FREIGHT TRANSPORT DEMAND MODELING: SPATIAL AND TEMPORAL ANALYSIS OF INTERNATIONAL FLOWS

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Abstract

This paper presents two approaches for modeling Chilean's freight transportation demand in the international scope. The final aim is to compare both methodologies in base of the goodness of fit results, and the prediction ability of each approach. The first method proposes a pure dynamic multivariate representation, i.e., a VAR model. The second approach corresponds to a STARMA specification, which considers both spatial and temporal interaction among the series. Both approaches were applied separately to Chilean's imports and exports demands. The VAR specification included external variables: the national or international GDP (for imports and exports respectively), and the real exchange rate. The results showed that the VAR specification was preferred to the STARMA model when the decision maker is interested in describing the phenomena taking place in each site. On the hand, if the aim is purely forecasting, the STARMA model should be preferred, due to smaller forecasting errors, and the fact that the STARMA model is more parsimonious.

Topic Area: D2 Freight Transport Demand Modelling

1. Introduction

The freight transportation system is a complex structure that affects a significant part of the economy of a nation. Its organization involves various factors, where the freight transportation demand (FTD) is a key component.

The literature shows different approaches to model the FTD according to an arbitrary classification scheme. Pendyala and Shankar (2000) mention that the modeling approaches differ in their level of complexity, geographic and temporal aggregation scale, and data requirements. Reagan and Garrido (2001) have classified models (on the basis of geographic field) into three groups; international, interurban and urban FTD models.

The literature presents three families of models for freight transportation analysis. Firstly, the standard theory of international trade that covers from the *absolute advantage* philosophy to the *spatial price equilibrium* theory introduced by Samuelson (1952), considering also the *ricardian* or *comparative advantage* concept and the *Heckscher-Ohlin* model (Isa and Garrido, 2001). The second approach is the input-output analysis introduced by Leontief (1973). The input-output tables describe transactions between producers and consumers in a certain region. This concept can be extended to a multiregional scenario, at different levels of geographical resolution. The third approach is based on time series analysis. There are several works that use this method to estimate and predict with FTD models. This type of methodology covers an extensive group of models that range from univariate to multivariate time series models with different forms of specification. They have the advantage that need fewer data; they can be used to obtain short-medium term forecasts, and allow incorporating a spatial component and. Therefore, this approach is the one that is followed in this paper, and their applications will be explained further on.

2. Theoretical Background

2.1. The VAR Model

The main advantages of modeling FTD with time series are: moderate data requirements, capability of making short/medium term forecasts and the possibility to incorporate a spatial component. Considering these advantages and after an exhaustive revision of the main specifications and applications of these models to FTD, the Vector Autorregression (VAR) models seem to be the most appropriate choice for a benchmark. Thus, the alternative specification is a Space-Time Autorregresive Moving Average (STARMA) model.

A VAR process of order p (VAR(p)), describes the dynamic interactions between k random variables according to the following specification:

$$y_t = c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \ldots + \Phi_p y_{t-p} + \varepsilon_t \qquad (1)$$

where y_t is a $(k \times 1)$ random vector, Φ_i are fixed $(k \times k)$ autorregresive coefficient matrices, c is a fixed $(k \times 1)$ vector of intercept terms, and ε_t is a $(k \times 1)$ *white noise* process[1]. Each component of the vector y_t is regressed against its own lags, as well as other variables lags to the p-th order. Another assumption implicit in these type of models is stationarity[2]. Unfortunately this assumption hardly holds in practice. The most common technique used to solve this problem in univariate cases, is the method of differentiation[3]. In multivariate cases this cannot be accomplished, because often the components of the vector y_t are interrelated, and this relationships can be distorted when a differentiation is applied. When this occurs, the variables are cointegrated.

A vector of series is cointegrated if each one of the series is integrated of first order, and exists a linear combination of them that follows a stationary process. The cointegration implies that even though each element of y_t can experiment permanent changes, there exists a long term equilibrium relationship represented by the above mentioned linear combination. The parameters associated to this relationship form the vector of cointegration. In most cases, there exists more than one relationship of cointegration, such that the result is a cointegration matrix composed by each of the

[1] A white noise process is a sequence of random variables that are not correlated, and have zero mean and constant variance.

[2] A stationary process assumes that the series remains in a certain equilibrium through time, with regard to a constant mean. In addition, the variance is also constant over time and the covariance between two time periods depends only on the lag between these periods.

[3] The method of differenciation creates a new random variable equivalent to the difference between the original series and itself, one lag apart. The new variable is known to be integrated of first order. An integration of greater order obviously implies differenciating more times, although the stationary is generally achieved with only one differenciation.

cointegration relationships. This matrix will be denoted hereafter by C, and its range is r, that corresponds to the number of cointegration relationships.

To include the cointegration matrix in the specification of the VAR model, the Vector Error Correction (VEC) representation seems to be the most appropriate (Engle and Granger, 1987). Its form is as follows:

$$\Delta y_t = v - HCy_{t-1} + F_1 \Delta y_{t-1} + \ldots + F_{p-1} \Delta y_{t-p+1} + u_t \qquad (2)$$

where Δ represents the first order differentiation of the vector of variables y_t, H is called loading matrix and contains the parameters associated to the cointegration matrix C, F_i corresponds to the parameter autorregresive matrix associated to the lag i, v is the fixed coefficients matrix, and u_t denotes the random disturbances associated to the model, which follow a white noise process. The hypotheses sustained for this specification are the same of those of the VAR process.

2.1.1. Applications to FTD

There are several applications of VAR and VEC processes to estimate demand functions for exports and imports. Moguillansky and Titelman (1993), Bahmani-Oskooee and Brooks (1999), Kulshreshtha, Nag and Kulshreshtha (1999), Veenstra and Haralambides (2000), Dutta and Ahmed (2001a, 2001b), Li, Luo and McCarthy (2002), are some examples.

Some authors propose to estimate separate FTD models for each economic sector, this is the case of Moguillansky and Titelman (1993) and Li Luo and McCarthy (2002). Others instead propose to estimate a single FTD model between a region and its major commercial partners, like in Bahmani-Oskooee and Brooks (1999). Another alternative is to estimate the FTD of a certain region considering a particular mode of transport, to measure its relevance in the economy of a nation. An example of this case is presented in Kulshreshtha, Nag and Kulshreshtha (1999). Veenstra and Haralambides (2000) present a combination of the latter approach and the one that disaggregates the flows by economic sectors.

2.2. The STARMA model

The STARMA model (Pfeifer and Deutsch, 1980a, 1980b) is characterized by the presence of spatial and temporal dependence. The independent variable $y_i(t)$ for the i-th site (i=1,…,N) is a linear combination of its own past observations and disturbances as well as its neighbors. Its specification is as follows,

$$y_i(t) = \sum_{k=1}^{p} \sum_{l=o}^{\lambda_k} \phi_{kl} \sum_{j=1}^{N} w_{ij}^{(l)} y_j(t-k) - \sum_{k=1}^{q} \sum_{l=0}^{m_k} \theta_{kl} \sum_{j=1}^{N} w_{ij}^{(l)} \varepsilon_j(t-k) + \varepsilon_i(t) \qquad (3)$$

where p denotes the autorregresive order, q is the moving average order, λ_k is the spatial order of the k-th autorregresive term, m_k corresponds to the spatial order of the k-th moving average term, $w_{ij}^{(l)}$ represents the spatial weight of order l[4] (Anselin, 1988) between sites i and j, ϕ_{kl} and θ_{kl} are parameters to be estimated and $\varepsilon_i(t)$ represents white noise random errors Normally distributed.

[4] The spatial weight is a measure of the interrelation between two sites.

The only applications of this model to FTD are the ones realized by Garrido (1998, 2000). In Garrido (1998), the FTD generation rate is considered as a stochastic process with both spatial and temporal interaction, which follows a STARMA process. Garrido (1998) concluded that the STARMA representation outperformed a purely time dependent specification.

Another application of the STARMA model is the one presented by Garrido (2000), where this process was used to model the truck flows trough the Mexico-Texas border. The results were employed to carry out an elasticity analysis to estimate short-term impacts of changes in the system at the operative level.

3. Model application

3.1. Methodology

In accordance with the different approaches to model FTD, this paper presents two approaches to model Chilean's FTD process. The first one is a multivariate dynamic model, which can be represented through a VAR or a VEC structure. This method suggests modeling separately the imports and exports demand function. For imports, the vector of exogenous variables considers the flow (traded goods per unit of time in CIF value), the national GDP, and the real exchange rate (to represent the price competition between the imported commodities and its national substitutes). In the exports case, the variables considered are the flow in FOB value, the international GDP, and the real exchange rate; these three variables have an analogous interpretation to the former case.

The second approach incorporates the spatial component, through a STARMA process (one for imports and another for exports). In both cases, the vector of variables only includes the flows of the different sites considered for each case, but there is no inclusion of exogenous variables. This representation assumes that the spatial interaction among the different locations account for a significant portion of the data variability.

The ultimate objective is to compare both methodologies in terms of goodness of fit, and prediction error.

3.2. Data Analysis

The data was obtained from a internet provider that supplies very detailed information about international flows. The period considered covered from January, 1997 to December, 2001, and the unit of time considered was the month.

Three modes were considered in this paper: maritime, air and land (excluding railway). The election of the border crossings to be considered was realized on the base of cargo movement, measured in CIF or FOB value, depending on the case. For the imports, four ports, one airport and one border crossing were considered For exports, six ports, one airport and one border crossing were considered.

3.3. Estimation

Several specifications were tried for each border crossing. In this section, only the best of them, (in terms of statistical significance of the estimated parameters, goodness of fit, parsimony, and whiteness and normality of the residuals) are described.

The first step was to estimate the vectors (or matrices) of cointegration. According to the results shown in Table 2, for most of the export models there was no evidence to reject the presence of cointegration. For these cases, different specifications were estimated, with and without considering cointegration. In the case of imports, only for one border crossing, the cointegration hypothesis was rejected; in this instance a VAR model was estimated considering first differences. For the rest of the export models, all of them had better results considering cointegration. The cointegration vectors are shown in Table 3 and 4 for exports and imports, respectively.

To improve the specification of the models, some dummy variables were added. In the case of imports, the observed seasonality during January and March with dummy variables. In the case of exports, there were shocks during January and February which were captured by two dummy variables. To take into account the evident seasonality that occurs every year, eleven dummies were added to the specification of the main port (Valparaíso). This approach was preferred to the differenciation technique, to avoid reducing the number of observations. All the dummies included are defined in the same way:

$$D_i \begin{cases} 1 & \text{if the time index corresponds} \\ & \text{to the month i} \\ 0 & \text{in other case} \end{cases} \qquad i = 1, 2, \ldots, 11 \qquad \textbf{(4)}$$

The results of the final estimations are shown in Table 5 and 6, for export and import models, respectively. Graphically, some examples of the fitness of certain models to the real data can be seen in Figures 3 to 8, where the predictions for the out-of sample are also reflected by dot lines. This topic will be discussed further on.

The results of each estimation showed good results in terms of goodness of fit. Even though some parameters are not statistically significant at 90% of confidence, they were not excluded because, the overall statistics would worsen if removed.

The examination of the residuals showed an adequate behavior in terms of accomplishment of the hypothesis associated to VAR processes. To check whiteness, the Portmanteau test (Lutkepohl, 1993) was applied, and the skewness and kurtosis test (Maddala, 1996) was used to verify normality. In conclusion, given these results, the best estimated models are statistically correct. These models correspond to the benchmark against which the alternative model will be compared.

3.4. Estimation of the STARMA Model

Two STARMA models were estimated to represent imports and exports. The series were analyzed to remove nonstationarities. In the case of imports, it was necessary to apply differentiation once, so the data used covered 59 observations. For the exports case, due to an evident associated to the port of Valparaíso, it was necessary to apply the following transformation:

$$\bar{z}_t = (1 - B)\left(1 - B^{12}\right) z_t \qquad \textbf{(5)}$$

where z_t corresponds to the original series, and B denotes the backshift lag operator (Box and Jenkins, 1976). The above expression shows that the first differentiation of twelve lags applied to the original series is used to remove seasonality, and the second one, of first order, looks for the removal of nonstationarities.

The W matrix was built taking into account the results from Garrido (1998) were the most suitable specification for W was the correlation between each pair of sites (i.e. the Pearson coefficient). The resulting W matrices in this research had dimension 8 and 6, for export and import models, respectively.

The estimation results for each model are shown in Table 7 and 8. The dummy variable that was added to the export model, took into consideration the high variations that were present in February, for most of the series. Some graphic results are shown Figures 3 to 8; in most of the cases the estimated series do not fit very well to the observed ones, as is reflected by the low values of goodness of fit (R^2).

The same hypotheses that were verified for the VAR models were checked for the estimated STARMA models. The Portmanteau test could not be applied in this case, because, the degrees of freedom associated to the statistic used to verify the hypothesis, were very large, such that their critical values were not tabulated. However, different LM tests were applied instead. The same normality tests associated to skewness and kurtosis were applied here. The results were very satisfactory, indicating that the models did fulfill the associated hypothesis.

4. Model comparison

To compare the two approaches studied in this paper, the goodness of fit results and the prediction ability were considered, as relevant indicators.

The results show that the models estimated using VAR or VEC specifications attain better goodness of fit than their STARMA counterpart. The latter is depicted in Figures 3 to 8.

Before the estimation process, a hold-out sample was selected to be used later to measure the predictive ability of the two modeling approaches.

The chosen forecasting method is based on the minimization of the mean squared error (MSE) (Maddala, 1996), equivalent to calculate the expected value of the series for the period of interest. In this case, this period covered from January, 2002, to May, 2002. These predictions were compared to the observed values.

Table 9 and 10 show the comparison results for exports and imports, respectively. The percentage of error was used as a term of comparison. Considering this indicator, there is no clear evidence of which method should be preferred. However, there is a small advantage of the STARMA models, over the others.

In econometric terms, clearly the STARMA specification is preferred, because the model is more parsimonious, and easier to estimate.

5. Conclusion

If the aim of the decision maker is to represent the phenomenon at each location and study their contemporaneous relations, it would be preferable to use a VAR specification, because the results indicate a better goodness of fit for this specification. In addition, the significance of the cointegration parameters indicate the presence of a long term equilibrium relation between the traded goods and other economic variables, which can be very helpful from a descriptive perspective.

On the other hand, if the objective is to use the estimated model for forecasting purposes, the STARMA model seems to be more suitable, because even though both specifications give similar predictions, the STARMA model is more parsimonious.

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APPENDIX 1: Figures

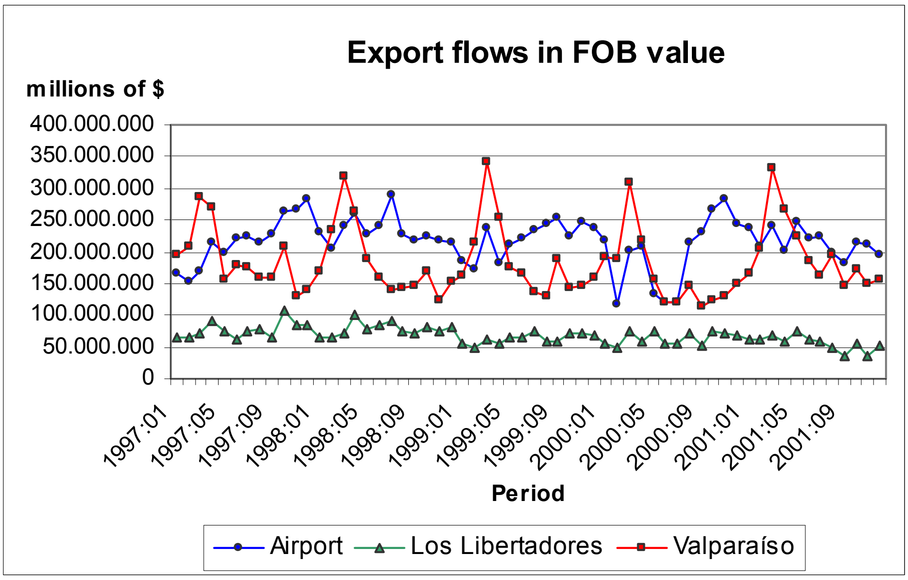

Figure 1: Some examples of export series

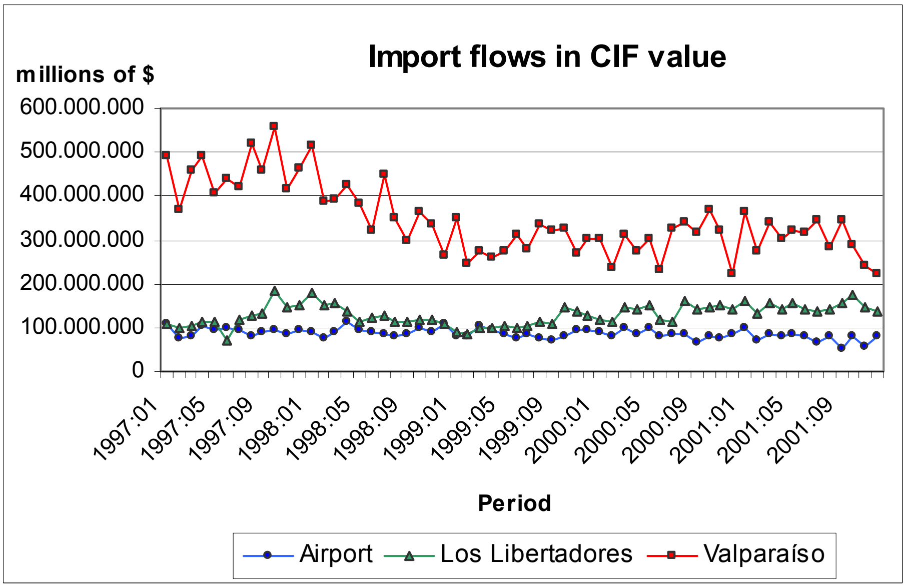

Figure 2: Some examples of import series

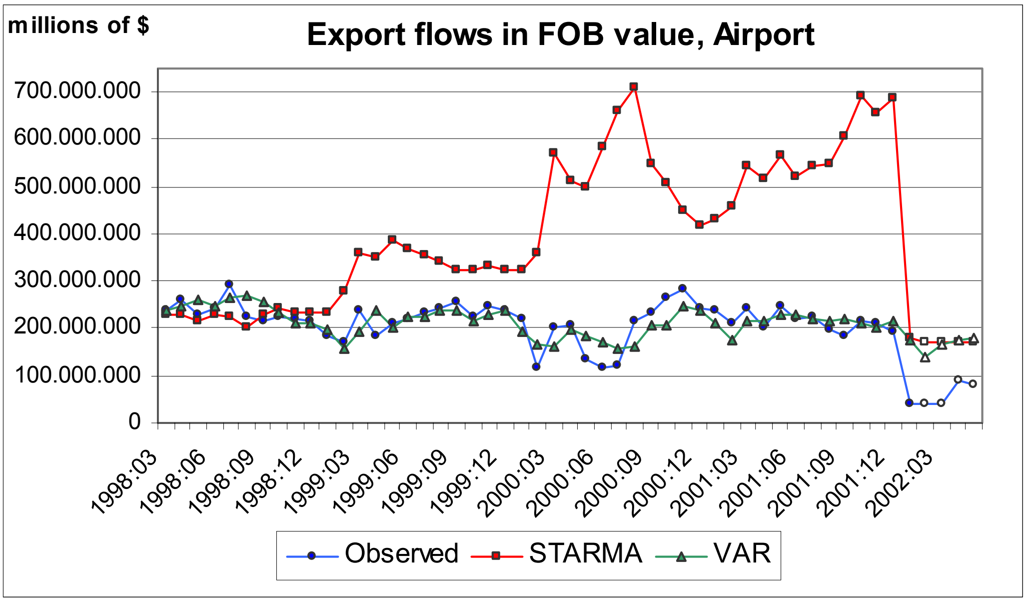

Figure 3: Graphic results of the application of both approaches to model the airport exports

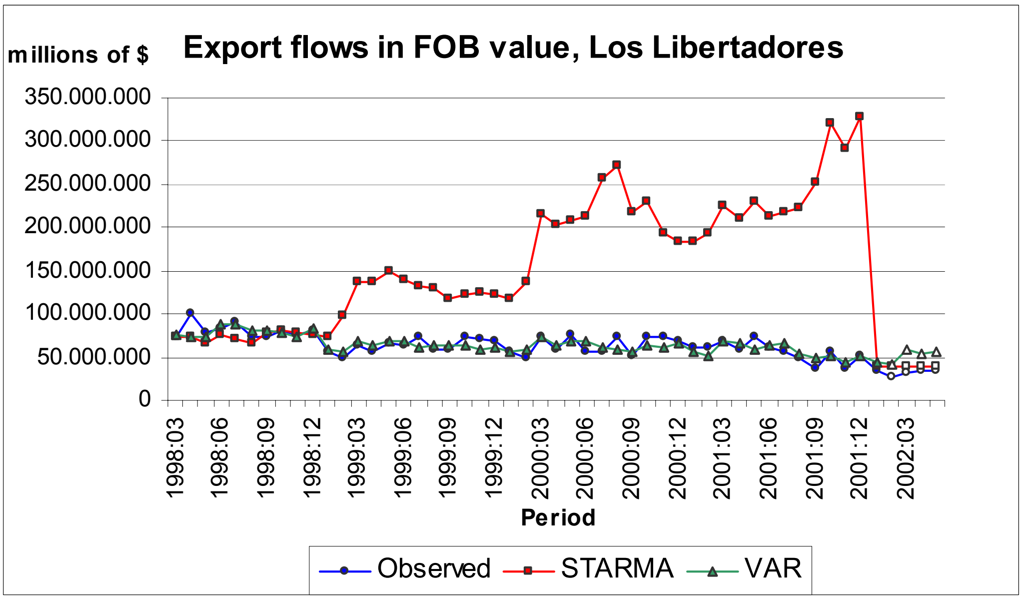

Figure 4: Graphic results of the application of both approaches to model Los Libertadores border crossing exports

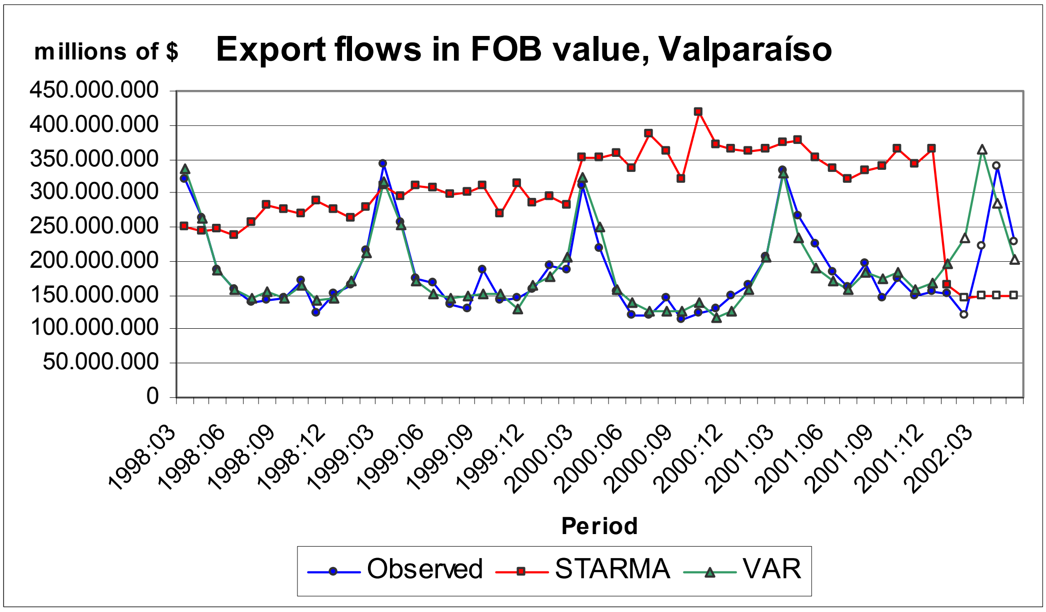

Figure 5: Graphic results of the application of both approaches to model Valparaíso exports

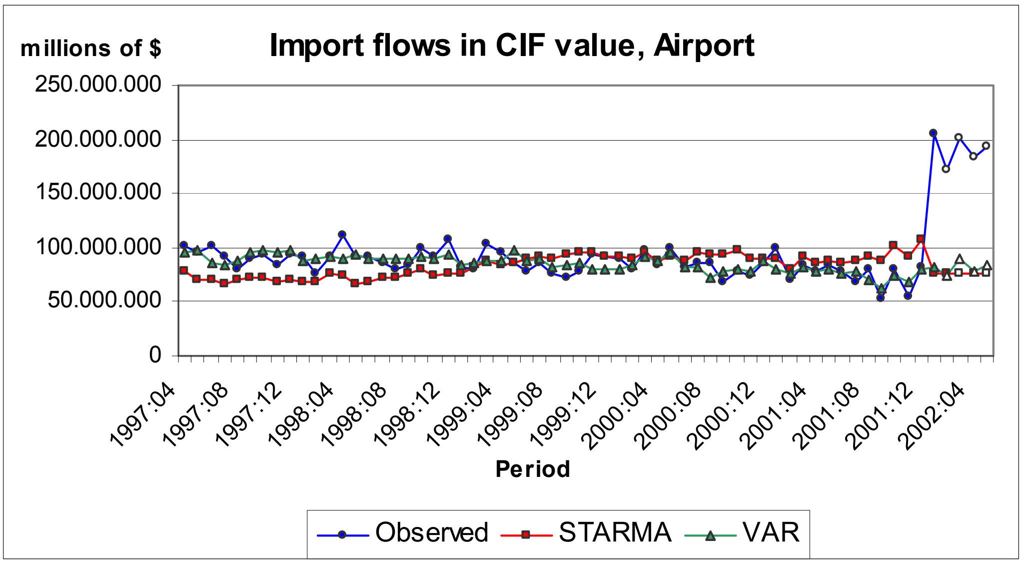

Figure 6: Graphic results of the application of both approaches to model the airport imports

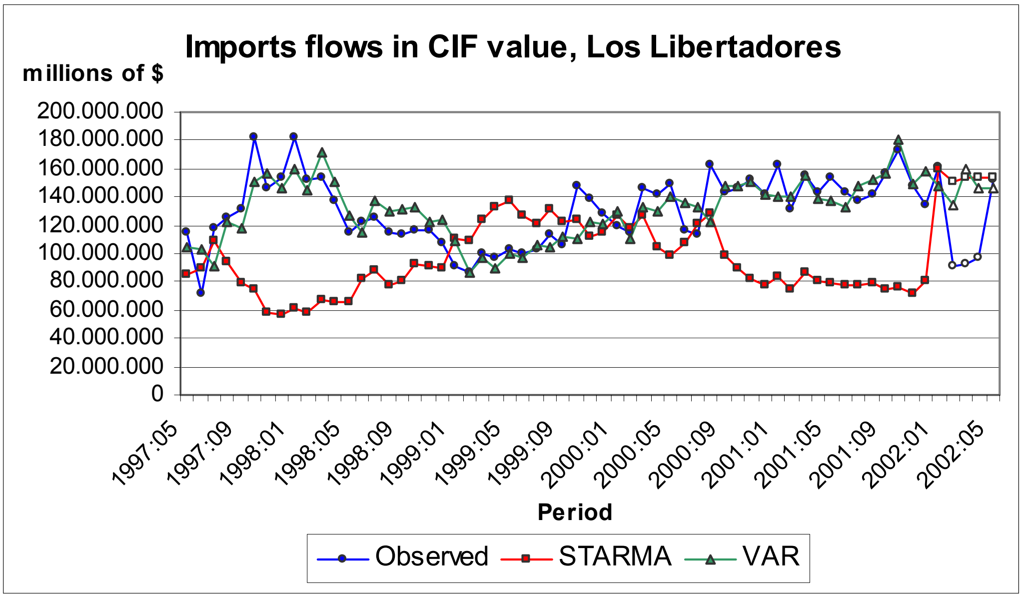

Figure 7: Graphic results of the application of both approaches to model Los Libertadores border crossing imports

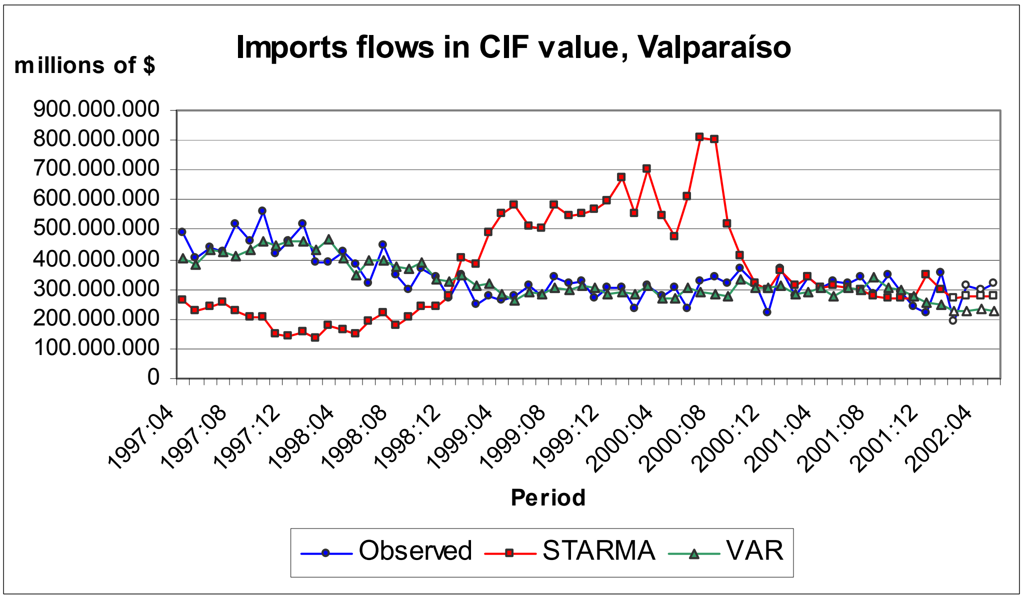

Figure 8: Graphic results of the application of both approaches to model Valparaíso imports

APPENDIX 2: Tables

Table 1: Results of the application of the ADF test[5]

VARIABLES	Levels (p=3)		Differences (p=2)		Conclusion	
	trend	no trend	trend	no trend	Level	Difference
Arturo Merino Benítez airport export flow (EXP_A1)	-28.23899	-26.71226	-109.28708	-108.02659	I(0)	I(0)
Los Libertadores border crossing export flow (EXP_F1)	-38.14783	-11.71466	-129.65483	-126.45923	I(1)	I(0)
Antofagasta port export flow (EXP_P1)	-24.60812	-10.46318	-206.92331	-207.08909	I(1)	I(0)
Arica port export flow (EXP_P2)	-15.87395	-7.22367	-160.60351	-158.26132	I(1)	I(0)
Caldera port export flow (EXP_P3)	-59.05415	-56.32274	-149.46116	-149.53043	I(0)	I(0)
San Antonio port export flow (EXP_P4)	-13.6701	-6.6216	-179.08667	-177.86023	I(1)	I(0)
Talcahuano port export flow (EXP_P5)	-14.32746	-4.12408	-307.69101	-304.42295	I(1)	I(0)
Valparaíso port export flow (EXP_P6)	-65.33298	-64.0186	-72.05215	-71.99604	I(0)	I(0)
Arturo Merino Benítez airport import flow (IMP_A1)	-56.28124	-16.97616	-151.33792	-149.85568	I(0)	I(0)
Los Libertadores border crossing import flow (IMP_F1)	-12.18296	-10.17541	-118.23109	-118.37621	I(1)	I(0)
Antofagasta port import flow (IMP_P1)	-11.73866	-10.06939	-157.27058	-156.99721	I(1)	I(0)
San Antonio port import flow (IMP_P2)	-12.25038	-8.78135	-123.07275	-122.53818	I(1)	I(0)
Talcahuano port import flow (IMP_P3)	-26.28483	-19.76251	-180.47601	-180.37816	I(0)	I(0)
Valparaíso port import flow (IMP_P4)	-8.62102	-2.70931	-212.53462	-212.58708	I(1)	I(0)
National GDP (PIB_N)	-43.78593	-3.63892	-116.32999	-116.2051	I(1)	I(0)
External GDP (PIB_E)	-4.60436	-1.78856	-61.17224	-59.65121	I(1)	I(0)
Real exchange rate (TC)	-16.68815	-1.99294	-41.39577	-37.209	I(1)	I(0)

[5] The 5% critical values of the ADF test correspond to –19.98 and-13.38, with and without trend, respectively. (Hamilton, 1994)

Table 2: Results of the application of the LR Johansen test

	Model (Abbreviation)	*λ-Max*			*Trace*			*Conclusion*
	H_0	**r = 0**	**r ≤ 1**	**r ≤ 2**	**r = 0**	**r ≤ 1**	**r ≤ 2**	
	H_1	**r = 1**	**r = 2**	**r=3**	**r = 1**	**r = 2**	**r = 3**	
EXPORTS	Arturo Merino Benítez Airport (EA1)	11.79	6.53	2.74	21.06	9.27	2.74	r = 0
	Los Libertadores Border crossing (EF1)	8.49	5.14	3.58	17.21	8.72	3.58	r = 0
	Antofagasta Port (EP1)	8.23	3.42	3.05	14.71	6.47	3.05	r = 0
	Arica Port (EP2)	25.68	3.76	1.87	31.31	5.63	1.87	r = 1
	Caldera Port (EP3)	20.75	3.97	1.55	26.27	5.52	1.55	r = 0
	San Antonio Port (EP4)	12.13	4.24	3.34	19.71	7.58	3.34	r = 0
	Talcahuano Port (EP5)	16.46	5.66	2.07	24.2	7.73	2.07	r = 0
	Valparaíso Port (EP6)	12.61	3.19	2.66	18.46	5.85	2.66	r = 0
IMPORTS	Arturo Merino Benítez Airport (IA1)	24.76	14.61	0.02	39.39	14.63	0.02	r = 1 or 2
	Los Libertadores Border crossing (IF1)	19.28	5.63	0.03	24.94	5.66	0.03	r = 0 or 1
	Antofagasta Port (IP1)	19.55	5.66	0.03	25.64	5.69	0.03	r = 0 or 1
	San Antonio Port (IP2)	17.38	4.63	0.07	22.08	4.7	0.07	r = 0
	Talcahuano Port (IP3)	19.5	13.27	0.12	32.89	13.39	0.12	r = 1 or 2
	Valparaíso Port (IP4)	17.51	2.86	0.15	20.52	3.01	0.15	r = 0
	Critical value at 5%	**21.28**	**14.6**	**8.08**	**31.26**	**17.84**	**8.08**	
	Critical value at 10%	**18.96**	**12.78**	**6.69**	**28.44**	**15.58**	**6.69**	

Table 3: Cointegration vectors estimated for each model of exports

MODEL	*COINTEGRATION VECTORS*	*VARIABLES*		
		EXP_Frontier Post	**PIB_E**	**TC**
Arturo Merino Benítez (Airport)	1	-6.504	-8.841	-1.999
	2	-3.111	4.599	7.979
Los Libertadores (Border Crossing)	1	-2.512	-25.622	18.979
Antofagasta (Port)	1	-8.291	5.385	-11.352
Arica (Port)	1	7.691	-44.088	10.083
	2	-0.183	-20.64	7.066
Caldera (Port)	1	-6.105	3.143	-5.57
	2	0.163	23.073	-9.705
San Antonio (Port)	1	8.597	-23.306	1.628
Talcahuano (Port)	1	-8.698	12.763	11.777
	2	0.996	23.443	-14.693
Valparaíso (Port)	1	-11.685	-28.571	22.371
	2	1.601	-6.637	-9.733

Table 4:Cointegration vectors estimated for each model of imports

MODEL	*COINTEGRATION VECTORS*	*VARIABLES*		
		IMP_Frontier Post	**PIB_E**	**TC**
Arturo Merino Benítez (Airport)	1	-19.459	-2.537	-14.028
Los Libertadores (Border crossing)	-	-	-	-
Antofagasta (Port)	1	0.772	26.072	-22.689
	2	2.834	1.845	1.84
San Antonio (Port)	1	0.728	-24.591	22.778
	2	-5.688	-3.7	-1.415
Talcahuano (Port)	1	2.9	14.775	-18.756
	2	-3.608	22.099	-10.778
Valparaíso (Port)	1	0.858	26.112	-22.374
	2	6.595	10.533	3.661

Table 5: Estimated models for exports

Regresors	MODEL (t-test in parenthesis)							
	EA1	EF1	EP1	EP2	EP3	EP4	EP5	EP6
$\Delta EXP\_Frontier\_Post_{t-1}$	-0.117 (-0.801)	-0.886 (-6.641)	-0.560 (-3.390)	0.243 (1.257)	-0.063 (-0.327)	-0.356 (-2.170)	-0.446 (-2.504)	-0.478 (-2.622)
$\Delta EXP\_Frontier\_Post_{t-2}$	-0.087 (-0.684)	-0.401 (-3.389)	-0.283 (-2.134)	0.067 (0.467)	-0.101 (-0.712)	-0.153 (-1.179)	-0.308 (-2.535)	-0.195 (-1.252)
ΔPIB_E_{t-1}	-1.439 (-0.709)	-2.168 (-1.139)	0.623 (0.323)	-4.301 (-1.239)	-6.256 (-1.773)	-1.008 (-0.493)	-3.383 (-1.440)	4.000 (2.301)
ΔPIB_E_{t-2}	-2.404 (-1.216)	0.164 (0.086)	1.315 (0.690)	-5.627 (-1.667)	5.037 (1.407)	-2.095 (-1.036)	0.306 (0.126)	-0.010 (-0.006)
ΔTC_{t-1}	-0.707 (-0.524)	-2.633 (-2.100)	-0.109 (-0.085)	2.965 (1.424)	1.951 (0.817)	1.029 (0.761)	0.006 (0.004)	-0.630 (-0.560)
ΔTC_{t-2}	2.200 (1.528)	-2.035 (-1.563)	-0.606 (-0.474)	-0.690 (-0.326)	2.523 (1.056)	-3.075 (-2.325)	-3.373 (-2.071)	0.269 (0.220)
EC_1	0.063 (3.078)	-0.015 (-0.756)	0.053 (2.652)	-0.153 (-4.737)	0.123 (3.350)	-0.071 (-3.399)	0.092 (3.815)	0.036 (2.330)
EC_2	0.010 (0.481)	-	-	0.002 (0.051)	-0.019 (-0.505)	-	0.011 (0.455)	-0.009 (-0.563)
Constant	19.315 (2.908)	-7.058 (-0.750)	5.382 (2.640)	-109.277 (-4.130)	16.457 (1.024)	-21.793 (-3.396)	-18.500 (-1.671)	23.843 (2.165)
D_1	-0.112 (-1.298)	-0.314 (-3.929)	-	-	-	-	-	0.170 (1.842)
D_2	-0.288 (-3.324)	-0.324 (-3.745)	-	-	-	-	-	0.342 (3.312)
D_3	-	-	-	-	-	-	-	0.738 (6.538)
D_4	-	-	-	-	-	-	-	0.349 (2.167)
D_5	-	-	-	-	-	-	-	-0.152 (-1.009)
D_6	-	-	-	-	-	-	-	-0.241 (-1.818)
D_7	-	-	-	-	-	-	-	-0.192 (-1.826)
D_8	-	-	-	-	-	-	-	-0.038 (-0.456)
D_9	-	-	-	-	-	-	-	-0.064 (-0.733)
D_{10}	-	-	-	-	-	-	-	0.043 (0.543)
D_{11}	-	-	-	-	-	-	-	-0.176 (-1.988)
goodness of fit (R^2 value)	**0.458**	**0.618**	**0.544**	**0.486**	**0.488**	**0.534**	**0.711**	**0.851**
Durbin-Watson statistic	**1.841**	**2.021**	**2.072**	**1.828**	**2.102**	**1.914**	**2.007**	**1.965**

Table 6: Estimated models for imports

Regresors	***MODEL (t-test in parenthesis)***					
	IA1	**IF1**	**IP1**	**IP2**	**IP3**	**IP4**
$\Delta IMP\_Frontier\_Post_{t-1}$	0.134 (0.531)	-0.343 (-2.283)	-0.222 (-1.442)	-0.180 (-1.233)	-0.254 (-1.514)	-0.680 (-4.433)
$\Delta IMP\_Frontier\_Post_{t-2}$	0.144 (0.731)	-0.242 (-1.635)	-0.206 (-1.464)	-0.143 (-0.979)	-0.064 (-0.458)	-0.356 (-2.549)
$\Delta IMP\_Frontier\_Post_{t-3}$	-	0.100 (0.688)	-	-	-	-
ΔPIB_N_{t-1}	-0.441 (-0.855)	-1.870 (-3.334)	-1.533 (-1.135)	-1.406 (-2.296)	-1.590 (-1.267)	-0.870 (-1.447)
ΔPIB_N_{t-2}	0.620 (1.225)	-1.558 (-2.559)	-2.679 (-2.308)	-1.455 (-2.773)	-2.577 (-2.412)	-0.740 (-1.467)
ΔPIB_N_{t-3}	-	-1.193 (-2.283)	-	-	-	-
ΔTC_{t-1}	-0.151 (-0.143)	-1.417 (-1.151)	-0.519 (-0.177)	-0.620 (-0.477)	-0.993 (-0.385)	0.795 (0.645)
ΔTC_{t-2}	-1.552 (-1.614)	-0.057 (-0.044)	2.207 (0.759)	-0.178 (-0.137)	-7.851 (-3.036)	-0.509 (-0.417)
ΔTC_{t-3}	-	-0.427 (-0.361)	-	-	-	-
EC_1	0.067 (4.817)	-	0.014 (0.296)	-0.012 (-0.586)	-0.090 (-2.228)	0.015 (0.779)
EC_2	-	-	-0.100 (-2.166)	0.040 (1.948)	0.110 (2.710)	-0.029 (-1.512)
Constant	30.419 (4.814)	0.054 (2.073)	4.440 (0.310)	3.859 (0.614)	-7.124 (-0.605)	4.176 (0.502)
D_1	0.103 (1.748)	-0.011 (-0.136)	-	-	-	-
D_2	-0.094 (-1.576)	-0.202 (-2.668)	-	-	-	-
D_3	0.091 (1.346)	-0.071 (-0.785)	-	-	-	-
goodness of fit (R^2 value)	**0.701**	**0.430**	**0.350**	**0.344**	**0.587**	**0.526**
Durbin-Watson statistic	**2.217**	**1.960**	**1.993**	**1.797**	**1.984**	**2.078**

Table 7: Results of the estimation of the STARMA model for exports

Parameters	***Estimated value***	***Test-t value***
Autorregresive (AR)	-0.166321795	-3.247287048
Moving Average (MA)	0.226345941	5.522520927
Dummy	-0.106629341	-2.832402704
goodness of fit (R^2)	**0.256387516**	

Table 8: Results of the estimation of the STARMA model for imports

Parameters	***Estimated value***	***Test-t value***
Autorregresive (AR)	-0.125355419	-1.259069501
Moving Average (MA)	0.253749379	3.847765336
goodness of fit (R^2)	**0.262718275**	

Table 9: Forecasting percentage errors for VAR and STARMA exports predictions

Prediction horizon	***EA1***		***EF1***		***EP1***		***EP2***	
	VAR	STARMA	VAR	STARMA	VAR	STARMA	VAR	STARMA
2002:01	-320.92%	-329.46%	-32.29%	-18.82%	27.79%	35.95%	-89.84%	-34.04%
2002:02	-248.61%	-332.74%	-61.34%	-52.90%	17.04%	28.65%	-78.06%	19.88%
2002:03	-294.44%	-306.36%	-82.01%	-23.45%	10.82%	34.34%	-88.59%	-4.57%
2002:04	-96.05%	-92.44%	-57.71%	-17.99%	1.82%	40.14%	-0.69%	39.78%
2002:05	-123.76%	-114.35%	-57.86%	-10.71%	-21.33%	38.67%	-3.90%	36.93%

Prediction horizon	***EP3***		***EP4***		***EP5***		***EP6***	
	VAR	STARMA	VAR	STARMA	VAR	STARMA	VAR	STARMA
2002:01	12.46%	-5.83%	-45.59%	-15.45%	64.80%	-6.84%	-28.42%	-8.47%
2002:02	-12.09%	-45.78%	-51.50%	-16.69%	49.12%	-19.65%	-95.01%	-20.88%
2002:03	8.06%	-9.87%	-31.43%	-1.49%	52.76%	-19.71%	-64.16%	32.63%
2002:04	0.34%	-7.12%	-1.98%	24.34%	65.77%	7.16%	16.22%	56.12%
2002:05	13.92%	2.06%	-10.21%	10.56%	59.77%	-6.39%	11.66%	34.51%

Table 10: Forecasting percentage errors for VAR and STARMA imports predictions

Prediction horizon	IA1		IF1		IP1	
	VAR	STARMA	VAR	STARMA	VAR	STARMA
2002:01	59.69%	63.15%	8.51%	1.09%	16.65%	2.83%
2002:02	56.14%	56.00%	-47.23%	-66.44%	-51.10%	-57.92%
2002:03	54.70%	62.19%	-72.79%	-66.85%	27.05%	1.06%
2002:04	57.33%	58.98%	-50.23%	-57.85%	34.73%	21.91%
2002:05	56.63%	60.83%	3.29%	-1.21%	31.72%	19.99%

Prediction horizon	IP2		IP3		IP4	
	VAR	STARMA	VAR	STARMA	VAR	STARMA
2002:01	14.61%	-3.04%	-80.39%	-17.06%	28.87%	16.55%
2002:02	-41.16%	-52.85%	-102.64%	-25.60%	-17.66%	-40.42%
2002:03	-1.00%	-19.47%	-73.18%	-20.34%	27.77%	11.16%
2002:04	-9.67%	-25.75%	-206.36%	-102.72%	21.34%	7.80%
2002:05	16.00%	4.04%	-28.51%	10.58%	28.28%	13.19%