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Abstract

We apply cross-spectral methods, dynamic correlation index of comovements and a VAR model to study the cyclical components of GDP and tourism income of Switzerland with annual data for the period 1980 – 2007. We find evidence of 4 dominant cycles for GDP and an average duration between 9 and 11 years. Tourism income is characterized by more cycles, giving an average cycle of about 8 years. There are also common cycles both in the typical business cycle and in the longer-run frequency bands. Lead / lag analysis shows that the two cyclical components are roughly synchronized. Simulations via a VAR model show that the maximum effect of 1% GDP shock on tourism income is higher than the maximum effect of 1% tourism income shock on GDP. The effects of these shocks last for about 12-14 years, although the major part of the shocks is absorbed within 5-6 years.

Keywords: Switzerland, Tourism Economics, Economic Fluctuations, Business Cycle, Spectral Analysis, Dynamic Correlation, VAR Models.

JEL classification: C51, E32, L83.

1. Introduction

The tourism sector is one of the most significant sectors in the modern world economy. However, despite its significance, the economics of tourism has not been given much attention, at least when compared with more core economics areas such as macroeconomics or econometric theory and methods, (Papatheodorou, 1999). Furthermore, within the economics of tourism literature, econometric tools are rather limited in comparison to those applied in macroeconomics, for example. However, in recent years, the number of papers using econometric methods and tools in tourism research has increased significantly. Several authors already employ standard econometric tools such as ARIMA modelling, Cointegration and Error Correction Mechanisms for forecasting purposes and to measure the long-run relationship between tourism and GDP, and when data are not available or are of low quality, Computable General Equilibrium models are implemented to assess the impact of tourism on other sectors. See, *inter alia*, Ballaguer and Catavella-Jorda (2002), Dritsakis (2004), Durbarry (2004), Papatheodorou and Song (2005), Narayan (2004), Sugiyarto *et al* (2003), Wyer *et al* (2004). Reviewing the relevant literature one can realize that the vast majority of econometric research in tourism is conducted almost exclusively in the time domain while frequency-domain (spectral and cross-spectral) methods are rather the exception. For example, out of 121 studies referring to modeling and forecasting of the tourism demand, only one (Coshall, 2000) apart from seasonality modeling, applied frequency-domain analysis, as it is evident from a review made by Song and Li (2008) of post 2000 research papers on the issue. In his research, Coshall (*op.cit.*) found that cycles of passenger flows from UK to France, Belgium and the Netherlands depend on cycles in exchange rates, not on the GDP cycle.

It is also interesting to note that frequency-domain methods studying the relationship between macroeconomy and tourism, to our knowledge, are not met in the literature for Switzerland. Frequency-domain methods are valuable in that they allow the decomposition of an economic time series into several periodic components with different weights, providing, thereby, a clearer picture within a particular frequency band, which otherwise would not be visible had classical time-domain methods been employed.

In this paper we would like to contribute to tourism research by studying the relationship between GDP and tourism income in Switzerland in the business cycle frequency and longer-run bands (i.e. cycles of 1.5 – 10, or even more, years) by means of classical spectral methods and the recently introduced dynamic correlation analysis, as well as of classical time-domain methods with Vector Autoregressive (VAR) models. Dynamic correlation, developed by Croux *et al*, (2001), is an index of comovement within the cross-spectral methods and measures the percentage of shared variance between two time series at a particular frequency band of interest. In particular, we seek to identify which individual cycles in both GDP and tourism income are important in terms of duration within the business cycle band. Further, we ask which of these individual cycles are more intensively correlated with each other and study the lead / lag relationships between these two cycles. Finally, since frequency-domain and time-domain methods are considered two alternative representations of the same stochastic process, highlighting different aspects of the process in question, we are also experimenting with a VAR model to investigate the interaction of GDP with tourism income by means of impulse response functions, in terms of magnitude, trajectory path and time required for the system to return to the long-run equilibrium. Our findings are: *First*, average cycles of 9 or 11 years (depending on the method of computation) for GDP, of 8 years for tourism income, and common cycles positively correlated in the business cycle and in the longer-run frequency bands. The dominant cycles of both variables are roughly synchronized. *Second*, the maximum effect of 1% GDP shock on tourism income is higher than the maximum effect of 1% tourism income shock on GDP. The effects of these shocks last for about 12-14 years, although the major parts of the shocks are absorbed within 5-6 years.

The remainder of the paper is organized as follows: In Section 2 we present a short description of the Swiss tourism sector. Section 3 deals with the statistical methodology (spectral analysis and VAR models) and in Section 4 we perform a series of preliminary tests and present the spectral estimates. Section 5 refers to the estimates of the VAR model, simulation of policy scenarios and the corresponding transmission mechanisms. Section 6 concludes the paper. Tables and Figures are given in Appendix A and a brief exposition of spectral methods and VAR models is given in Appendix B.

2. A Short Description of the Swiss Tourism Sector

Tourism is an important sector for Switzerland. It accounts for 5%-6% of the GDP of the Confederation and employs a workforce corresponding to 335000 full time employees, accounting for 10% of total employment. At some cantons the importance of tourism is very high. For example, in the canton of Grison, tourism accounts for 30% of the cantonal GDP and 30% of the employment. In the canton of Valais, the figures are 25% and 27% for the cantonal GDP and the employment, respectively (Swiss Tourism in Figures, 2008). The multiplier effect of tourism in the total economy is particularly high in Switzerland. This can be ascribed to the fact that the country has specialized in tourism for more than a century, leading to high productivity per employee. Indeed, in Switzerland there are many natural beauties (e.g. the Alps and the lakes) along with high quality resort centers, and, probably, in these areas not many alternatives for development, beyond tourism, exist. At the word level, Switzerland still holds one of the top positions on the basis of many of indices of tourism. According to a new index compiled by the World Economic Forum, Switzerland has been recognised as the most competitive travel and tourism sector in the world. As an example, in the World Economic Forum's first Travel and Tourism Competitiveness Index (TTCI), and according to the Travel & Tourism Competitiveness Report 2007, Switzerland outranked 124 other countries based on its safety record and high quality staff in the tourism sector (World Economic Forum website). This is a very positive evaluation for the tourism sector of the country despite the fact that Swiss tourism has lost much of the dominant position it had enjoyed in its heyday of the "belle époque" in the 19th century. Due to the importance of the tourism sector for the country, the Swiss government and parliament again decided to consider tourism as a strategic sector of the economy during the parliament's summer session in June 2000 (OECD, 2000).

3. Methodology: Spectral Analysis and VAR Models

Spectral analysis has not been very frequently met in economic literature as in other disciplines, such as engineering or physics. However, spectral analysis is the subject of growing interest among economists during the last decades. See, for example, Granger and Hatanaka (1964), Granger and Watson (1984), Granger (1966), Baxter and King (1995), Levy and Dezhbakhsh (2001), Iacobucci (2005). On the other hand, VAR models both in their 'atheoretical' form (e.g. see Sims, 1980) and in their connection to economic theory (e.g. the cointegration variants, see *inter alia*, Johansen (1988) and Johansen and Juselius (1990, 1992, 1994)), have been employed for a long time in economics and are now considered standard tools in economic analysis. Appendix B presents some basics of spectral analysis and VAR models that are relevant to the present paper.

4. Data, Descriptive Statistics, Stationarity Tests and Spectral Estimates

4.1 Data

Annual GDP and tourism income data, expressed in logarithms, covering the period 1980 – 2007 at constant 2000 prices (in Swiss Francs), deflated by the GDP deflator, are used in our analysis and have been obtained from the OECD and the Swiss National Bank websites (www.oecd.org and www.snb.ch, respectively). Each of theses series, denoted by y_t, is decomposed as $y_t = Tr_t + C_t + u_t$, where Tr_t, C_t, u_t are the (unobserved) long-run trend, the cyclical and the irregular (noise) components of the series, respectively. Therefore, it holds that *cyclical component* + *noise* $=$ *actual data* - *estimated trend.* The long-run trends have been estimated by the Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997) with smoothing parameter $\lambda = 100$. Since the HP filter has been applied in the logarithms of the series y_t (the actual series), the difference *actual data* - *estimated trend* expresses, approximately, the percentage change of each observation at time t from the estimated trend (extracted by the HP filter) at time t. The long-run developments of the variables are presented in Figure 1 and the cyclical components in Figure 2. It seems from Figures 1 and 2 that the HP filter captures quite well all the recessions of the past decades since 1980. In general, the Swiss business cycle follows the same path as the European cycle. See Parnisari (2000) for the recessions in Switzerland and their connections with the European business cycle.

4.2 Descriptive Statistics

Descriptive statistics of these series are presented in Table 1. From these statistics we observe that the volatility (measured by the standard deviation) of the tourism income cycle is almost double that of the volatility of GDP cycle. This reflects the higher uncertainty tourism income exhibits, relative to GDP, and it is a well-established fact in the literature. Further, the minimum points (the troughs) of the cycles also differ: tourism income cycle has reached even 5.6% below the trend line whereas GDP cycle has reached at 2.9% below the trend line. Both cycles follow the normal distribution, as this is evident from the Jarque – Bera (JB) statistics which indicate that the null hypothesis of normality cannot be rejected at any conventional significance level (1%, 5%, 10%). The mean of both series is zero, since the cycles have been constructed as deviations from the flexible HP trend line. Last, but not least, cross-correlation coefficients, displayed in Table 2, show that the maximum correlation 0.65 occurs at zero lag / lead, while the correlations at other leads and lags are quite lower. On the basis of the cross-correlation coefficients, this is an indication that the tourism income cycle is mainly procyclical.

4.3 Stationarity Tests

The above tests are meaningful only if both cycles are stationary. Although we expect them to be stationary on theoretical grounds, statistical tests are required to verify the stationarity properties of the variables. We initially employ the ADF test (Dickey and Fuller, 1979) and the SIC, i.e. the Schwarz information criterion (Schwarz, 1978) for the determination of the integration order of these two series. However, since we use a VAR model for the study of the transmission mechanism of the stochastic shocks, we also employ the Johansen (*op.cit.*) cointegration test to determine the integration order of the series. Table 3 and Tables 4(a) and 4(b) display the ADF test and the Johansen (*op.cit.*) cointegration test (with trace and maximum eigenvalues statistics), for which the lag length has been determined according to SIC, shown in Table 5. Finally, as a further indication of the integration order, we provide in Table 6 the roots of the inverse characteristic polynomial of the VAR model. From the ADF test we conclude that the null hypothesis of a unit root process is rejected for both series at 5% and 10% significance levels. Hence, on the basis of this test, both series are stationary. Tables 4(a) and 4(b) present the Johansen (*op.cit*.) cointegration test with a constant in the cointegration space and no trend in the data. Both trace and maximum eigenvalue statistics confirm that the cointegrating rank equals 2, implying that the VAR model is stationary. Table 5 presents several information criteria for the determination of the optimal lag length. According to Likelihood Ratio (LR), Final Prediction Error (FPE) (see Patterson, 2000), and SIC criteria, the optimal lag length is 2, whereas according to AIC (Akaike, 1974), and HQ (Hannan and Quinn, 1979), the optimal lag length is 8. Given the small sample (28 observations), we decided to consider that optimal lag length is 2 and not 8, in order to save valuable degrees of freedom, required for better statistical properties of the estimators. The selection of 2 lags still ensures the statistical adequacy of the VAR model, see Table 11 and Figures 9 and 10. The stationarity of the VAR can also be confirmed from the inverse roots of the characteristic polynomial of the VAR, shown in Table 6 and Figure 3, where all roots are inside the unit circle of the complex plane. All inverse roots are complex and have modulus less than 1, a fact that verifies the stationarity of the VAR.

From all these tests concerning the integration order of our processes, we conclude that both processes are of zero integration order, that is, they are stationary. Therefore, the information concerning the descriptive measures, displayed in Tables 1 and 2, is statistically valid and meaningful from an economic point of view.

Stationarity is also required for meaningful spectral estimates, given in the following Section 4.4.

4.4 Spectral Estimates and Reconstruction of the Cycles

4.4.1 Univariate Spectral Analysis

We now proceed to spectral estimates. Figure 5 shows the univariate spectral densities of GDP and tourism income. Table 7(a) and Table 7(b) display the amplitudes of cosine and sine terms, the periodogram values and the spectral density both for GDP and tourism income, respectively. The spectral window used here, which acts as a filter in the periodogram in order to produce consistent estimates of the power intensities, is the one suggested by Bartlett (Oppenheim and Schafer, 1999), whose $M = 11$ weights and shape are given in Figure 4. The number of weights M has been determined as $M = 2\sqrt{T}$, where T is the number of observations in the sample, (Chatfield, 1989). From these cycles, 4 have been identified as the most significant ones, accounting for about 85% of the total variance of the GDP cycle. They are cycles of 9.3 years (45%), 14 years (24%), 5.6 years (9.8%) and 7 years (5.3%). The relative importance of each of these cycles has been calculated on the basis of the periodogram values but the picture is roughly the same with the spectral density values instead of the periodogram. See Table 7(a) and Figure 5. Despite that the dominant cycle being 9.3 years, all 4 cycles are required to reconstruct the original GDP cycle in such a way that the simulated and the original cycles are in phase as much as possible. From these estimates, the average cycle is about 9 years (from the periodogram), and about 11 years from the spectral density.

Using the same reasoning above, we identify the cycles of tourist income. Here we have many cycles of almost equal importance, in contrast with the GDP cycle. We reconstruct the cycle of the tourism income by cycles of 7, 9.3, 14, 5.6, 4.7, 4, 3.5 and 3.1 years, all having equal importance about 10%, with the exception of one having importance approximately 4%. Overall, these cycles account for about 74% of the total variance (on the basis of the spectral density estimates). The average cycle is about 8 years. The relevant information is given in Table 7(b) and Figure 5.

On the basis of these cycles and their relative importance, the GDP and income cycles are reconstructed in Figure 8. Both simulated cycles capture fairly well the troughs and the peaks of the actual cycles in most of the cases. In some other cases (GDP cycle in 1996, 2003 and the tourism income in 1982 and 1987) the simulated peaks or troughs deviate about 1 year from the actual peaks or troughs.

4.4.2 Cross-Spectral Analysis and Dynamic Correlation

The next step is to identify the relationship between GDP and tourism income in business cycle frequencies. Cross-spectral analysis reveals some interesting characteristics of the relationship of two variables in the frequency domain. In particular, Figure 6 displays the cross-spectral densities and the squared coherency estimates, while Figure 7 presents the phase spectrum and the dynamic correlation estimates. In addition, Tables 8(a) and 8(b) show the same plus other relevant information in numerical form. According to these estimates, cycles existing in the band of 5.6 up to 14 years are common in both cycles. This is evident from the fact that squared coherency, Figure 8(b), takes the highest values in this frequency band. The common cycles account for about 72% of the common variance (estimated as the sum of the cross-spectral density percentages in the corresponding frequencies). These estimates offer support for the view that GDP and tourism income cycles are linked together both in the typical business cycle frequencies (cycles of 5.6 – 9.3 years) and in the longer-run (the cycle of 14 years). Knowing the phase spectrum, we can also find the lead / lag relationship between GDP and tourism income. The time of lead or lag (in months) for a particular period is computed as $\frac{Phase \times Period}{2\pi} \times 12$. If phase is negative, then GDP leads tourism income and if it is positive then GDP lags the tourism income. Thus, the cycles of 9.3 and 14 years have negative phase, meaning that GDP cycles at these frequencies lead the tourism income cycles by 1.9 and 2.7 months, respectively. On the contrary, the cycles of 5.6 and 7 years have positive phase, implying that GDP lags tourism income by 1.2 and 0.3 months, respectively. Therefore, on average, the lead / lag effect is small and GDP and tourism income can be considered rather synchronized at these frequencies, which account for the major part of the common variance (72%). This also verifies the evidence provided by the cross-correlation coefficient at zero lead / lags (0.65) that tourism income is procyclical.

The dynamic correlation sheds light on the relationship between two variables for individual frequencies or for frequency bands and serves as an index of comovement. Figure 8(b) presents the dynamic correlation which, in all frequencies, is between 0.65 and 0.79. Especially, in the frequency band of 5.6 – 14 years (the frequency of interest in this paper) dynamic correlations take values from 0.69 – 0.77 and this is an indication that the two series are correlated in a high degree both in the business cycle and the longer-run frequency bands.

5. VAR Model and Transmission Mechanisms

5.1 Estimates and Diagnostics

The estimated VAR model and some diagnostics are given in Tables 9 and 10. The estimates are meaningful only if the model is statistically adequate. Indeed, a well-specified model must be free of residual autocorrelation, ARCH effects (Engle, 1982), non-normality and must exhibit stability in its estimated parameters. Table 11 shows the diagnostics for autocorrelation, ARCH effects and normality. Figures 9 and 10 present two sorts of stability tests: the Cusum and the Cusum of Squares Test (Brown *et al*, 1975), both at 5% significance level, and the recursive coefficients tests. The autocorrelation tests (Portmanteau test and Lagrange Multiplier test) cannot reject the no-autocorrelation null hypothesis at any conventional significance level. The same applies to ARCH effects and the normality tests: the null hypothesis cannot be rejected at the conventional significance levels. Also, stability analysis, based on the Cusum and the Cusum of Squares test shows no evidence of structural instability within the sample. Given this picture, we hold that the VAR model is suitable for policy scenarios and simulations.

5.2 Policy Scenarios and Simulations

We now examine the transmission of stochastic shocks generated in GDP and tourism income. We simulate two policy scenarios and we trace the trajectory path of the transmission by impulse response functions. In particular, Scenario 1 generates a positive stochastic structural shock in the GDP equation of 1% in magnitude for one period (one year) and no shock to tourism income equation. However, due to the interdependence of the two variables, both variables will be affected by the GDP shock. The trajectory path of GDP is the Transmission Mechanism 1 (TM1) and the trajectory path of tourism income is the Transmission Mechanism 2. Scenario 2 generates a positive stochastic structural shock in the tourism equation of 1% in magnitude for one period (one year) and no shock to GDP equation. The trajectory path of GDP is the Transmission Mechanism 3 (TM3) and the trajectory path of tourism income is the Transmission Mechanism 4 (TM4). Again, due to the interdependence of the variables in the VAR system, both variables will be affected by the tourism shock. Table 12 presents the scenarios and the 4 corresponding transmission mechanisms and Figure 11 shows the trajectory path that each variable follows under the 4 transmission mechanisms. All trajectories have an oscillating pattern due to the complex roots in the inverse characteristic polynomial of the VAR.

TM1 shows that the effect of the GDP shock to itself has a maximum 1% and lasts about 13-14 years, but the major part of the shock is absorbed within the first 4 years.

TM2 and TM3 are interesting since they capture the effects of two shocks, from GDP to tourism income and from tourism income to GDP, respectively. TM2 shows a maximum response of 0.62%, the duration of the cycle is about 12-13 years and the major part of the shock is absorbed within the first 5 years.

TM3 shows that the response of GDP cycle to tourism income shock is zero for the first two years and it reaches a maximum response of 0.15% on the fourth year. From that year onwards the effect on GDP declines, it reaches a minimum of -0.05% on the seventh year and the whole cycle decays within 13-14 years. The major part of the shock is absorbed within the first 6 years.

Lastly, TM4 shows that the effect of the tourism income to itself has a maximum of 1%, it lasts about 6 years and the major part of the shock is absorbed within the first 3 years. It is interesting to note that the maximum effect of the GDP shock on tourism income is higher (0.62%) than the effect of the tourism income shock on GDP (0.15%).

6. Concluding Remarks

In this paper we have studied the spectral properties of the cyclical components of the Swiss GDP and tourism income and their interaction by means of a VAR model during the period 1980 – 2007. We found that the Swiss GDP is dominated by 4 cycles, listed in descending order of significance, of 9.3 years, 14 years, 5.6 years and 7 years. These cycles account for about 85% of the total variation of the cyclical component of the GDP. The average GDP cycle is 9 or 11 years (according to the periodogram or the spectral density, respectively).

The tourism income is dominated by 7 cycles of 7, 9.3, 14, 5.6, 4.7, 4, 3.5 and 3.1 years, all having equal importance about 10%, with the exception of one having importance approximately 4%. The average duration of the tourism income cycle is about 8 years. Overall, these cycles account for about 74% of the total variance (on the basis of the spectral density estimates). The average tourism cycle is about 8 years.

Cycles existing in the band of 5.6 up to 14 years are common in both GDP and tourism income cyclical components and the comovements of these (and all of the remaining) cycles are strong, on the basis of both squared coherency and dynamic correlation indices. The common cycles account for about 72% of the common variance. For the common cycles of 9.3 and 14 years, it has been shown that GDP leads the tourism income by 1.9 and 2.7 months, respectively, whereas for the common cycles of 5.6 and 7 years, the GDP lags the tourism income by 1.2 and 0.3 months, respectively. Thus, on average, the lead lag effect is small and the two cycles are synchronized in the sense that their simulated peaks and troughs do not deviate very much from the original ones.

Further, and as the VAR analysis shows, all trajectory paths are oscillatory. This is due to the complex roots of the inverse characteristic polynomial of the VAR.

The findings of the TM2 and TM3 are interesting from a tourism policy point of view. The implications are that a negative GDP shock affects the tourism income negatively and vice-versa. In a hypothesized (though not tested) symmetry of shocks, the implication of TM2 is that 1% negative GDP shock will result in 0.62% (at maximum) negative growth in tourism income and this lasts for a period of about 13-14 years, although the major part of the negative shock is absorbed within the first 5 years. Further, and according to the findings of TM3, a negative 1% shock in tourism income results in 0.15% (at maximum) negative growth in GDP, lasting 12-13 years, but the major part of the negative shock will be absorbed within the first 6 years.

Our estimates are based on a set of assumptions that are implicitly built into the methods used (the HP filter, the sinusoid basis functions of Fourier transform / spectral analysis, and the identification scheme of the VAR model). It is probable that different filtering procedures, different identification schemes especially in case of VAR models of higher dimension and different basis functions for spectral estimates (e.g. in a wavelet analysis context) may produce different findings. In this sense, our conclusion should be considered as indicative and tentative.

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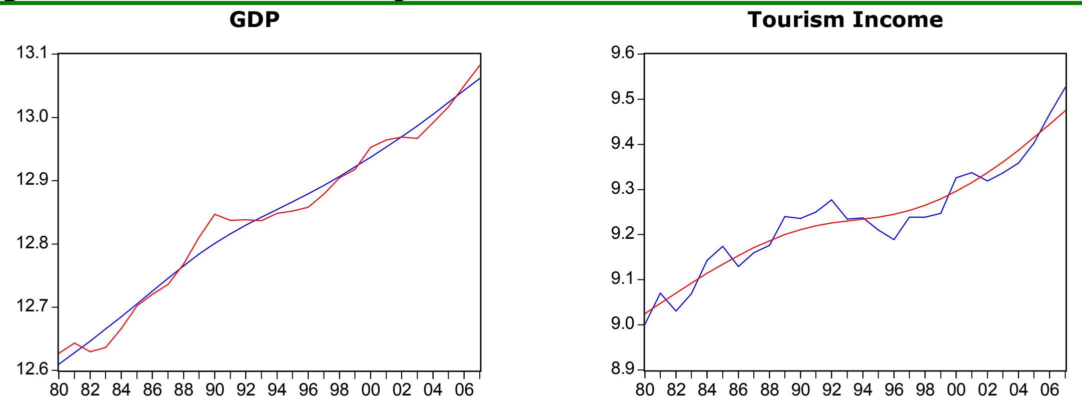
APPENDIX A: Figures and Tables

Figure 1: Actual Data and Long-run Trends



Note: GDP, Tourism Income: logarithms of GDP and Tourism Income, respectively. The long-run trends have been estimated by the HP filter with smoothing parameter $\lambda = 100$. The smoothed line is the trend.

Figure 2: GDP and Tourism Income Cycles

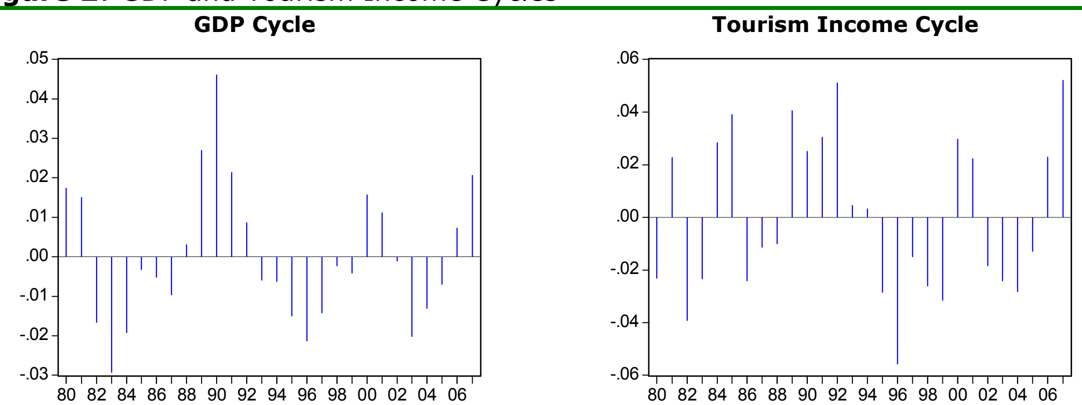
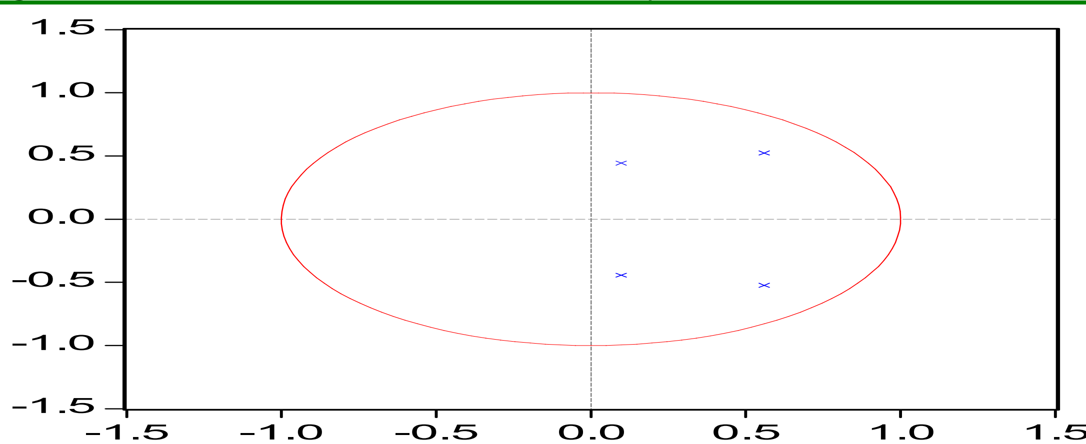
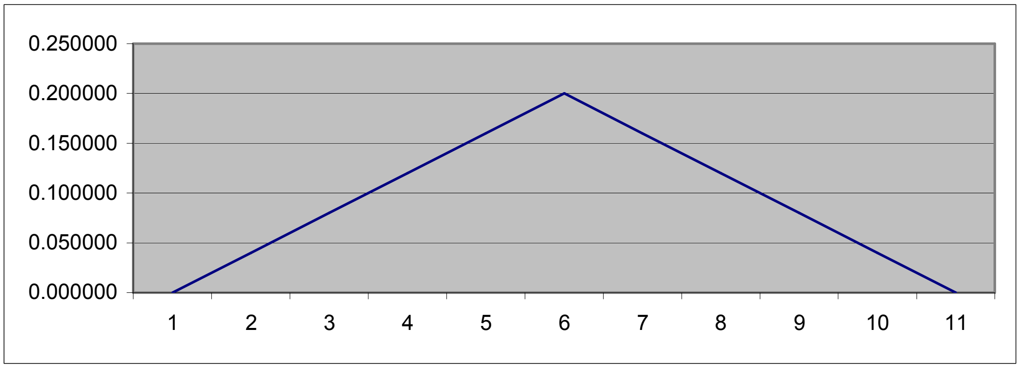


Figure 3: Roots of the Inverse Characteristic Polynomial



Note: All roots are inside the unit circle of the complex plain. VAR is stationary**.**

Figure 4: Bartlett Window ($M = 11$)



0.00	0.04	0.08	0.12	0.16	0.20	0.16	0.12	0.08	0.04	0.00

Note: The figures in the bottom are the 11 weights of the Bartlett window.

Figure 5: Spectral Densities: GDP and Tourism Income

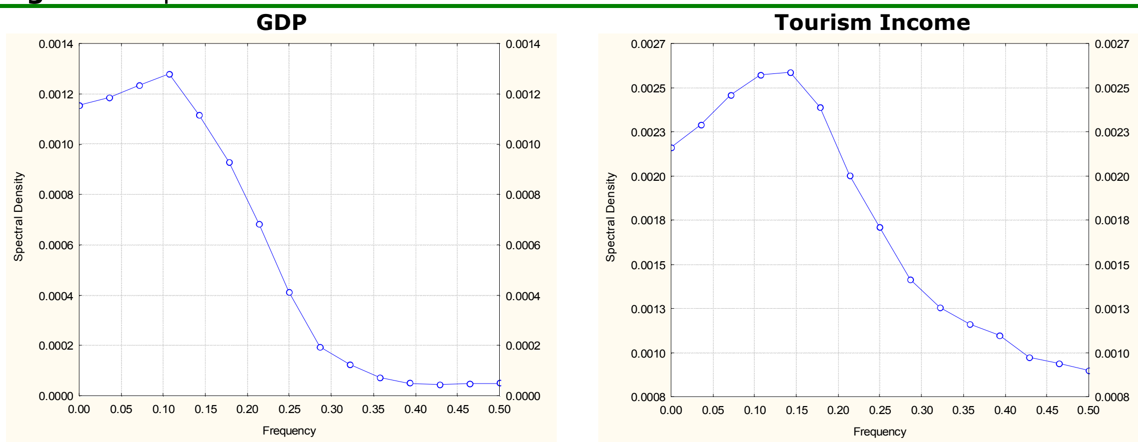


Figure 6: GDP and Tourism Income Cycles: Cross-Spectral Density and Squared Coherency

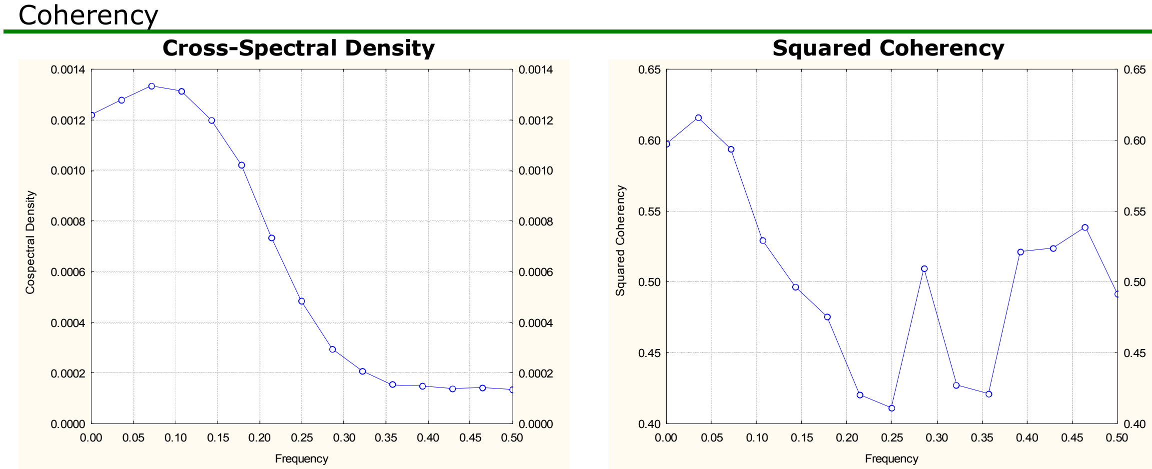


Figure 7: Phase Spectrum and Dynamic Correlation

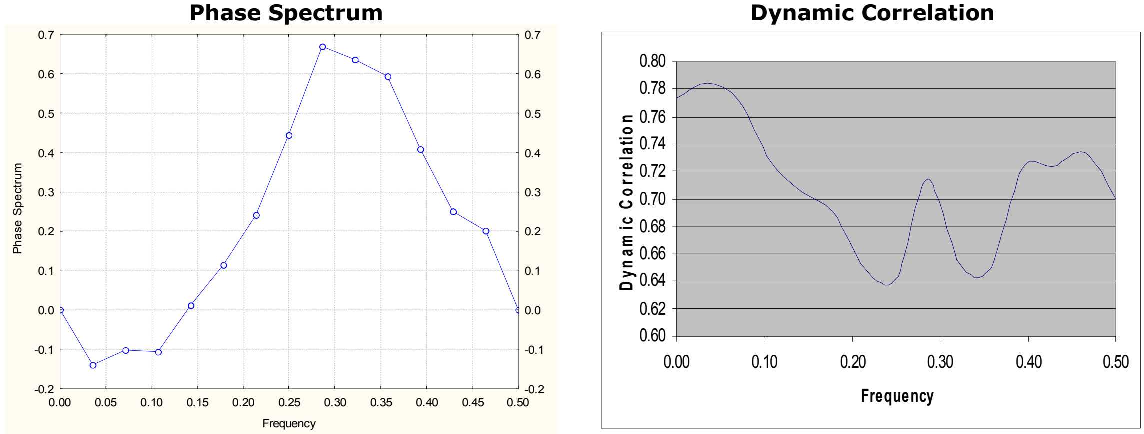
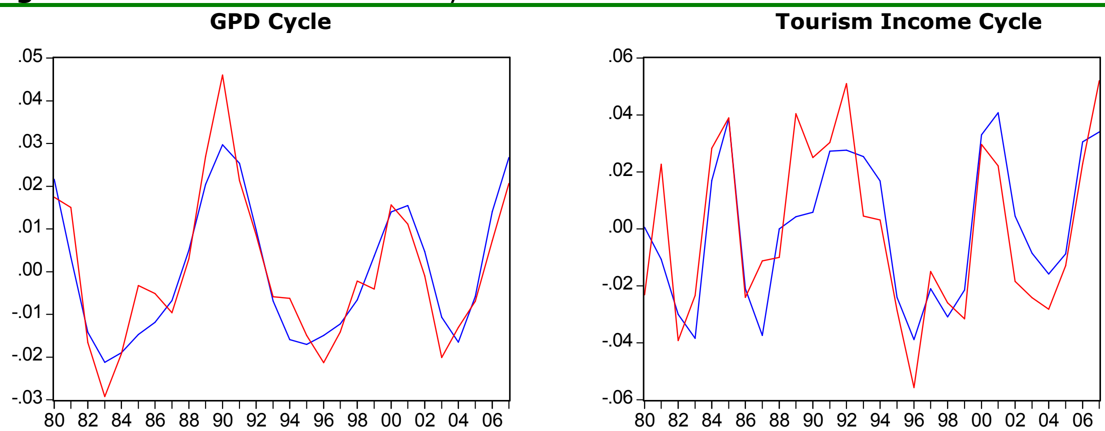
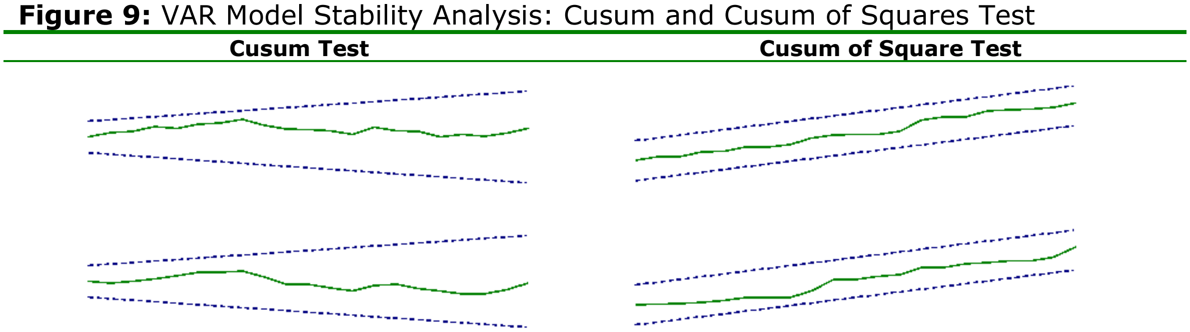


Figure 8: Actual and Simulated Cycles



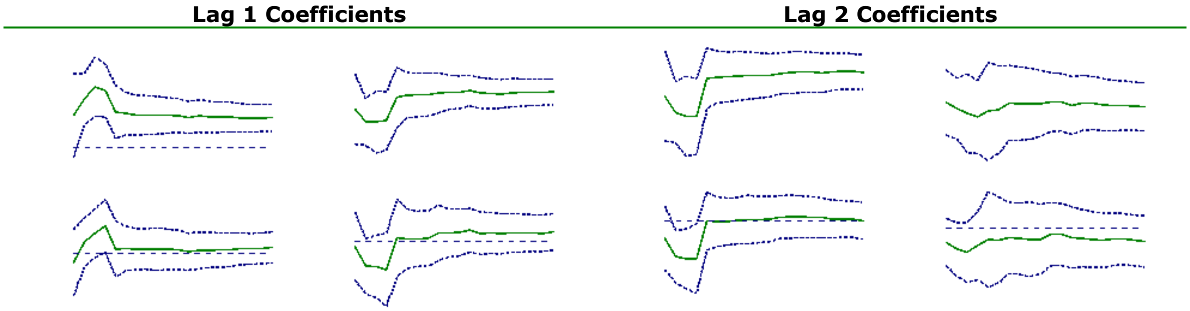
Note: The blue (continuous) line is the simulated cycle and the red (dashed) line is the actual cycle.

Figure 9: VAR Model Stability Analysis: Cusum and Cusum of Squares Test



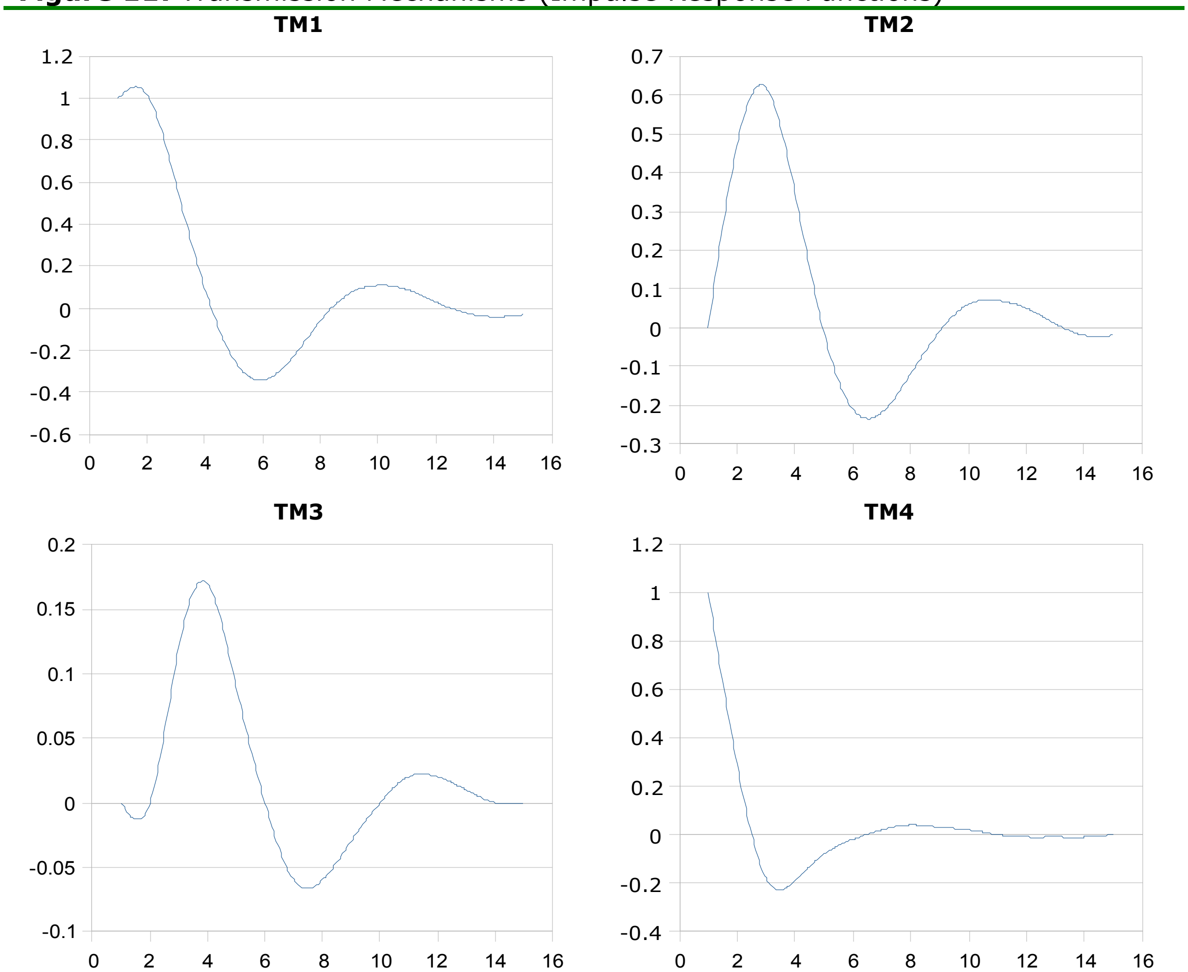
Note: Both tests verify the structural stability of the model within the sample. The external lines define a 95% confidence interval.

Figure 10: VAR Model Stability Analysis: Recursive Coefficients



Note: Lag 1 Coefficients: Top panel, from left to right: coefficients of the first equation: GDP and tourism income. Lag 1 Coefficients: Bottom panel, from left to right: coefficients of the second equation: GDP and tourism income. Lag 2 Coefficients: Top panel, from left to right: coefficients of the first equation: GDP and tourism income. Lag 2 Coefficients: Bottom panel, from left to right: coefficients of the second equation: GDP and tourism income. All recursive coefficients verify structural stability of the model within the sample. The external lines define a 95% confidence interval.

Figure 11: Transmission Mechanisms (Impulse Response Functions)



Note: Transmission Mechanisms (TMs): TM1 refers to the response of GDP to its own stochastic shock. TM2 refers to the response of tourism income to the GDP shock. TM3 refers to the response of GDP to the tourism income shock. TM4 refers to the response of tourism income to its own stochastic shock.

Table 1: Descriptive Statistics of the GDP and the Tourism Income Cycles

Variable	Mean	Standard Deviation	Maximum	Minimum	Normality JB Statistics
GDP Cycle	0	0.017	0.046	-0.029	1.905, p-value: 0.385
Tourism Income Cycle	0	0.030	0.052	-0.056	1.864, p-value: 0.413

Table 2: Cross-Correlation Coefficients between GDP and Tourism Income Cycles

Lag / Lead i	$Corr(y_{1t}, y_{2t-i})$ **Lag**	$Corr(y_{1t}, y_{2t+i})$ **Lead**
0	0.65	0.65
1	0.35	0.33
2	-0.04	0.16
3	-0.22	0.13

Note: y_1 is the GDP cycle, y_2 is the tourism income cycle.

Table 3: ADF Test

Variable	ADF t statistic	SIC Lag Length
GDP Cycle	-3.771998	1
Tourism Income Cycle	-3.229050	0

Note: MacKinnon *et al*, (1999) one-sided p-values: 1%: -3.699871, 5%: -2.976263, 10%: -2.627420.

Table 4(a): Cointegration Test with Trace Statistic

Hypothesized Number of Equations	Eigenvalue	Trace Statistic	5% CV	1% CV
$k = 0$	0.412526	23.18650	15.49471	0.0029
$k \leq 1$	0.326682	9.888420	3.841471	0.0017

Note: Trace Statistic suggests that cointegrating rank equals 2. VAR is stationary at both 5% and 1% significance levels. CV: Critical Value.

Table 4(b): Cointegration Test with Maximum Eigenvalue Statistic

Hypothesized Number of Equations	Eigenvalue	Maximum Eigenvalue	5% CV	1% CV
$k = 0$	0.412526	15.39606	14.26460	0.0330
$k \leq 1$	0.326682	9.614142	3.841466	0.0019

Note: Maximum eigenvalue statistic suggests that cointegrating rank equals 2. VAR is stationary at both 5% and 1% significance levels. CV: Critical Value.

Table 5: Determination of Optimal Lag Length

Lag	Logl	LR	FPE	AIC	SIC	HQ
0	104.9472	NA	1.16e-07	-10.29472	-10.19515	-10.27529
1	111.3482	10.88157	9.16e-08	-10.53482	-10.23610	-10.47650
2	119.3572	**12.01353**	**6.24e-08**	-10.93572	**-10.43785**	-10.83853
3	120.9218	2.034026	8.29e-08	-10.69218	-9.995169	-10.55612
4	122.0710	1.264055	1.19e-07	-10.40710	-9.510937	-10.23216
5	131.4858	8.473323	7.92e-08	-10.94858	-9.853270	-10.73476
6	133.3653	1.315698	1.23e-07	-10.73653	-9.442081	-10.48384
7	139.4938	3.064239	1.47e-07	-10.94938	-9.455782	-10.65781
8	153.1038	4.083013	1.17e-07	**-11.91038**	-10.21764	**-11.57994**

Note: LogL: Log Likelihood. LR, Likelihood Ratio, AIC: Akaike Information Criterion, FPE: Final Prediction Error, SIC: Schwarz Information Criterion, HQ: Hannan – Quinn Information Criterion. Bold font indicates the values of the criteria corresponding to the optimal lag length (also in bold).

Table 6: Inverse Roots of the Characteristic Polynomial of the VAR

Roots	Moduli
0.559381 - 0.523355i	0.766034
0.559381 + 0.523355i	0.766034
0.097614 - 0.443933i	0.454539
0.097614 + 0.443933i	0.454539

Note: All moduli are less than one. VAR is stationary.

Table 7(a): GDP: Cosine and Sine Terms, Periodogram and Spectral Density

Frequency	Period	Cosine Coefficients	Sine Coefficients	Perio-dogram	Perio-dogram %	Spectral Density	Spectral Density %
0.000000	NA	0.000000	0.000000	0.000000	NA	NA	NA
0.035714	28.0000	-0.001803	0.003618	0.000229	2.9	0.001186	16.0
0.071429	14.0000	-0.000767	-0.011788	0.001954	24.4	0.001232	16.6
0.107143	**9.33333**	**0.015460**	**0.004383**	**0.003615**	**45.2**	**0.001280**	**17.2**
0.142857	7.00000	0.003598	-0.004152	0.000423	5.3	0.001117	15.0
0.178571	5.60000	0.003343	-0.006712	0.000787	9.8	0.000930	12.5
0.214286	4.66667	0.003921	0.003723	0.000409	5.1	0.000682	9.2
0.250000	4.00000	-0.002203	0.004202	0.000315	3.9	0.000411	5.5
0.285714	3.50000	0.001152	-0.000192	0.000019	0.2	0.000196	2.6
0.321429	3.11111	-0.001034	-0.000486	0.000018	0.2	0.000126	1.7
0.357143	2.80000	-0.001676	0.000904	0.000051	0.6	0.000073	1.0
0.392857	2.54545	0.000025	-0.000946	0.000013	0.2	0.000050	0.7
0.428571	2.33333	-0.001585	0.001270	0.000058	0.7	0.000046	0.6
0.464286	2.15385	-0.001959	0.000870	0.000064	0.8	0.000049	0.7
0.500000	2.00000	0.001883	-0.000000	0.000050	0.6	0.000050	0.7

Note: The dominant frequency of 0.107 cycles (9.3 years), the corresponding periodogram values and the spectral density are displayed in bold. The average cycle is 9 years, from the periodogram, and 11 years from the spectral density.

Table 7(b): Tourism Income: Cosine and Sine Terms, Periodogram and Spectral Density

Frequency	Period	Cosine Coefficients	Sine Coefficients	Perio-dogram	Perio-dogram %	Spectral Density	Spectral Density %
0.000000	NA	0.000000	0.000000	0.000000	NA	NA	NA
0.035714	28.0000	0.000607	0.012164	0.002077	8.3	0.002289	9.6
0.071429	14.00000	0.000200	-0.014296	0.002862	11.5	0.002461	10.4
0.107143	9.33333	0.007351	0.011630	0.002650	10.6	0.002570	10.8
0.142857	**7.00000**	**0.001944**	**-0.018410**	**0.004798**	**19.2**	**0.002587**	**10.9**
0.178571	5.60000	0.001644	-0.015123	0.003240	13.0	0.002391	10.1
0.214286	4.66667	0.002733	-0.004664	0.000409	1.6	0.002004	8.4
0.250000	4.00000	0.003465	0.009826	0.001520	6.1	0.001711	7.2
0.285714	3.50000	-0.002246	0.001671	0.000110	0.4	0.001414	6.0
0.321429	3.11111	-0.012363	-0.002341	0.002217	8.9	0.001256	5.3
0.357143	2.80000	-0.006049	0.009230	0.001705	6.8	0.001160	4.9
0.392857	2.54545	-0.006064	-0.006333	0.001076	4.3	0.001099	4.6
0.428571	2.33333	-0.001977	0.001673	0.000094	0.4	0.000972	4.1
0.464286	2.15385	-0.007753	0.003677	0.001031	4.1	0.000941	4.0
0.500000	2.00000	-0.009233	-0.000000	0.001193	4.8	0.000900	3.8

Note: The dominant frequency of 0.143 cycles (7 years), the corresponding periodogram values and the spectral density are displayed in bold. The average cycle is 8 years (on the basis of the spectral density).

Table 8(a): Periodogram and Cross-Spectral Density

Frequency	Period	Periodogram (Real)	Periodogram (Imaginary)	Cross Spectral Density	Cross Quadratic Spectrum	Cross Amplitude
0.000000	NA	0.000000	0.000000	0.001220	0.000000	0.001220
0.035714	28.00000	0.000601	0.000338	0.001280	-0.000180	0.001293
0.071429	**14.00000**	**0.002357**	**-0.000187**	**0.001335**	**-0.000136**	**0.001342**
0.107143	9.33333	0.002305	-0.002066	0.001312	-0.000140	0.001320
0.142857	7.00000	0.001168	0.000814	0.001198	0.000013	0.001198
0.178571	5.60000	0.001498	0.000553	0.001022	0.000117	0.001029
0.214286	4.66667	-0.000093	0.000399	0.000736	0.000181	0.000758
0.250000	4.00000	0.000471	0.000507	0.000486	0.000231	0.000538
0.285714	3.50000	-0.000041	-0.000021	0.000294	0.000233	0.000375
0.321429	3.11111	0.000195	0.000050	0.000209	0.000154	0.000260
0.357143	2.80000	0.000259	0.000140	0.000155	0.000104	0.000186
0.392857	2.54545	0.000082	0.000083	0.000150	0.000065	0.000163
0.428571	2.33333	0.000074	0.000002	0.000138	0.000035	0.000142
0.464286	2.15385	0.000257	0.000006	0.000142	0.000029	0.000145
0.500000	2.00000	0.000000	-0.000000	0.000134	0.000000	0.000134

Note: The highest cross-spectral estimates are in the frequency of 0.07 cycles (14 years), displayed in bold.

Table 8(b): Squared Coherency, Phase Spectrum, Lead / Lag Time and Dynamic Correlation

Frequency	Period	Squared Coherency	Phase Spectrum	Lead / Lag Time in Months	Dynamic Correlation
0.000000	NA	0.60	0.000000	NA	0.77
0.035714	28.00000	0.62	-0.139691	-7.5 Ld	0.78
0.071429	**14.00000**	**0.59**	**-0.101799**	**-2.7 Ld**	**0.77**
0.107143	**9.33333**	**0.53**	**-0.106436**	**-1.9 Ld**	**0.73**
0.142857	**7.00000**	**0.50**	**0.010825**	**0.1 Lg**	**0.70**
0.178571	**5.60000**	**0.48**	**0.113528**	**1.2 Lg**	**0.69**
0.214286	4.66667	0.42	0.241527	2.2 Lg	0.65
0.250000	4.00000	0.41	0.444370	3.4 Lg	0.64
0.285714	3.50000	0.51	0.669736	4.5 Lg	0.71
0.321429	3.11111	0.43	0.636078	3.8 Lg	0.65
0.357143	2.80000	0.42	0.592255	3.2 Lg	0.65
0.392857	2.54545	0.52	0.408985	2.0 Lg	0.72
0.428571	2.33333	0.52	0.250606	1.1 Lg	0.72
0.464286	2.15385	0.54	0.201688	0.8 Lg	0.73
0.500000	2.00000	0.49	0.000000	0.0	0.70

Note: Ld: GDP leads tourism income. Lg: GDP lags tourism income. Bold letters indicate the most important common cycles in the business and the longer-run frequency bands.

Table 9: VAR Model Estimates

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} -0.001 \\ +0.001 \end{pmatrix} + \begin{pmatrix} 1.023 & 0.003 \\ 0.468 & 0.291 \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} -0.446 & -0.128 \\ 0.009 & -0.269 \end{pmatrix} \begin{pmatrix} y_{1t-2} \\ y_{2t-2} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

where: y_1 is GDP, and y_2 is tourism income. Sample range: [1982, 2007], effective number of observations $T = 26$, $corr(u_{1t}, u_{2t}) = 0.069$.

Table 10: Diagnostics of the VAR Model

R^2	0.63	0.21
Adjusted R^2	0.56	0.06
Residual Sum of Squares	0.002750	0.018395
Standard Error of Error Term	0.011443	0.029596
F-statistic	8.897186	1.409434
Log likelihood	82.11291	57.40695
AIC Akaike	-5.931763	-4.031304
SIC Schwarz	-5.689821	-3.789362

VAR Model Statistics: Log Likelihood: 147.9865, AIC: -10.61435, SIC: -10.13047, Determinant of the residuals covariance matrix (d.o.f adj.): 5.98E-08. Determinant of the residuals covariance matrix: 3.90E-08

Table 11: VAR Model: Autocorrelation, ARCH and Normality Diagnostics

Autocorrelation Tests	ARCH Effects Test	Normality Test
Pormanteau adj. test statistic (16 lags): 56.6144 p-value: 0.4519	Multivariate ARCH-LM test statistic (5 lags): 47.5341 p-value: 0.3698	JB test statistic for the GDP equation: 0.0638 p-value: 0.9886
LM test statistic (5 lags): 24.8379. p-value: 0.2077		JB test statistic for the tourism income equation: 0.6723 p-value: 0.7145

Note: No autocorrelation, ARCH effects and non-normality are evident. VAR is a well-behaved model, suitable for policy scenarios.

Table 12: Policy Scenarios and Transmission Mechanisms

Scenario	Shock / Variable	Transmission Mechanisms (TMs)
1	1% shock in GDP and no shock in tourism income	TM1: effect on GDP
		TM2: effect on tourism income
2	No shock in GDP and 1% shock in tourism income	TM3: effect on GDP
		TM4: effect on tourism income

Table 13: Transmission Mechanisms (Impulse Response Functions)

Year	TM1	TM2	TM3	TM4
1	1.00	0.00	0.00	1.00
2	1.02	0.47	0.00	0.29
3	0.60	0.62	0.12	-0.18
4	0.10	0.35	0.17	-0.19
5	-0.24	-0.01	0.09	-0.08
6	-0.34	-0.21	0.00	-0.02
7	-0.24	-0.22	-0.06	0.02
8	-0.06	-0.12	-0.06	0.04
9	0.07	-0.01	-0.03	0.03
10	0.11	0.06	0.00	0.02
11	0.09	0.07	0.02	0.00
12	0.03	0.05	0.02	-0.01
13	-0.02	0.01	0.01	-0.01
14	-0.04	-0.02	0.00	-0.01
15	-0.03	-0.02	0.00	0.00

Note: Transmission Mechanisms (TMs): TM1 refers to the response of GDP to its own stochastic shock. TM2 refers to the response of tourism income to the GDP shock. TM3 refers to the response of GDP to the tourism income shock. TM4 refers to the response of tourism income to its own stochastic shock. Duration is estimated approximately on visual inspection.

Table 14: Dynamic Convergence to Equilibrium: Trajectory Path, Maximum Magnitude and Duration

Transmission Mechanisms	Trajectory Path	Maximum Magnitude	Maximum Duration (in years)
TM1	Oscillating	1.00%	13-14
TM2	Oscillating	0.62%	12-13
TM3	Oscillating	0.15%	13-14
TM4	Oscillating	1.00%	6

Note: Transmission Mechanisms (TMs) as defined in Table 13. Duration is estimated approximately on visual inspection.

APPENDIX B: Spectral Analysis and VAR Models

Spectral Analysis

Important characteristics of the cyclical components of our series can be revealed by means of spectral analysis. The basic premise of spectral analysis, in its univariate version, is the decomposition of a stationary and ergodic time series in different frequencies and the estimation of amplitudes and phase shifts in individual time series. This decomposition allows for a more insightful view of the cyclical behaviour of series in comparison to the traditional time-domain analysis. An extension of the univariate spectral analysis, the bivariate cross-spectral analysis, employed in the present paper, attempts to find correlations at different frequencies. For example, the decomposition of the GDP in various frequencies might reveal that a periodic component of this series at some particular frequency (or frequencies) is correlated with a periodic component of the tourism income at the same frequency (or frequencies), a fact that traditional correlation analysis cannot show because it assigns equal weights at all frequencies.

Consider a real stationary and ergodic stochastic zero mean process x_t with autocorrelation function $\gamma_x(k)$ at the lag k. Then, the spectral density $s_x(\omega)$ (the spectrum) of x_t is defined as the Fourier transform of $\gamma_x(k)$, i.e. $s_x(\omega) = \frac{1}{2\pi}\int_{\infty}^{\infty} \gamma_x(k) e^{-ik\omega} dk$. This is a transform from time domain into frequency domain, where $\omega = 2\pi f, f = 1/T$ with T being the period of the x_t wave. Thus, by its definition, the spectrum of a series decomposes its total variation into frequencies of various periodic components. The 'typical' business cycle frequencies are between $\pi/16$ and $\pi/3$, corresponding to waves of 1.5 and 8 years, respectively. In a seasonally adjusted time series, frequencies below $\pi/3$ correspond to longer cycles (more than 8 years) and frequencies higher than $\pi/16$ correspond to cycles with shorter duration (less than 1.5 years), i.e. noise. In the same way we can define the spectrum $s_y(\omega)$ for another real zero mean process y_t as $s_y(\omega) = \frac{1}{2\pi}\int_{\infty}^{\infty} \gamma_y(k) e^{-ik\omega} dk$. Consider now two stationary and ergodic zero mean processes y_t and x_t with cross-correlation function $\gamma_{xy}(k)$ and its Fourier transform $s_{xy}(\omega) = \frac{1}{2\pi}\int_{\infty}^{\infty} \gamma_{xy}(k) e^{-ik\omega} dk$. This is the cross-spectral density of the two real processes x_t and y_t, which, however, is complex. Then, we define an index $h_{xy}(\omega)$ of comovement, called coherency, as $h_{xy}(\omega) = \frac{s_{xy}(\omega)}{\sqrt{s_x(\omega) \cdot s_y(\omega)}}$. Since this is a complex function of ω, its interpretation is difficult. Because of this undesired property of the coherency, the literature suggests a more convenient measure of comovement, called squared coherency, $h^2{}_{xy}(\omega)$, defined as $h^2{}_{xy}(\omega) = \frac{\left| s_{xy}(\omega)^2 \right|}{s_x(\omega) \cdot s_y(\omega)}$, a measure analogous to the coefficient of multiple determination R^2 in the regression context, for a particular frequency ω. But this index has the drawback that it is invariant with respect to a shift in the time process, that is, $h^2{}_{xy}(\omega) = h^2{}_{xz}(\omega)$ with z being a shifted process of x (i.e. $z_t = x_{t \pm k}$). It is exactly this disadvantage of the squared coherency that made Croux *et al* (*op.cit.*) to propose an alternative measure of comovement, called dynamic correlation, denoted as $\rho_{xy}(\omega)$ and defined as $\rho_{xy}(\omega)=\frac{c_{xy}(\omega)}{\sqrt{s_x(\omega)\cdot s_y(\omega)}}$ with $c_{xy}(\omega)$ being the real part (sometimes called co-spectrum) of the cross-spectral density $s_{xy}(\omega)$. This new index has the advantages that it is real, it takes values between -1 and 1 and depends on the shift in the time process. Therefore, it can be interpreted as a meaningful index of comovement between two processes.

We can also extend the definition of the dynamic correlation from a particular frequency ω to a frequency band, (e.g. the typical business cycle frequency band). Define the following bands: $\Omega=\Omega_+\cup\Omega_-$ with $\Omega_+=\left[\omega_1,\omega_2\right)$ and $\Omega_-=\left[-\omega_1,-\omega_2\right)$ with $0\leq\omega_1\leq\omega_2\leq\pi$. Then, the dynamic correlation coefficient between x_t and y_t over the frequency band Ω_+ is defined by $\rho_{xy}(\Omega_+)=\frac{\int_{\Omega+} c_{xy}(\omega)d\omega}{\sqrt{\int_{\Omega+} s_x(\omega)d\omega\cdot\int_{\Omega+} s_y(\omega)d\omega}}$. In the special case that $\omega_1=0$ and $\omega_2=\pi$, then the dynamic correlation coefficient coincides with the static correlation coefficient.

VAR Models

The transmission mechanism of stochastic shocks is discussed by means of a VAR model in the context of cointegration analysis. The VAR model of order n is defined as

$$\mathbf{y}_t = \mathbf{A}_1\mathbf{y}_{t-1} + \mathbf{A}_2\mathbf{y}_{t-2} + \ldots + \mathbf{A}_n\mathbf{y}_{t-n} + \mathbf{u}_t,$$

where $\mathbf{y}_t$ is a $m\times 1$ vector of endogenous variables, $\mathbf{A}_i$ $m\times m$ coefficient matrices, $\mathbf{u}_t$ a $m\times 1$ vector of stochastic disturbances, assumed to be white noise processes. In our paper $m=2$. After suitable rearrangements (see Favero, 2001; Enders, 1995) in order to achieve stationarity we end up with

$$\Delta\mathbf{y}_t = \sum_{i=1}^{n-1}\Pi_i\Delta\mathbf{y}_{t-i} + \Pi\mathbf{y}_{t-n} + \mathbf{u}_t = \sum_{i=1}^{n-1}\Pi_i\Delta\mathbf{y}_{t-i} + \alpha\beta'\mathbf{y}_{t-n} + \mathbf{u}_t.$$

where

$$\Pi_i = -(\mathbf{I} - \sum_{j=1}^{i}\mathbf{A}_j),$$

$$\Pi = -(\mathbf{I} - \sum_{i=1}^{n}\mathbf{A}_i),$$

and $\mathbf{I}$ is a $m\times m$ identity matrix.

This reparameterized form of the initial VAR is the Vector Error Correction Model (VECM). The rank k of matrix Π gives the statistical properties of the VAR. Full rank $k=m$ implies that VAR is stationary. $k=0$ implies that VAR is non-stationary but with no cointegrating equations. Reduced rank $k<m$ means k cointegrating equations. In this case Π can be decomposed as $\Pi=\alpha\beta'$ where α is $m\times k$ matrix of weights and β is a $m\times k$ matrix of parameters determining the cointegrating

relationships. The columns of β are interpreted as long-run equilibrium relationships between the variables and matrix α determines the speed of adjustment towards these equilibria. Values of the entries of α close to unity imply high inertia and slow convergence. The $\beta'\mathbf{y}_{t-1}$ term is the equilibrium error and is a measure of the deviation from the long - run equilibrium. The $\mathbf{A}$'s are $m \times m$ parameters matrices, corresponding to the lag structure of the model, determined, in practice, by an information criterion. In this paper we have adopted (among other criteria) the SIC (Schwartz Information Criterion, Schwartz, *op.cit.*) which is

$$SIC = -2l / T + q \log(T) / T ,$$

where $q = m(1 + pm)$ the total number of parameters in the VAR, m the number of equations, p the number of parameters per equation, l the log of the likelihood function under the hypothesis of the multivariate normal distribution of the error terms in the VAR and T the effective sample size. We select the lag which corresponds to the minimum value of SIC. Johansen (*op.cit.*) have developed a statistical procedure that allows the determination of the estimation of the VAR model. This procedure is based on the fact that the rank of a matrix equals its characteristic roots that differ from zero. Having obtained estimates for the Π matrix, we associate with them the estimates for the m roots of the characteristic polynomial (the characteristic roots) of Π and order them as follows: $\lambda_1 > \lambda_2 > ...\lambda_m$. If the variables are not cointegrated, then the rank of Π is zero and all the characteristic roots are zero. If, instead, the rank of Π is one and $0 < \lambda_1 < 1$, then $\ln(1-\lambda_1)$ is negative and $\ln(1-\lambda_2) = \ln(1-\lambda_3)... = \ln(1-\lambda_m) = 0$. Johansen (*op.cit.*) derives a test on the number of characteristic roots that are different from zero by considering the trace and the maximum eigenvalue statistics:

$$\lambda_{trace}(k) = -T \sum_{i=k+1}^{m} \ln(1-\hat{\lambda}_i) \text{ and } \lambda_{\max}(k, k+1) = -T \ln(1-\hat{\lambda}_{k+1}),$$

where T is the number of effective observations used to estimate the VAR. The trace statistic tests the null hypothesis that the number of distinct cointegrating vectors is less than or equal to k against a general alternative. The trace statistic is zero when all λ_i are zero. The further the estimated characteristic roots are from zero, the larger the trace statistic. The maximum eigenvalue statistic tests that the number of distinct cointegrating vectors is k against the alternative of $k+1$ cointegrating vectors. Once again, the further the estimated characteristic roots are from zero, the larger the maximum eigenvalue statistic. Both statistics are small under the null hypothesis. Therefore, high values imply evidence in favour of the alternative hypothesis. Critical values are tabulated by Johansen (*op.cit.*) and they depend on the number of the non-stationary components under the null and on the specification of the deterministic component of the VAR, both in the data and the cointegration space. Given that, in the present analysis, we employ the cyclical components of GDP and tourism income, it is expected that the VAR system is of full rank $k = 2$, i.e. it is stationary. Once VAR is estimated, the transmission of stochastic shocks to the system can be simulated by reparameterizing the VAR into a moving average representation, i.e. $\mathbf{y}_t = \mu + \sum_{i=0}^{\infty} \phi_i \varepsilon_{t-i}$, *where* μ, ϕ_i and ε_t are (structural) constants, coefficients and shocks, respectively. To achieve identification of the VAR system (a one-to-one mapping between the structural and the reduced-form parameters), we apply the Cholesky decomposition of the variance – covariance residual matrix, with the GDP cyclical component to be ordered first. This implies that structural shocks in GDP depend on the structural shocks of tourism income but not vice-versa.