10.4m). In relative terms, the share of Germans travelling to Spain in all outbound German tourists rose from 14.0% in 1997 to 18.3% in 2001 but fell continuously back to 14.4% in 2004.

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

2. The econometric model

Most of the time series work examining the relationship between international trade and tourism is based on cointegration. However, that methodology imposes a priori the assumption that the individual series must share the same degree of integration, usually 1. In other words, each series must be I(1), and they will be cointegrated if there exists a linear combination of them that is I(0) stationary.[1]

In the context of the series analyzed in the present article (which are aggregate wine imports and total tourism), we face 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 later series presents a clear seasonal pattern, while the former does not. If the two series

[1] For the purpose of the present article 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.

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 of 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 criticized in recent years on the basis that seasonal data contains some statistical relevant information by themselves. In this article 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 then represents monthly growth rates. Looking at the orders of integration of the two deseasonalised series, we still face the problem that both series are now I(1), while wine import is I(0), invalidating an analysis based on cointegration.[2]

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

[2] As an alternative approach to model the seasonal structure, and in line with the methodology used in the paper, we could have removed the seasonal component using (seasonal) fractional integration techniques (Gil-Alana and Robinson, 2001; Gil-Alana, 2002). However, since the wine import series does not present evidence of seasonality, that approach would be invalid in a regression model relating the two variables. (See Section 4).

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:

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

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, $(1 - L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - d\,L + \frac{d\,(d-1)}{2} L^2 - \ldots$. 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" (e.g., ARMA) x_t 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, x_t can be viewed as becoming "more nonstationary", for example, in the sense that the variance of partial sums increases in magnitude.[3] The fractional differencing parameter d plays a crucial role in describing the persistence in the series: the higher the d, the higher the level of association between the observations.[4]

We now consider the following model,

$$(2) \qquad y_t \; = \; \beta' z_t \; + \; x_t, \qquad t \; = \; 1, 2, \ldots,$$

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 test of the null hypothesis:

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

[4] 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).

(3) $H_o: d = d_o,$

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

$$\hat{u}_t = (1-L)^{d_o} y_t - \hat{\beta}' w_t, \quad t=1,2,\ldots, \text{ where } \hat{\beta} = \left(\sum_{t=1}^{T} w_t w_t'\right)^{-1} \sum_{t=1}^{T} w_t (1-L)^{d_o} y_t;$$

$w_t = (1-L)^{d_o} z_t$, where T means the sample size. Thus, if $d_o = 1$, we are testing for a unit root, and, if $d_o = 0$ we are in a standard linear regression model, though other fractional values of d_o 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 very mild regularity conditions: $\hat{r} \rightarrow_d N(0,1)$ as $T \rightarrow \infty$, and also the Pitman efficiency of the test against local departures from the null[5] Thus, we are in a classical large sample-testing situation: an approximate one-sided 100α% level test of H_o (3) against 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.

3. The time series data

The trade series (German imports of Spanish wine in current euro) were obtained from two different Eurostat databases. First, aggregate imports 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

[5] 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.

contains about two dozen different wine categories. The eight most important ones from this data (referred to as products A to H in our analysis) were chosen (see table 1). Most of these wines are quality wines produced in specific areas because it could be expected that returned tourists look exactly for the products of the region they were holidaying in. These eight products taken together represent on average about 62% of total German wine imports over the period of investigation. The period from 1998m1 to 2004m11 was selected due to data availability. Except for the sparkling wine (A) and Sherry category (H), all products are quality wines produced in distinct Spanish areas sold under a certified geographical label.

(Insert table 1 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 some peaks but no 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.[6]

(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). While it would have been desirable to use tourist data

[6] 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 mimic that behaviour.

at a regional level in order to match our trade data for wines produced in different Spanish areas and thus to exploit existing cross-sectional variation, none such disaggregated data were available. 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.[7]

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 Kwiatkowski, Phillips, Schmidt and Shin (KPSS, 1992).[8]

The results of the above procedures for the Aggregate Wine Imports are displayed in table 2(i). 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.

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 stylised fact that the above

[7] 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.

[8] 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.

methods have very low power if the alternatives are of a fractional form (Diebold and Rudebusch, 1991; Hassler and Wolters, 1994, etc.). Across table 2(ii) and (iii) 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 2(ii) 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:

(4) $$y_t = \alpha + \beta t + x_t; \quad (1 - L)^d x_t = u_t,$$

assuming that u_t is white noise and also autocorrelated. In the latter case, we use the Bloomfield (1973) exponential spectral model.[9] We display the 95% confidence intervals of the values of d_o where H_o (3) cannot be rejected for the three cases of no regressors, 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 (d_o = -2, -1.99, …, 0, …, 1.99, 2). 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 table, (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

[9] This is a non-parametric approach of modelling the I(0) disturbances that produces autocorrelations decaying exponentially as in the AR(MA) case. An empirical application of this procedure can be found in Gil-Alana and Robinson (1997).

estimate.[10] 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 2 about here)

As an alternative approach to estimate d, we also use a semiparametric method. It is semiparametric in the sense that we do not have to specify any model for the I(0) disturbances u_t. The estimator (Robinson, 1995) is basically a local "Whittle estimate" in the frequency domain, based on a band of frequencies that degenerates to zero. 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: $\sqrt{m}\,(\hat{d} - d_o) \to_d N(0, 1/4)$ as $T \to \infty$, where m is a bandwidth parameter number, d_o is the true value of d and with the only additional requirement that $m \to \infty$ slower than T.

Table 2(iii) displays the estimates of d for values of m from 1 to T/2. We also include in the figure the 95%-confidence interval 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 table 2 suggest that the aggregate wine imports series is stationary I(0).

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

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 and use seasonal dummies to remove that component. The plots of the deseasonalised series (DST), though not reported, showed that the series may be nonstationary. 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 monthly growth rate (MGRT). Similarly to the previous case, nonstationarity was found in this series.

(Insert tables 3 and 4 about here)

Across tables 3 and 4 we display the same type of analysis as the one performed before for the wine import series, referring now to the deseasonalised series (table 3) and the monthly growth rates (table 4). The results are very similar in both series: using classic methods (tables 3(i) and 4(i)) evidence of a unit root is found in all cases when using the test statistic with most realistic assumptions. Using the fractional framework, ((ii) and (iii)) 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). Thus, given the different nature of the processes under analysis and their possible fractional underlying structures, we consider in the following section a dynamic regression model relating two variables through a fractional integration approach.

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

Denoting Aggregate Wine Imports by AWI_t and Deseasonalised Tourism as DT_t, (either as DST_t or $MGRT_t$) we employ through the model given by (1) and (2), testing H_o (3) for given values d_o = -2, -1.99, …, 0, …, 1.99, 2, assuming that u_t is white noise and Bloomfield (with p = 1).[11] However, in order to examine the dynamic structure underlying the two series, we use as a regressor lagged values of the tourism series.[12] In other words, we test the null model,

$$(5) \qquad AWI_t \;=\; \alpha \;+\; \beta DT_{t-k} \;+\; x_t,$$

$$(6) \qquad (1 \;-\; L)^{d_o}\, x_t \;=\; u_t,$$

with k in (5) equal to 1, 2, …, and 12. As an alternative approach, we could have employed a dynamic lag-structure for DT in (5) 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. First, we employ the deseasonalised tourism series based on the seasonal dummies. Table 5a reports the results for white noise disturbances, while table 5b refers to the Bloomfield model. In both cases, we report, for each k, the estimates for

---

[11] p refers to the number of parameters required to describe the short run dynamics. Other values of p were also employed and the results were very similar to those reported in the article with p = 1.

[12] 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.

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 5 - 7 about here)

Starting with the case of white noise u_t, 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 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 5b, 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.

Table 6 is similar to table 5 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 (5) and (6), using specific types of wine rather than the aggregate flow.[13]

In table 7 we use the DT_t series (with seasonal dummies), for the two cases of white noise (in table 7a) and Bloomfield disturbances (7b). 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.[14] Very similar results were obtained when using the monthly growth rate of tourism as a regressor.

[13] Alternatively we could have employed a multivariate system for all wine categories. However, in the context of fractional processes, multivariate models are not yet fully theoretically justified.

[14] One possible reason for the 5-months delayed reaction of imports to tourism flows in the case of sparkling wine and Penedús red could be that they may be goods in particular demand for New Year's Eve and Christmas respectively. Contrary to the other analyzed wine types, these two import series peak at around November while the tourism series' main peak is in May, thus pointing to a possible link for some wine types between the choice of festivity drinks and a recent holiday destination.

6. Conclusions

In this article we have examined the relationship between German imports of Spanish wines and German tourism to Spain. For this purpose, we first analyzed each of the series separately, and it was found that wine imports were 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 regression model, using tourism retarded k periods (k = 1, …, 12) as a weakly exogenous variable. The results about the order of integration in the regression model indicate that this value is negative. However, the fact that the null hypothesis about the order of integration cannot be rejected when d = 0 suggests that the conclusions presented below should not substantially change if standard regression models were applied. Nevertheless, the estimated parameters in the regressions are supposed to be more precisely estimated once the appropriate order of integration is taken into account.

(Insert table 8 about here)

The obtained results are summarized in table 8. The first row lists the average duration of effects while the second row gives the total effect as the sum of all monthly effects in euros.[15] The average lengths of the import-promoting effects is

[15] The numbers are the average (mean) of the estimates given in tables 5 and 7. The interpretation of the estimates for the monthly growth rates series is not directly comparable to the ones obtained from the deseasonalised traveller series, therefore they have not been included in the summary calculation of table 8.

[16] Most accurately one would have used the series of German tourists travelling to specific Spanish areas rather than the overall German-tourists-travelling-to-Spain series for the estimation of the β-parameters. However, such regional-travellers series were not available and it can be assumed that

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 analyzed cases, tourism has a positive impact on the travel destination economy which lasts for many months after the tourists have already left the country. On average, the total import enhancing effect of tourism on total yearly wine imports of Spanish wine into Germany amounted to about 950,000 euros over the analyzed period. This represents about 0.4% of total imports. Our estimates also show that much (869,000 euros) of this sum can be attributed to sparkling wine, assuming that as a wine type produced in several areas and available in restaurants and retail outlets all over the country, more or less all German tourists may come in contact with it during their stay. For three quality reds (from Navarra, Penedús and Valdepeñas) we find the highest parameter estimates and longest-lasting effects but we are not able to calculate the accumulated total sum of tourism effects. The reason for this is that these wines are regional products and one would need to have the number of German tourists travelling to these specific areas and not the overall German tourists travelling to Spain for an accurate calculation of the accumulated effect.[16]

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 8 also lists unit values (import value/import quantity) as a proxy for import prices of the analyzed wine types. The two most-expensive red wine types (Penedús and Valdepeñas) also display the strongest import-

their inter-temporal variance should be highly correlated to the one of the national-travellers series, thus resulting in similar parameter estimates.

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 has been found. A possible explanation for this exception may be the fact that Rioja reds (accounting for on average 19% of imports during the period of investigation) 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 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.

Overall, this analysis has shown that the export-promoting effects of international tourism, in some cases at least, are statistically significant, positive, relatively long-lasting, but not overly high in magnitude. Nevertheless, tourism promotion as a means for export development may still work and could be cost-effective in some cases. But while a "watering can"-policy approach, spending money indiscriminately on each tourism group will not be useful, policy makers and industry- as well as tourism-development officials are rather advised to make appropriate planning and budget allocation decisions only after important identification work has been done as to which manufactured goods and tourist groups display significant connections. Based on this information, effective foreign-marketing programs and strategies for exploiting existing tourism-trade interaction effects could be implemented. Further academic research should focus on providing overall guidance for the identification of those goods and tourism groups (i.e., source countries) which in general can be expected to display the strongest links. In addition, more knowledge is needed on the causes of and determinants for these relationships.

From a methodology point of view, the approach employed in this paper, based on fractional integration, solves the dichotomy produced by the I(0)/I(1) specifications, and, given the different stochastic nature of the two series considered here, the use of I(d) regression models where one of the variables is weakly exogenous allows us to examine the dynamic behaviour of the series in a very flexible way. The frequency domain formulation of the test statistic used here seems 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 model of Bloomfield is used. A following-up step in this direction would be to examine the relationship between the two variables using fractional cointegration techniques (Hualde and Robinson, 2003) and work in this direction is now under progress.

References

Albisu, L. M. (2004) Spain and Portugal, in *The World's Wine Markets – Globalization at Work* (Ed.) K. Anderson, Edward Elgar, Cheltenham, pp. 98-109.

Anderson, K. (2004) Introduction, in *The World's Wine Markets – Globalization at Work* (Ed.) K. Anderson, Edward Elgar, Cheltenham, pp. 3-13.

Aradhyula, S. and R. Tronstad (2003) Does Tourism Promote Cross-Border Trade?, *American Journal of Agricultural Economics*, **85**(3), 569-579.

Baillie, R. T. (1996) Long memory processes and fractional integration in econometrics, *Journal of Econometrics*, **73**, 5-59.

Bloomfield, P. (1973) An exponential model in the spectrum of a scalar time series, *Biometrika*, **60**, 217-226.

Dickey, D. A. and W. A. Fuller (1979) Distribution of the Estimators for Autoregressive Time Series with a Unit Root, *Journal of the American Statistical Association*, **74**, 27-431.

Diebold, F. X. and G. Rudebusch (1991) On the power of Dickey-Fuller tests against fractional alternatives, *Economic Letters*, **35**, 155-160.

Easton, S. T. (1998) Is Tourism Just Another Commodity? Links between Commodity Trade and Tourism, *Journal of Economic Integration*, **13**, 522-543.

Felzenstein, C., S. Hibbert and G. Vong (2004) Is the Country of Origin the Fifth Element in the Marketing Mix of Wine? A Critical Review of the Literature, *Journal of Food Products Marketing*, **10**(4), 73-84.

Fischer, C. (2004) The influence of immigration and international tourism on the demand for imported food products, *Food Economics*, **1**(1), 21-33.

Gil-Alana, L. A. (2002) Seasonal long memory in the aggregate output, *Economics Letters*, **74**, 333-337.

Gil-Alana, L. A. and P. M. Robinson (1997) Testing of unit roots and other nonstationary hypotheses in macroeconomic series, *Journal of Econometrics*, **80**, 241-268.

Gil-Alana, L. A. and P. M. Robinson (2001) Seasonal fractional integration in the UK and Japanese consumption and income, *Journal of Applied Econometrics*, **16**, 95-114.

Hassler, U. and J. Wolters (1994) On the power of unit root tests against fractional alternatives, *Economic Letters*, **45**, 1-5.

Hualde, J. and P. M. Robinson (2003) Cointegration in fractional systems with unknown integration orders, *Econometrica*, **71**, 1727-1766.

Hyllerberg, S., R. F. Engle, C. W. J. Granger and B. S. Yoo (1990) Seasonal integration and cointegration, *Journal of Econometrics*, **44**, 215-238.

Kulendran, N. and K. Wilson (2000) Is there a relationship between international trade and international travel?, *Applied Economics*, **32**, 1001-1009.

Kwiatkowski, D., P. C. B. Phillips, P. Schmidt and Y. Shin (1992) Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root, *Journal of Econometrics*, **54**, 159-178.

Mandelbrot, B. B. (1977) *Fractals. Form, chance and dimension*, Freeman, San Francisco.

Phillips, P. C. B. and P. Perron (1988) Testing for a unit root in a time series regression, *Biometrika*, **75**, 335-346.

Robinson, P. M. (1991) Testing for serial correlation and dynamic conditional heteroskedasticity in multiple regression, *Journal of Econometrics*, **47**, 67-84.

Robinson, P. M. (1994) Efficient Tests of Nonstationary Hypotheses, *Journal of the American Statistical Association*, **89**,1420-1437.

Robinson, P. M. (1995) Gaussian Semiparametric Estimation of Long Range Dependence, *Annals of Statistics*, **23**, 1630-1661.

Shan, J. and K. Wilson (2001) Causality Between Trade and Tourism: Empirical Evidence from China, *Applied Economic Letters*, **8**, 279-283.

Storchmann, K. and G. Schamel (2004) Germany, in *The World's Wine Markets – Globalization at Work* (Ed.) K. Anderson, Edward Elgar, Cheltenham, pp. 110-123.

Tanaka, K. (1999) The nonstationary fractional unit root test, *Econometric Theory*, **15**, 549-582.

World Tourism Organization (various issues) *World Travel Statistics*, WTO, Geneva.

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, and g above is a known function coming from the spectral density of u_t, $f = (\sigma^2/2\pi)g$.

Appendix B

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

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

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

where m is a bandwidth parameter number.

Table 1. Overview of Wine Types Used in the Empirical Analysis

Abbre-viation	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

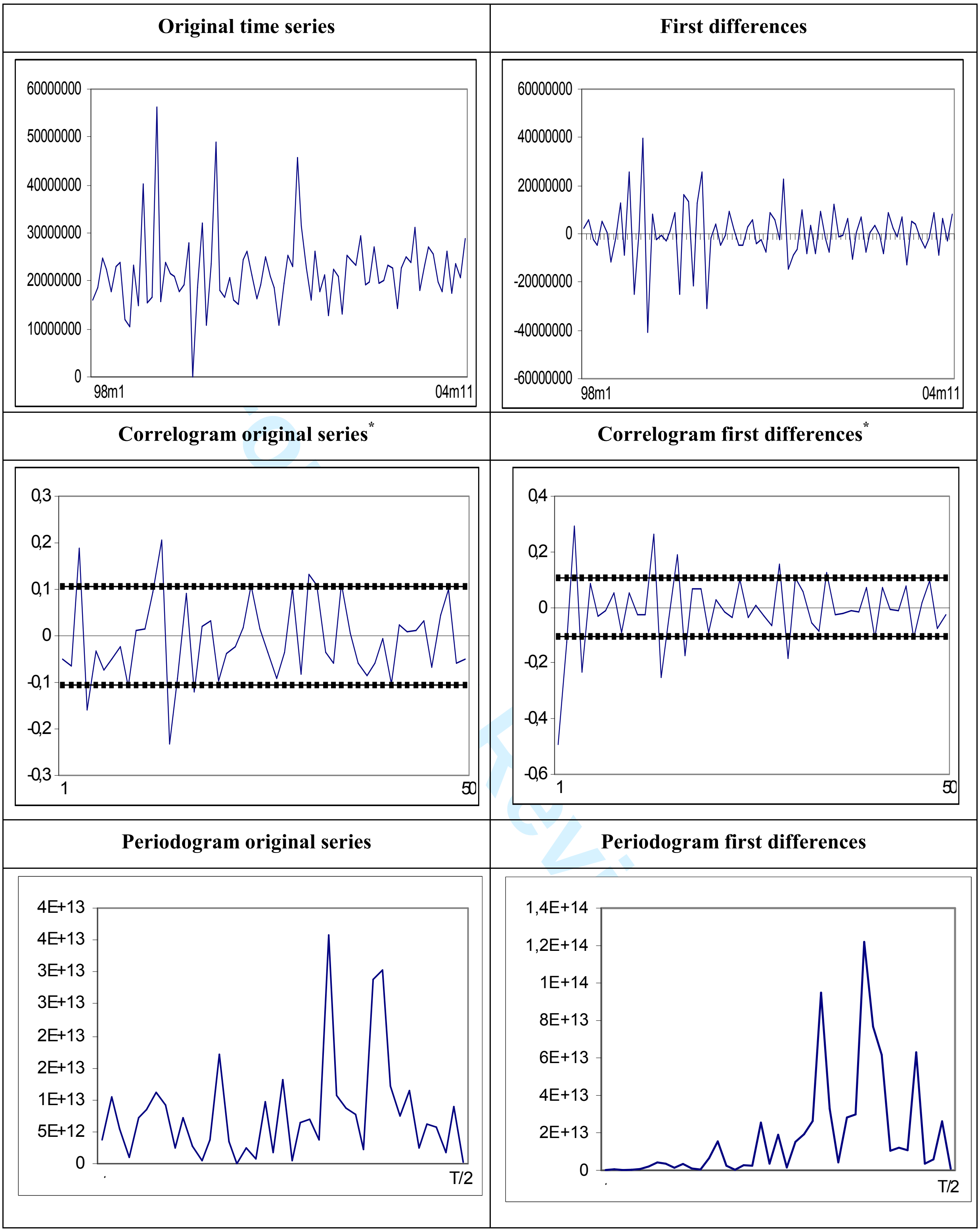


Figure 1. German Aggregate Wine Imports from Spain, 1998m1-2004m11

Note: The large sample standard error under the null hypothesis of no autocorrelation is $1/\sqrt{T}$ or roughly 0.038. The periodograms were computed based on the discrete Fourier frequencies $\lambda_j = 2\pi j/T$, j = 1, 2, …, T/2.

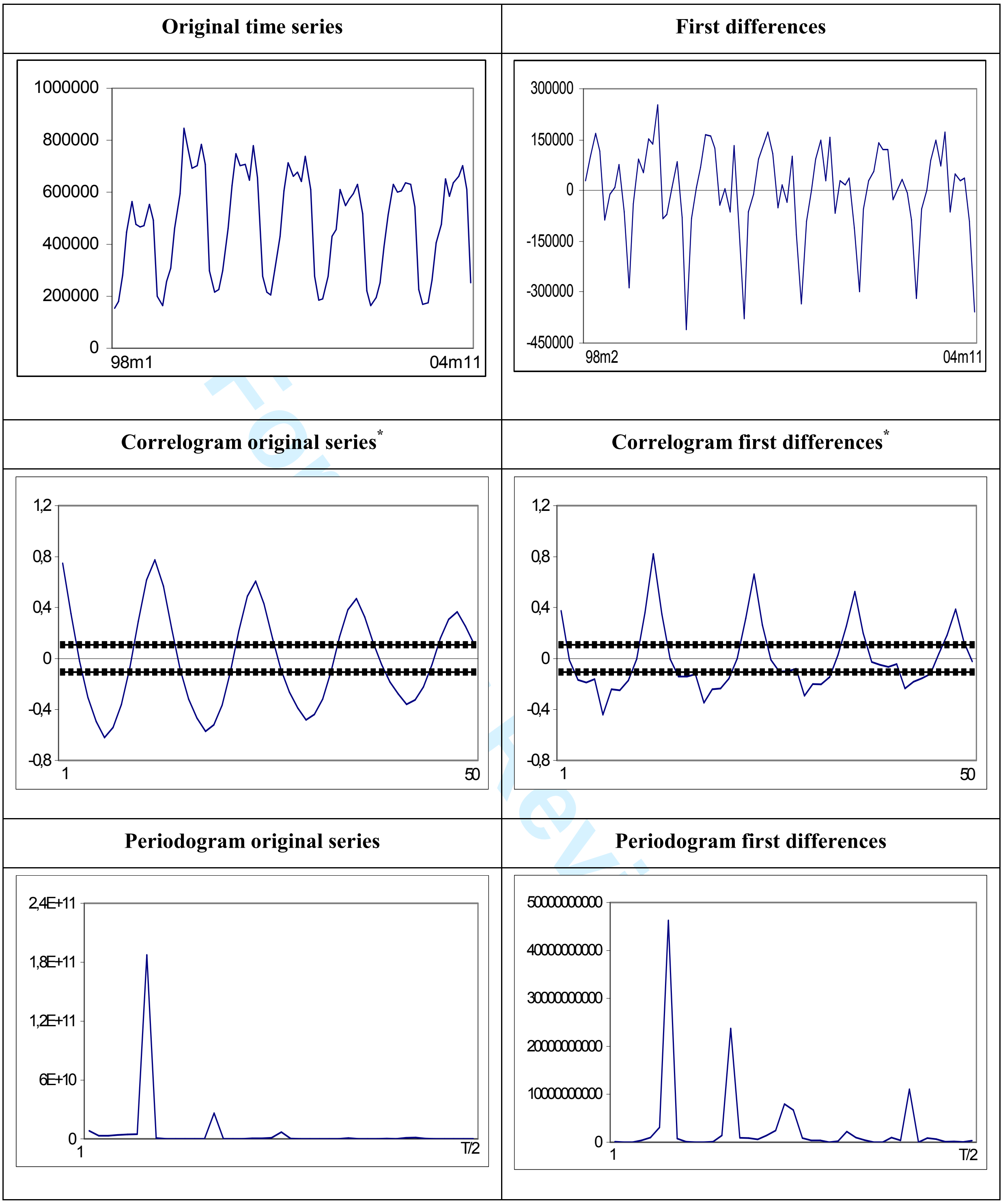


Figure 2. German Travellers to Spain, 1998m1-2004m11

Note: The large sample standard error under the null hypothesis of no autocorrelation is $1/\sqrt{T}$ or roughly 0.038. The periodograms were computed based on the discrete Fourier frequencies $\lambda_j = 2\pi j/T$, $j = 1, 2, \ldots, T/2$.

Table 2. Statistics for the Aggregate Wine Imports Series

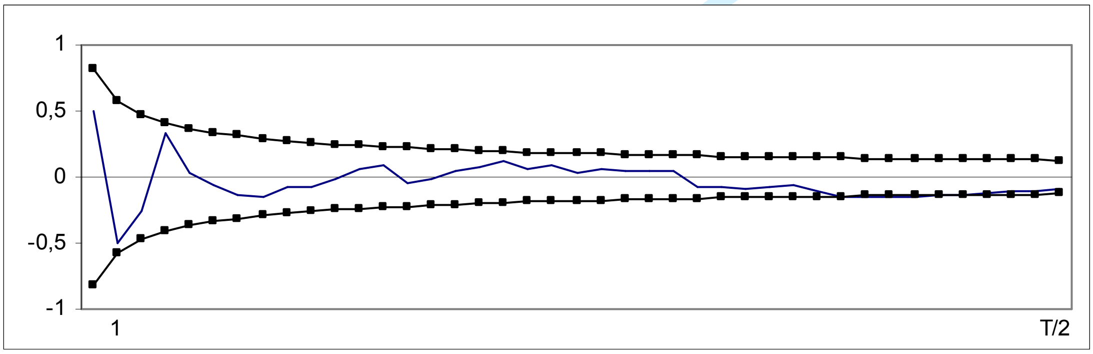
2(i) Unit Root Tests

	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)

2(ii) 95% Confidence Intervals of the Non-Rejection Values of d

	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]

2(iii) Estimates of d Based on the Gaussian Semiparametric Estimate



Notes: 2(i): In parenthesis the critical values at the 5% level. 2(ii): The values in parenthesis within the brackets refer to the value of d producing the lowest statistic. 2(iii): The horizontal axis 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.

Table 3. Statistics for the Deseasonalised Travellers (DST) series

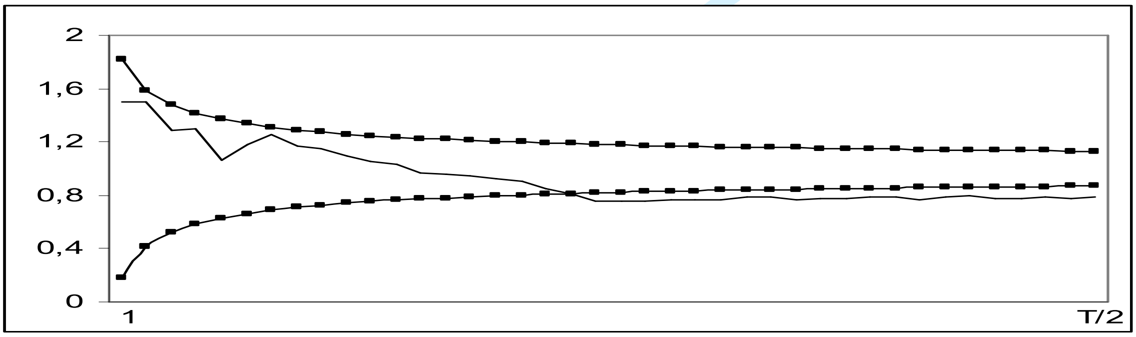
3(i) Unit Root Tests

	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)

3(ii) Confidence Intervals of the Non-Rejection Values of d

	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]

3(iii) Estimates of d Based on the Gaussian Semiparametric Estimate



Notes: 3(i): In parenthesis the critical values at the 5% level. 3(ii): The values in parenthesis within the brackets refer to the value of d producing the lowest statistic. 3(iii): The horizontal axis 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.

Table 4 Statistics for Monthly Growth Rate of Travellers (MGRT) Series

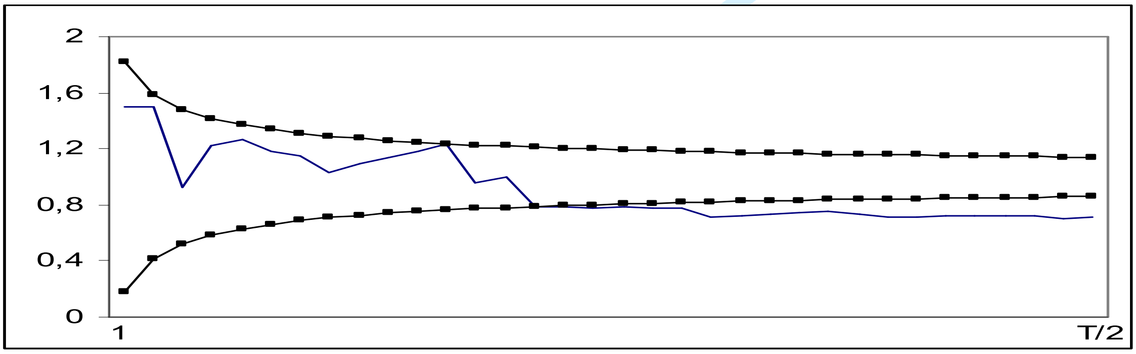
4(i) Unit Root Tests

	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)

4(ii) 95% Confidence Intervals of the Non-Rejection Values of d

	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]

4(iii) Estimates of d Based on the Gaussian Semiparametric Estimate



Notes: 4(i): In parenthesis the critical values at the 5% level. 4(ii): The values in parenthesis within the brackets refer to the value of d producing the lowest statistic. 4(iii): The horizontal axis 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.

Table 5. Estimates of Parameters in AWI_t and $TRAV_{t-k}$ Relationship, Using the DST Series: $AWI_t = \alpha + \beta DST_{t-k} + x_t; \quad (1-L)^d x_t = u_t$

5a) 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
5b) 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

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

Table 6. Estimates of Parameters in AWI_t and $TRAV_{t-k}$ Relationship Using the MGRT Series: $AWI_t = \alpha + \beta MGRT_{t-k} + x_t; \quad (1-L)^d x_t = u_t$

6a) 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
6b) 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

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

Table 7. Slope Coefficients in the Regression Using the DST Series

7a) With 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
7b) With 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

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

Table 8. Summary Results from Estimated Regressions: Relationship Between German Tourists to Spain and German Imports of Spanish Wine

	Wine type				
	Aggregate (total) (AWI)	Sparkling (A)	Quality red from Navarra (D)	Quality red from Penedús (E)	Quality red from Valdepeñas (G)
Average lengths of effect (months)	5.5	3	10	8	11
Average sum of effects (euros per year)*	950,000	869,000	---	---	---
Contribution to total yearly category imports (in %)	0.4	0.8	---	---	---
Average share in AWI value (%), Jan. 1997 to Nov. 1994	100	38.8	2.6	1.2	2.9
Import unit value (euros per liter), 2003	1.34	2.72	1.64	3.11	2.70

Notes: *The average sum of effects has been calculated as the average of the monthly effects in table 7a and 7b multiplied by the average amount of monthly German tourists traveling to Spain and by the average length of effects (first row in the above table). For the AWI and sparkling wine category it seems save to assume that imports directly related to total German tourists. However, for the regional wine categories (D), (E) and (G), only the fraction of German tourists traveling to these specific areas can be used for calculating the overall effect in euros. Unfortunately, these figures have not been available to us.

Unit values have been calculated from Eurostat data. The 2003 import unit values for the other analyzed products are: white wine from Penedús (B): 2.78 euros per liter; white wine from Rioja (C): 1.89; red wine from Rioja (F): 2.31; Sherry (H): 2.32.