Intermodal Competition and Temporal Interdependencies in Passenger Flows: Evidence from Emerald Coast

Massimiliano Castellani. Department of Economics, University of Bologna, Bologna, Italy and The Rimini Centre for Economic Analysis (RCEA), Rimini, Italy. E-mail: m.castellani@unibo.it

Pierpaolo Pattitoni. Department of Management, University of Bologna, Bologna, Italy and The Rimini Centre for Economic Analysis (RCEA), Rimini, Italy. E-mail: pierpaolo.pattitoni@unibo.it

Lorenzo Zirulia. Corresponding Author. Department of Economics, University of Bologna, Bologna, Italy, The Rimini Centre for Economic Analysis (RCEA), Rimini, Italy, and CRIOS, Bocconi University, Italy. Address: University of Bologna, Department of Economics. Piazza Scaravilli 2, 40126 Bologna, Italy. Phone: +39.051.2098888. Fax: +39.051.2098040. E-mail: lorenzo.zirulia@unibo.it

Abstract
This chapter analyses the effects of intermodal competition on the time series of passenger flows. Our conceptual framework suggests negative correlations of arrivals, both within and across transport modes, during low-season periods, and positive correlations during high-season periods. Using daily passenger arrivals at the airport and seaport of Olbia, from 2005 to 2008, and Threshold-VAR models to test these suggestions, the findings support our conceptual framework.
Keywords: intermodal competition, passenger arrivals, Threshold-VAR.
JEL Classification: R4; L91; C32.

X.1 Introduction

Travellers commonly perceive available transport modes (e.g. planes and ships) as substitutes, forcing transportation providers into competition for the same routes. Existing research in the literature on intermodal competition focuses on the determinants of traveller preference (Park and Ha 2006; Rigas 2009; Behrens and Pels 2012; De Witte et al. 2013) and

the effects of intermodal competition on prices and quality of service (Ivaldi and Vibes 2008; Bilotkach et al. 2010; Albalate et al. 2015).

Another strand of transport literature focuses on time series analysis of passenger flows. Most of these studies analyse univariate or multivariate air passenger arrival time series using monthly data (e.g. Jorge-Calderón 1997; Abed et al. 2001; Marazzo et al. 2010; Castellani et al. 2011; Tsui et al. 2014) and, to a lesser extent, higher-frequency data such as daily time series (e.g. Haldrup et al. 2007; Divino and McAleer 2010; Chen and Wei 2011).

Very little attention has been paid, however, to the connection between the two lines of research, i.e. intermodal competition and time series analysis of passenger flows. This is surprising, since in contexts where intermodal competition does matter, time series models that do not consider intertemporal interdependencies may be problematic, and the analyses based on them, such as forecasting exercises, flawed. In order to start filling this gap, we develop a Threshold-VAR (TVAR) regression model that simultaneously takes into account the intertemporal interdependencies between the airport and seaport arrival time series generated by the intermodal competition and the existence of (possibly) multiple time regimes due to the temporal heterogeneity in traveller preferences. Our analysis focuses on daily passenger arrivals at Olbia (Italy) airport and seaport from 2005 to 2008. Olbia is a major regional logistics hub, and the most populous city of north-eastern Sardinia, the second largest island in the Mediterranean Sea. Situated on the Emerald Coast, Olbia is a well-established elite tourist destination, and one of the most exclusive seaside resorts of Europe.

This island provides an ideal setting to test the implications of intermodal competition for passenger arrival time series, since travellers can only arrive by air or sea, meaning these two modes of transport are (at least partially) substitutable and in competition with each other. Additionally, the distribution of traveller preference for mode of transport is likely

characterized by a certain degree of temporal heterogeneity across the year, since tourists typically travel during the summer period.

Our results show that intertemporal interdependencies and multiple time regimes do indeed exist. In particular, we find negative correlations in the two time series both within (autocorrelation) and across (cross-correlation) transport modes when the level of demand is low (i.e. in the low-season regime) and positive correlations (at one lag) when the level of demand is high (i.e. in the high-season regime). In addition, during the high season, the strongest correlation is observed within the mode (instead of across modes).

These empirical results are interpreted within a conceptual framework that includes key factors such as traveller preferences for both mode of transportation and departure date, and capacity constraints in the transport mode. We argue that capacity constraints may explain the opposite sign in the correlation of arrival time series (both within and across transport modes) observed for the low and high seasons. The heterogeneity in the travellers' preferences (and specifically a stronger relative preference for the transport mode over the departure date) may explain the strongest correlation observed within the mode in the high season.

The remainder of the chapter is structured as follows. Section X.2 presents the conceptual framework; Section X.3 is concerned with the empirical analysis; Section X.4 provides a brief discussion of results; and, finally, Section X.5 concludes.

X.2 A conceptual framework

Our premise recognizes that passenger flows (with intermodal competition) should be analysed within a framework accounting for the choice travellers must make between the

different transport modes.[1] In a static perspective, travellers' choices will be determined by preferences for modes and prices. At equal prices, each traveller will choose the mode containing the largest amount of characteristics she attaches more value to. However, a sufficiently large price differential may reverse consumer choices. In a dynamic framework, travellers also value the departure date. In fact, as economic theory suggests, different goods or services offered on different dates can indeed be treated as different goods (Mas-Colell et al. 1995). In some cases, such as for instance for business travellers or in the case of demand associated with specific events, the departure date may indeed be the most relevant characteristic, but in general travellers can be characterized by a certain degree of flexibility regarding their departure dates.

Therefore, what becomes relevant is the relative importance the travellers attach to mode and departure date. Some travellers may have a strong preference for mode, so that, if their preferred mode is not available on their preferred date because of exhausted capacity, they prefer to keep the mode but change the date. Other travellers, however, may have relatively weak preferences for the mode, which would lead to the opposite choice. For instance, with reference to our empirical application, long-distance travellers from Sardinia (and in particular travellers for whom reaching ports is particularly expensive) clearly have a strong preference for the air mode, while travellers who intend to bring their own car to the island (e.g. tourists) have a strong preference for the ship mode. Other travellers could assign more importance to price and thus less to the mode.

In order to derive the implications of our approach for temporal interdependencies in passenger flow, we point out that the relative preference for the mode only matters when the risk that the capacity for a specific mode on a specific date might become exhausted is substantial. In our empirical analysis, we first specifically consider two "seasons" (regimes)

[1] See De Witte et al. (2013) for a recent survey of the empirical literature on modal choice.

over the year, corresponding to different levels of overall demand for transport services by travellers: during the low season capacity constraints are not binding; during the high season capacity constraints are binding.

During the low season, travellers are always able to select their preferred mode and date. Since the level of the demand is low, positive demand shocks (for a specific transport mode) are typically more intense than negative ones and are immediately followed by a reversal adjustment in the time series, thereby generating negative auto and cross-correlation, i.e. within and between modes. The above argument is summarized in the following proposition.

Proposition 1 *In low season, the passenger arrival time series are characterized by negative autocorrelation (within mode) and cross-correlation (between modes).*

In the high season, the capacity for travellers' preferred date and mode can be exhausted. In this case, travellers' choices will depend on the strength of their relative preference for the mode: travellers with strong preferences for the mode will prefer to keep the mode and change the date; consumers with weak preferences for the mode will make the opposite choice. While the existence of travellers with strong preferences for the mode generates positive autocorrelation in the within-mode arrival time series, the presence of travellers with weak preferences for the mode generates positive cross-correlation across the two time series. In addition, the distribution of preferences among travellers, and in particular the prevalence of strong or weak preferences, affects the magnitude of the correlation coefficients. The following proposition summarizes our argument.

Proposition 2 *In high season:* i) *if some travellers have strong preferences for the mode, autocorrelations of arrivals are positive;* ii) *if some travellers have weak preferences for the mode, cross-correlations of arrivals are positive;* iii) *if travellers with strong preferences are*

more frequent in the population than travellers with weak preferences, the magnitude of the autocorrelation is greater than that of cross-correlation.

X.3 Empirical set-up

In this section, we first describe our data set (Section X.3.1). Then we estimate two TVAR regression models. In Section X.3.2, we initially consider a reduced model with one lag and two regimes. Then, we extend the model to a number of lags and regimes that are endogenously (and optimally) determined, and we discuss the empirical results in light of our conceptual analysis.

X.3.1 Data set description

Our data set includes daily passenger arrivals at Olbia airport and port from 1 January 2005 to 31 December 2008 (1095 observations). We gathered our data from the Olbia airport Management Company (airport arrivals) and the Italian Ministry of Transportation and Navigation (port arrivals).[2]

Figure X.1 plots the two series, which present a clear seasonal pattern: arrivals tend to be concentrated during the summer and reach the lowest values during the winter. Table X.1 presents some descriptive statistics using both the levels and logarithms of the two series. Port arrivals exhibit a higher average and median than airport arrivals. However, airport arrivals show a higher range of variation, standard deviation and coefficient of variation, indicating a more heterogeneous behaviour than the port. Both series are non-symmetrical and leptokurtic, implying non-normality. Indeed, normality tests indicate that both series (in

[2] While all port arrivals are from Italy, a third of airport arrivals are from abroad. Sardinia has three international airports (Alghero Airport, Olbia Costa Smeralda Airport and Cagliari Elmas Airport) and seven ports (Porto Torres, Olbia, Golfo Aranci, Arbatax, Santa Teresa Gallura, Palau and Cagliari). Most of the passengers directed to Costa Smeralda arrive at Olbia airport and port, i.e. those that we analyse in our research.

levels and logarithms) are non-normal, the only exception being the logarithm of the port series.[3]

Before analysing the stochastic interdependence of airport and port arrivals, we removed from our series any deterministic component. In particular, we use auxiliary regression models in which the logarithm of the two series is regressed on a deterministic trend, and on a set of dummies that account for any year, month and day-of-the-week effects. Table X.2 shows the results. The trend component is statistically non-significant for both series. However, year, month and day-of-the-week effects are all statistically significant. Arrivals are concentrated in July and August, and during the weekend. Conversely, October and November, and the working days register the lowest values of arrivals. The residuals of these auxiliary regression models (i.e. the deseasonalized series) are used in the following empirical analyses and are referred to as airport and port arrivals for simplicity.

The stationarity of airport and port arrivals is assessed using the Augmented Dickey-Fuller test (ADF), the Phillips-Perron test (PP) and the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS). In Table X.3, we present our results. The ADF and PP tests strongly rejected the null hypothesis of unit root for both series, and the KPSS test reinforces this conclusion by not rejecting the null hypothesis of stationarity.

X.3.2 Threshold-VAR models

One lag and two regimes We first model airport and port arrivals (denoted by y_{At} and y_{Pt}) through a bivariate TVAR model with two regimes, corresponding to the low and high

[3] Considering the whole time period (2006–08), the ratio between airport arrivals and total arrivals is about 36%. However, this ratio is significantly higher during the summer and at the weekend. This result may suggest that tourists, who travel mostly during the summer, prefer aeroplanes over ships for their travel. The opposite applies to non-tourists.

seasons (denoted by the superscript L and H respectively), and one lag of each dependent variable. Following Tsay (1998 and 2005), our TVAR model takes the form:

$$\begin{cases} \begin{bmatrix} y_{At} \\ y_{Pt} \end{bmatrix} = \begin{bmatrix} c_A^L \\ c_P^L \end{bmatrix} + \begin{bmatrix} \phi_{AA}^L & \phi_{AP}^L \\ \phi_{PA}^L & \phi_{PP}^L \end{bmatrix} \begin{bmatrix} y_{At-1} \\ y_{Pt-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{At}^L \\ \varepsilon_{Pt}^L \end{bmatrix} & \text{if} \quad y_{At-2} + y_{Pt-2} \le \theta \\ \begin{bmatrix} y_{At} \\ y_{Pt} \end{bmatrix} = \begin{bmatrix} c_A^H \\ c_P^H \end{bmatrix} + \begin{bmatrix} \phi_{AA}^H & \phi_{AP}^H \\ \phi_{PA}^H & \phi_{PP}^H \end{bmatrix} \begin{bmatrix} y_{At-1} \\ y_{Pt-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{At}^H \\ \varepsilon_{Pt}^H \end{bmatrix} & \text{if} \quad y_{At-2} + y_{Pt-2} > \theta \end{cases} \tag{X.1}$$

where all c s and ϕ s are parameters to be estimated, and all ε s are serially uncorrelated error terms. We choose the sum of lagged airport and port arrivals (total arrivals) as a threshold variable.[4] If this sum is below the threshold value θ, the two series are in the low season; the opposite applies if total arrivals are above θ. θ has been chosen from a grid of values taking the best fit as the final estimate. In light of our two propositions, we expect:

1. ϕ_{AA}^L, ϕ_{AP}^L, ϕ_{PA}^L, ϕ_{PP}^L <0 (negative auto and cross-correlations in the low season);

2. ϕ_{AA}^H, ϕ_{AP}^H, ϕ_{PA}^H, ϕ_{PP}^H >0 (positive auto and cross-correlations in the high season). Also, $\phi_{AA}^H > \phi_{AP}^H$ and $\phi_{PP}^H > \phi_{PA}^H$ will suggest a predominance of travellers with strong preferences for the mode.

Table X.4 presents the results. The estimated coefficients are consistent with our propositions. In the low-season case, all coefficients are negative (although the lagged value for port is not statistically significant in the port equation). Similarly, in the high-season case, all coefficients are positive. Also, we notice that coefficients within modes are always greater than coefficients across modes, suggesting that for the air and sea transport modes travellers with strong preferences for mode over date of departure are the majority. The difference

[4] Our threshold variable is stationary according to the results of ADF, PP and KPSS tests. We considered lagged values of airport and port arrivals as alternative threshold variables. Since, in our application, results are unaffected by the choice of the threshold variables, we continue our analysis using total arrivals.

between the coefficients is larger for the airport arrival time series, suggesting that for the "air-oriented" travellers in the high season (which include also foreign tourists), the sea mode option is considered only a weak substitute.[5]

Extended model In the previous section, we estimated a bivariate TVAR model with two regimes and one lag of each dependent variable. In this section, we propose an extension of that model which allows for an arbitrary number of regimes and autoregressive order. This extended model takes the form:

$$\begin{bmatrix} y_{At} \\ y_{Pt} \end{bmatrix} = \begin{bmatrix} c_A^j \\ c_P^j \end{bmatrix} + \sum_{i=1}^{n} \begin{bmatrix} \phi_{iAA}^j & \phi_{iAP}^j \\ \phi_{iPA}^L & \phi_{iPP}^L \end{bmatrix} \begin{bmatrix} y_{At-i} \\ y_{Pt-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{At}^j \\ \varepsilon_{Pt}^j \end{bmatrix} \quad \text{if} \quad \theta_{j-1} < y_{At-n-1} + y_{Pt-n-1} \leq \theta_j \tag{X.2}$$

where $j = 1, \ldots, s$ is a superscript indicating the regime that the two series are in, s is the maximum number of regimes and n is the autoregressive order.

We used likelihood ratio tests to choose the number of regimes. In particular, we followed Lo and Zivot (2001), who proposed a multivariate extension of the linearity test of Hansen (1999). Their test compares the covariance matrices of each model and has non-standard asymptotic distribution. We used bootstrap methods to compute approximate p-values. We limited the maximum number of regimes to three. First, we checked the need to use a threshold model testing a simple VAR model (one regime) against both a two-regime TVAR model and a three-regime TVAR model. Then, we tested the two-regime TVAR model against the three-regime TVAR model. The test results, reported in Table X.5, suggest choosing a specification with three regimes ($s = 3$).

[5] In the text, we comment on the economic difference between the coefficients. This comparison is possible as the scale of the two dependent variables after the logarithmic transformation is approximately the same. With regard to the statistical significance (tests are not reported), we found a statistical difference between the coefficients in the airport equation but no statistical difference between the coefficients in the port equation.

For any given n and keeping $s = 3$ fixed, all θ_j have been chosen from a grid of values taking the best fit as the final estimate. Multivariate BIC has been used to detect the autoregressive order of the model. In particular, limiting the maximum autoregressive order to 31, we choose $n = 2$. The estimated model is, thus, a TVAR model with three regimes and two lags of each dependent variable.

Table X.6 presents the estimation results. The interdependence between the arrivals at Olbia via airport and port is confirmed. While in the first and in the third regimes we observe a bidirectional feedback between the series, in the second regime the lag structure suggests that the airport Granger causes port. As for the signs of the coefficients, these can be interpreted in light of the conceptual framework. Regime 1 corresponds to the low-season case, and, as expected, it gives rise to negative coefficients. Regime 3, corresponding to high season, shows all positive coefficients for the first lag. Regime 2, which is an intermediate case, exhibits mixed results, although it appears more similar to the high-season case (the first lag coefficients that are statistically significant are all positive). A final aspect we can comment upon is that second lags always have a negative sign. One way to account for this is to rely on a mechanism similar to the one we hypothesized for the low-season case, i.e. a negative coefficient may be observed if a positive shock for demand in a given period reduces the probability that travellers "appear" later on.

X.4 Discussion

As we indicated in the Introduction, our work is intended as a first step toward bridging the gap between two streams of literature, i.e. intermodal competition and time series analysis. In that respect, beyond the specific case of interest, our chapter may have a pedagogical value in showing the opportunities raised by considering the complex interplay of factors that

influence travellers' preferences regarding transportation modes and intermodal competition dynamics. These may concern other forms of intermodal competition (e.g. high-speed trains vs planes) and other data frequencies (e.g. weekly data).

As for implications, we deem that our contribution, and other works along these lines, may be relevant for both public and private decision-makers. On the one hand, policymakers are interested in forecasting the passenger demand to make decisions about investments in transport infrastructure and, thus, improve the transport efficiency and the quality of the supplied services (Tsekeris 2011), or in evaluating the impact of negative shocks induced by phenomena such as natural disasters or terrorist attacks. On the other hand, private decision-makers, such as airline and shipping companies, are interested in forecasting the passenger demand to develop corporate plans that take capacity utilization, manpower requirements and financial projections into account and thus reduce their business operative risk (Abed et al. 2001). Our work, by showing the significance of cross-correlation coefficients, and then the existence of intertemporal interdependencies across transport modes, implies that relying on a single-equation (single-mode) analysis would have missed relevant information, with a possible impact on the quality of the decision-making process.

Our work may also be of relevance for the literature on tourism demand modelling (Song and Li 2008). In this context, time series analysis has traditionally played an important role. Our contribution suggests that opening the "black box" of tourist arrival data by distinguishing between modes can be important in assessing the overall impact of investments (or negative shocks) affecting specific modes; moreover, seasonality turns out to be crucial not only in explaining the total number of arrivals, as is the case for most destinations, but also in affecting the nature of the relationship between arrivals by different modes.

X.5 Conclusions

In this chapter, we analyse empirically and try to rationalize within a simple conceptual framework the consequences of intermodal competition for the time series of passenger flows.

Taking into account travellers' preferences regarding transport modes and departure dates and the capacity constraints in the transport mode, on the basis of our conceptual framework we expect negative correlations of arrivals, both within and across transport modes, during the low-season period (when the level of demand is low), and positive correlations during the high-season period (when the level of demand is high). Moreover, if most travellers have strong relative preferences for mode with respect to departure date in the high-season period, we expect stronger correlations within modes.

We test these predictions, which we state in two propositions, by analysing daily passenger arrivals at Olbia airport and port from 2005 to 2008. Our empirical analysis supports all predictions. Furthermore, a generalization of our empirical model (which considers three regimes and an autoregressive order of two) suggests that the intertemporal relationship between port and airport arrivals may be more complicated than that described by a simple TVAR model with one regime an autoregressive order of one.

Needless to say, our work could be extended in several directions. For instance, the collection and analysis of data on prices, in addition to quantities, in this or in another context of intermodal competition is surely a fruitful direction for future work; and the interaction between intermodal and intramodal competition could also be investigated.

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Figure X.1 – Time series plot of airport and port arrivals.

Table X.1 – This table presents descriptive statistics on the airport and port series both in levels and logarithms. The table also reports the Jarque-Bera normality test statistics.

	Level		Log	
	Airport	Port	Airport	Port
Average	2334	3540	7.49	8.11
Median	1629	3271	7.4	8.09
Range	9553	7322	4.02	2.28
Standard Deviation	1793.78	1269.73	0.72	0.35
Coefficient of variation	0.77	0.36	0.1	0.04
Skewness	1.37	0.99	0.26	0.04
Kurtosis	4.32	3.89	2.12	3.07
Jarque-Bera normality test	562.58***	289.38***	62.98***	0.67

***, ** and * indicate statistical significance at the 1%, 5% and 10% level.

Table X.2 – This table presents test statistics of an auxiliary regression including a linear trend (time effect) and seasonal effects (year, month and day-of-the-week effects). The time effect is tested through a t-test, while F-tests are used to test the joint significance of dummy sets. Inference is based on HAC standard errors.

Test	Airport		Port	
Time effect	0.1		1.05	
Year effect	4.88	***	2.09	*
Month effect	638.55	***	220.66	***
Day-of-the-week effect	85.28	***	39.66	***

***, **, * indicate statistical significance at the 1%, 5%, 10% level.

Table X.3 – This table presents results from three unit root tests: the Augmented Dickey-Fuller test (ADF), the Phillips-Perron test (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

	ADF		PP		KPSS
Airport	-12.39	***	-910.25	***	0.09
Port	-11.98	***	-952.91	***	0.09

***, ** and * indicate statistical significance at the 1%, 5% and 10% level.

Table X.4 – This table presents the estimation results of a TVAR model with one lag and two regimes. Standard errors are reported in parentheses.

	Low Season		High Season	
	Airport	Port	Airport	Port
Intercept	-0.3199***	-0.2053***	-0.0063	-0.0069
	(0.0430)	(0.0359)	(0.0064)	(0.0053)
Airport(1)	-0.2014*	-0.1903*	0.4680***	0.2060***
	(0.0940)	(0.0786)	(0.0352)	(0.0294)
Port(1)	-0.2126*	-0.0573	0.0922*	0.2771***
	(0.0885)	(0.0740)	(0.0416)	(0.0348)
θ	-0.4598			

***, ** and * indicate statistical significance at the 1%, 5% and 10% level.

Table X.5 – This table presents the multivariate extension proposed by Lo and Zivot (2001) of the linearity test of Hansen (1999).

Test		
Linear Var vs. 1-threshold-TVAR	181.21	***
Linear Var vs. 2-threshold-TVAR	274.8	***
1-threshold-TVAR vs. 2-threshold-TVAR	93.59	***

***, ** and * indicate statistical significance at the 1%, 5% and 10% level.

Table X.6 – This table presents the estimation results of a TVAR model with two lags and three regimes. Standard errors are reported in parentheses.

	Regime 1		Regime 2		Regime 3	
	Airport	Port	Airport	Port	Airport	Port
Intercept	-0.3909***	-0.2518***	-0.0508***	-0.0515***	0.0146	-0.0115
	(0.0505)	(0.0405)	(0.0148)	(0.0118)	(0.0135)	(0.0108)
Airport(1)	-0.2372**	-0.1817**	0.3344***	0.1448**	0.4587***	0.2332***
	(0.0949)	(0.0761)	(0.0773)	(0.0619)	(0.0566)	(0.0453)
Port(1)	-0.2622***	-0.0861	-0.0409	0.0015	0.1379**	0.4833***
	(0.0901)	(0.0722)	(0.0934)	(0.0748)	(0.0551)	(0.0441)
Airport(2)	-0.0304	-0.12	-0.0763	-0.0824**	-0.0002	-0.1010***
	(0.1037)	(0.0831)	(0.0482)	(0.0387)	(0.0461)	(0.0369)
Port(2)	-0.3536***	-0.1737*	-0.0514	-0.1893***	-0.2179***	-0.2405***
	(0.1214)	(0.0973)	(0.0637)	(0.0510)	(0.0509)	(0.0408)
θ_j	-0.4598	0.0298				

***, ** and * indicate statistical significance at the 1%, 5% and 10% level.