Pricing strategies: who leads and who follows in the air and rail passenger markets in Italy

Angela S. Bergantino* Claudia Capozza† Mauro Capurso‡

Abstract

In this paper, we aim at empirically uncovering the existence of price leadership in the passenger transport market, whose oligopolistic structure facilitates the strategic interaction among companies, with price being one of the principal elements of competition. The strategic interaction is particularly favoured by the growing Internet penetration that, through dedicated online searching tools, makes readily available to all competitors the price of all transport services for an observed connection. The analysis focuses on selected Italian city-pair markets that differ from one another with respect to the number of competing companies and to characteristics of the transport services provided. We exploit this heterogeneity to study the strategic interaction under different competitive environments. We find evidence of the existence of price leadership. Results differ across city-pair markets, although it emerges that the role of leader is held by incumbent companies in the air or in the rail sector.

Keywords: strategic interaction, price leadership, passenger transport.
JEL codes: L13, L91

* Department of Economics, Management and Business Law, University of Bari Aldo Moro, Italy. Email: angelastefania.bergantino@uniba.it

† Ionian Department of Law, Economics and Environment, University of Bari Aldo Moro, Italy. Email: claudia.capozza@uniba.it.

‡ Institute for Transport Studies, University of Leeds, UK, & University of Bari Aldo Moro, Italy. Email: m.capurso@leeds.ac.uk.

1. Introduction

Oligopolistic markets are often characterized by strategic interaction among competing firms. A form of strategic interaction is the price leadership, that occurs when a principal firm first establishes the price, with the other firms in the market being followers. If the principal firm has the largest market share, the price leadership is of a dominant type. On the other side, if the principal firm does not have the largest market share, price leadership could be collusive if the price is higher than competitive level, or barometric if the price is around the competitive level.

From a theoretical viewpoint, the price leadership has been widely investigated by scholars. Deneckere and Kovenock (1992) provide the theoretical foundation for the dominant price leadership overcoming the limitations of previous literature, taking as given that large firms act as price leader and small firms are passive. By introducing the strategic interaction among firms in a duopolistic framework, they show that the high capacity firm becomes the leader and the low capacity firm strictly prefers to be the follower. Cooper (1997) develops a model for the barometric price leadership, showing that under asymmetric information, the informed firm play the role of leader. From Rotemberg and Saloner (1990), some contributions demonstrate that price leadership facilitates collusion because a price increase serves as signal to the other firms to raise their prices (see, also, Ishibashi, 2008). Mouraviev and Rey (2011) prove that price leadership enhances the sustainability of collusion by making it easier to punish deviations by the leader. Maskin and Tirole (1988) in a seminal paper, later extended by Eckert (2003) and Noel (2008), show that the strategic interaction can generate in equilibrium the Edgeworth price cycle. Starting from a price higher than the marginal cost, firms sequentially undercut each other prices to increase their market share. The undercutting continues until the price lowers to the marginal cost. At this point, one firm increases its price and the other firm certainly follows the price rise. When the price is restored to a high level, a new phase of undercutting starts again.

While theoretical evidence on price leadership abounds, the empirical evidence is relatively limited and tries to prove the existence of price leadership in the observed market. Most empirical papers on price leadership concentrates on the gasoline market for testing the Edgeworth price cycle theory. Noel (2007) and Atkinson (2009) provide some evidence of price leadership in the price restoring phase. More recently, Lewis (2012) performs a comprehensive analysis including 52 cities in the United States. His results reveal a great deal of both within and across market price coordination and price leadership in the gasoline market. Seaton and Waterson (2013) propose a narrow definition of price leadership, occurring when a price change by the leader is followed in a short period by the other firm by making a price change of the same monetary amount on the same product. Using this definition, the existence of price leadership is tested on British supermarkets. Considerable evidence of price leadership is found and, specifically, more leadership in price reduction than in price rise is observed.

This paper contributes to this strand of research. We empirically investigate the price leadership in the passenger transport market, whose oligopolistic structure facilitates the strategic interaction among firms. To the best of our knowledge, the passenger transport market has never been explored with this purpose.

In the last decades, the growing penetration of the Internet all over the world has changed the way producers sell and compete between themselves. Information on prices and features of (almost) all goods and services can be easily found and compared across world-based producers with a click and (close to) zero searching costs. By reducing information asymmetries, the price turns out to be a more important determinant during transactions, even when products and services are not completely homogeneous. Among the markets that have been more influenced by this phenomenon, we can mention the transport market.[4] Dedicated online searching tools allow easy comparisons among prices set by companies for all transport services available on a specific connection. This further favours the strategic interaction since prices are readily available to all competitors.

We explore the Italian passenger transport market, a meaningful case study since both the air and the rail transport are fully liberalised. This is the only market where there is on-track competition on some connections. The empirical analysis is focused on three selected city-pairs, namely Rome-Bari, Rome-Milan, and Rome-Venice. Each city-pair shows some distinctive features, regarding the transport companies and the service provided, leading to different competitive environments. This heterogeneity enables us to study the strategic interaction in price setting, and thus the existence of leader-follower relationships, under different competitive conditions. Moreover, we aim at ascertaining whether leader-follower relationships change or emerge during peak hours. Indeed, the increased demand of transport services during peak hours certainly leads transport companies to adapt their pricing, but it might also modify the strategic interaction among competing companies.

The database we construct is unique and not replicable. The fares have been collected from transport companies' website by simulating the purchase of tickets, starting from 30 days prior to departure, for 417 airline and railway services operated from November 2015 to June 2016 on the three city-pairs. To identify possible leader-follower relationships, the econometric tool we use is the panel vector auto-regressive (PVAR). The Granger (1969) test would allow us to uncover any causal relations among daily percentage changes of fares, over the period of 30 days before departure, of *all* transport companies (both airlines and railways) in the observed city-pair markets.

The reminder of the paper is as follows. In Section 2 we describe the city-pair markets under investigation. The literature on pricing strategies in the passenger transport market is surveyed in Section 3. In Section 4 we describe the data collection, while in Section 5 we illustrate the empirical model constructed for the analysis of price leadership. In section 6 we show the results, and finally, in section 7 we draw some conclusions.

2. The Italian city-pair markets

In Italy, the passenger transport market appears to be rather competitive. Across city-pair markets, we can observe competition between airlines, competition between railways and competition between airlines *and* railways (i.e. intermodal competition). Indeed, there is a

[4] Orlov (2011) shows that the Internet penetration among consumers has contributed to lower the average level of airline fares and to increase the ability of airlines to discriminate among their consumers. Sengupta and Wiggins (2014) use actual transactions data for the US market to show that online fares where up to 30% lower than offline ones, confirming Orlov's results on the effect of the Internet on the average level of fares.

good number of companies operating flight connections, with Alitalia being the incumbent company, sometimes the only one flying on some city-pairs. While competition between airlines is quite common worldwide, competition between railways is not.

Following the liberalization process of the railway sector in Europe,[5] Italy has opened up competition in the high-speed domestic transport to any licensed operator and, currently, is the only country where *two* companies provide high-speed rail (HSR) services on some city-pairs. The private company Nuovo Trasporto Viaggiatori (NTV) has entered the market providing only HSR services. In 2012, NTV began offering HSR services on the Rome-Milan corridor in competition with Trenitalia, the incumbent state-owned company, and in the later years has entered other city-pair markets.

The development of the HSR network over the past decades[6] and the recent NTV entry have fostered the intermodal competition between airlines and railways. Indeed, flights and train rides are considered substitutes when the total travelling time (pure travelling time plus access/egress time) is quite similar, preferably less than 4 hours, and the distance from origin to destination is between 200 and 800 km (Button, 2012). Therefore, on short-medium haul city-pairs connected with HSR, a strong intermodal competition might take place. However, in Italy the railway network is not equally developed on the territory. HSR services are provided by Trenitalia and NTV in the north-central Italy. The southern Italy is mostly served by Trenitalia, that provide high-capacity services (HC) which are faster than conventional services but are not high-speed.

The combination of all these elements results in different competitive environments across city-pair markets. This heterogeneity can be exploited for studying the strategic interaction in price setting, and thus the existence of leader-follower relationships, under different market conditions. Moreover, we can understand whether the strategic interaction occurs only between airlines and only between railways or, instead, it occurs also between airlines and railways.

We focus the empirical analysis on three selected city-pairs, namely Rome-Bari, Rome-Milan, and Rome-Venice, exhibiting different competitive environments. For each city-pair market, we report in Table 1 the companies providing transport services together with the average in-vehicle travelling time.

Table 1. Average in-vehicle travelling time.

City-pair	**Airline companies**			**Railway companies**	
	Alitalia	**Ryanair**	**EasyJet**	**Trenitalia**	**NTV**
Rome - Bari	1h 05min	1h 5min		4h 02min	
Bari - Rome	1h 2min	1h 5min		4h 04min	
Rome - Venice	1h 03min			3h 38min	3h 43min
Venice Rome	1h 04min			3h 40min	3h 41min
Rome - Milan	1h 10min		1h 20min	3h 07 min	3h 13min
Milan - Rome	1h 10min		1h 20min	3h 11min	3h 08min

Source: Authors' elaboration on data available on companies' website.

[5] After a series of legislative initiatives by The European Commission to achieve the gradual liberalization and market-opening process, the 3rd railway package led to the complete open access for international passenger operators.

[6] See Bergantino (2015) for a discussion on the changes that the European railway market has undergone in the recent decades.

The Rome-Milan city-pair market has the greatest number of companies, two airlines (Alitalia and EasyJet) and two railways (Trenitalia and NTV). Moreover, the total travelling time of air and rail transport basically matches, considered to the in-flight travelling time should be added about two hours to account for the access/egress time.

On the Rome-Bari city-pair market there are two airlines, Alitalia and Ryanair, flying on the same origin-destination (i.e. same airports) and one railway company, Trenitalia. However, the total travelling time does not perfectly match between the two transport modes, since Trenitalia provides HC services (not high-speed). Instead, on the Rome-Venice city-pair market there is only Alitalia and two railway companies, Trenitalia and NTV. In this case, the total travelling time of air and rail transport is very similar.

Overall, the Rome-Bari is the city-pair market that exhibits the relatively milder intermodal competition, and by this can be considered as the less competitive one. By this reasoning, the Rome-Venice city-pair market show more competition. Although there is only one airline flying, there are two railway companies that directly link the two city-centres with a totalling time that equals that of the air service. Finally, the Rome-Milan city-pair market is the most competitive since it has the largest number of companies, airlines and railways, whose total travel times perfectly match.

In Table 2 we report some statistics on the daily number of transport services provided by each company on the observed city-pairs in the period under investigation (November 2015 to June 2016), that are usefully accompanied with indications on aircrafts' and trains' capacity.

Alitalia and Trenitalia, the incumbent companies in the air sector and in the rail sector, show a greater average daily frequency compared to other companies in the related transport sector. Looking also at the number of seats, Alitalia and Trenitalia are the companies with a greater capacity. Considering the discussion of the previous section, Alitalia and Trenitalia might be the leader in the observed city-pair markets.

Table 2. Daily frequency and number of seats.

City-pair		**Alitalia**		**Ryanair**		**EasyJet**		**Trenitalia**		**NTV**	
		Daily frequency	*Seats*	*Daily frequency*	*Seats*	*Daily frequency*	*Seats*	*Daily frequency*	*Seats*	*Daily frequency*	*Seats*
Rome-Bari	Mean	5		2,2				3,5			
	Min	4	138-200	1	189			3	489		
	Max	6		3				4			
Bari-Rome	Mean	4,7		2,2				3,6			
	Min	4	138-200	1	189			3	489		
	Max	5		3				4			
Rome-Venice	Mean	6,4						20,2		3,8	
	Min	4	138-200					18	432-600	3	460
	Max	7						23		5	
Venice-Rome	Mean	6,1						18,5		3,7	
	Min	5	138-200					17	432-600	3	460
	Max	7						21		4	
Rome-Milan	Mean	25,2				1,8		44,7		16,8	
	Min	16	138-200			1	156-180	43	500-600	13	460
	Max	28				2		48		20	
Milan-Rome	Mean	24,9				1,8		45,3		17,2	
	Min	12	138-200			1	156-180	44	500-600	16	460
	Max	27				2		48		18	

Source: Authors' elaboration on data available on companies' website.

3. Literature review

In this section, we discuss the empirical literature on pricing behaviour in passenger transport market, started by Borenstein (1989) on the airline industry. Considering US routes, Borenstein (1989) shows that the ability of raising fares by an airline company is strongly influenced by the market share held both at route-level and at airport level. Consistent results are found on European markets (Bachis and Piga, 2007 and Gaggero and Piga, 2010), where fares appear to be higher in more concentrated markets. Brueckner et al. (2013) provide a comprehensive analysis on the effect of competition on airline fares in domestic US markets, finding that competition has a downward impact of fares and, to a greater extent, the competition from low-cost airlines.

A related strand of research focuses on price discrimination. Early papers by Borenstein and Rose (1994) and Stavins (2001) on the US industry find strong empirical evidences about the use of price discrimination strategies by airlines, particularly in most competitive markets. Recent works exploring the inter-temporal price discrimination show that fares follow a non-monotonic path over the booking day (Alderighi and Piga, 2010 and Bergantino and Capozza, 2015a). Also, Gaggero and Piga (2011) find that inter-temporal price discrimination is applied more in less competitive markets by airlines on Ireland-UK routes, whereas Bergantino and Capozza (2015a) reach the opposite result on Italian domestic routes.

As long as high-speed rail (HSR) services become actually available all over the world and perceived as a substitute to the air transport, they start exerting competitive pressures on airlines. Therefore, the research scope on pricing behaviour has been enlarged, considering also the effects of inter-modal competition on airline and railway fares.

Bergantino et al. (2015) find that airlines significantly reduce fares on the Rome-Milan line when flights are in direct competition with HSR services. Moreover, Bergantino and Capozza (2015b) show that, on Italian city-pairs, airlines set higher fares when the inter-modal competition is limited. The non-monotonic distribution of fares over booking days is more pronounced in presence of inter-modal competition to better segment the market and to extract a larger part of passenger surplus. Capozza (2016) measures the effect of rail travel time on airline fares and finds that airline fares are increasing in rail travel time. This is the evidence that airlines feel the competitive pressure from rail services as long as rail services becomes faster and, thus, closer substitutes to airline services.

Wei et al. (2016) use the difference-in-difference approach to show that, right after the opening of the Jing-hu HSR line linking Beijing to Shanghai, the average airline fares on routes covered by this new HSR service markedly felt. This result varies depending on the pre-existing market structure. The average fares decrease the most on those routes served by two airlines (duopoly) and less in those with more than two airlines (oligopoly), followed by the routes in which there is only one airline (monopoly).

Looking at the impact of inter-model competition on HSR fares in France, where HSR services are provided by a monopolistic company constrained by price cap regulation, Perennes (2014) shows that the presence of airline competition reduces HSR fares, thus preventing the railway company to behave as a monopolist.

Overall, there is an extensive literature on pricing behaviour in the transport industry. As it clears from the discussion above, there is a plentiful evidence that airlines and railways modify their pricing strategies depending on the degree of competition in the market. However, there is no paper investigating the causal relationship between fares charged by *all* companies competing on the observed markets. This paper fills this gap by shedding light on strategic interaction in price setting, with the aim of testing for the existence of leader-follower relationships among airline ad railway companies.

4. The empirical strategy

To identify the existence of price leadership we implement the panel vector auto-regressive (PVAR) modelling introduced by Holtz-eakin et al. (1988).[7]

Pooling cross-sectional units have some advantages: first, the assumption of time stationarity can be relaxed since the presence of a large number of cross-sectional units allows for lag coefficients that vary over time; second, the asymptotic distribution theory for a large number of cross-sectional units does not require the vector auto-regression to satisfy the usual conditions that rule out unit and explosive roots.[8]

We specify the following k-variate PVAR model represented by the following system of linear equations:

$$\Delta P_{it} = A_0 + A(L)\, \Delta P_{it} + \nu_i + d_{it} + \varepsilon_{it} \qquad [1]$$

$$i \in \{1, \ldots, N\}, t \in \{1, \ldots, T_i\},$$

where:

- the cross-sectional dimension i is a unique combination of transport services provided by competing airlines and railway companies;
- t is the time dimension defined by the booking days before departure;
- ΔP_{it} is the vector of dependent variables constructed as daily percentage change of fares: $(P_{it} - P_{it-1})/P_{it-1} \times 100$;
- L is the lag operator;
- A represents the matrices of parameters to be estimated;
- ν_i are dependent variable-specific fixed effects;
- d_{it} are the company-specific time effects (i.e. booking day dummies) introduced for capturing the inter-temporal pricing behaviour of each transport company and the gradual increase in the load factor resulting from departure approaching;
- ε_{it} is the idiosyncratic error term.

The dependent variable is defined as the daily percentage change of fares for two main reasons. First, it is appropriate for the investigation of price leadership, since we can test

[7] PVAR modelling has been widely used in macroeconomics and finance (see Canova and Ciccarelli, 2013 for a review), whereas a very few studies use this methodology in microeconomics and industrial organization to analyse firm pricing behaviour. Actually, there are several applications of VAR modelling to the real estate sector (Hannah et al., 1993, Miller and Page, 2006, and Deng et al., 2009), to the e-commerce product pricing (Kauffman and Wood, 2007), to pricing strategy of milk processors (Graubner et al., 2011) and to fresh products' pricing of leading supermarket chains (Revoredo-Giha and Renwick, 2012). However, all these applications use only time-series data (i.e. they not have any cross-sectional dimension).

[8] See Holtz-eakin et al., 1988, page 1373.

whether a fare change by one company is followed by a fare change by the other companies. Second, the series of fares might contain a trend, due to the date of departure that progressively approaches, that we can remove with first differencing. This is verified thought appropriate testing.

Because of the correlation between ν_i and the regressors we apply the Helmert transformation (i.e. forward mean-difference) to remove ν_i. The system of equation is estimated by GMM using the lags of the regressors as instruments (Arellano and Bover, 1995; Blundell and Bond, 1998). We estimate three PVAR models, one for each of the selected city-pair markets.

4.1 Pre - estimation: Model (lag) selection criteria

To define the optimal lag order, we use the moment and model selection criteria (MMSC) for GMM models proposed by Andrews and Lu (2001), resembling the widely-used BIC, AIC and HQIC, based on Hansen's J (1982) test statistics of over-identifying restrictions. Andrews and Lu (2001) conduct a Monte Carlo experiment to evaluate the finite sample performance of the model selection criteria. The MMSC BIC is found to perform better in selecting the correct model and moment conditions in a variety of contexts when dynamic panel data are used. For this reason, we include the number of lag for which the MMSC BIC point to a lower value.

4.2 Post - estimation: Granger causality test

The Granger (1969) causality test ascertains whether the lags of the endogenous variables enter the equation of another endogenous variable (Enders, 2008). In this paper, the Granger causality allows to understand if a fare change by one company (represented on the right-hand-side of equation [1]) Granger-causes, in the following period, a fare change by the other company (represented on the left-hand-side). We can end up with the following scenarios:

1. if a *unidirectional and positive causality* is found, then a fare change by one company (the *leader*) causes a fare change in the *same direction* by one or more companies in the following period (the *followers*). This would suggest that a *leader-follower* relationship exists;
2. if a *unidirectional and negative causality* is found, then a fare change by one company causes a fare change in the *opposite direction* by the one other or more companies in the following period. This would be the indication of a weak form of oligopolistic competition;
3. if a *bidirectional and positive causality* is found, then a fare change by one company causes a fare change in the *same direction* by the one other or more companies in the following period, but also the vice versa happens. This would be indicative of both strong competition and collusion. In this case, the average price on the market needs to be considered to ascertain whether competition or collusion is occurring;
4. if a *bidirectional and negative causality* is found, then a fare change by one company causes a fare change in the *opposite direction* by the one other or more companies in the following period, but also the vice versa happens. This would be the indication of a non-collusive oligopolistic competition;

5. if a *bidirectional causality with opposite signs* is found, a strategic interaction in price setting is occurring, but it is difficult to exactly determine which form of competition is taking place;
6. finally, if Granger causality does not exist, the companies are supposed to be independent in their pricing strategies.

5. Data collection and preliminary analysis

The database we construct is unique and not replicable. One-way cheapest fares have been collected by simulating the purchase of tickets from each transport company's website for the 30 days prior to departure for 417 airline and railway services operated from November 2015 to June 2016 on the three city-pairs: Rome-Bari and return, Rome-Venice and return, and Rome-Milan and return. The air and rail transport services included in the database are supposed to be in competition because, as already mentioned, the total travelling time (pure travelling time plus access/egress time) is similar, less than 4 hours, and the distance is between 200 and 800 km.

To ensure a good coverage of the typical trips on these corridors, several business services (same day return) and leisure services (short and long weekend visits) have been identified (see Table 3).

Table 3. Details of the data collection.

Origin-Destination	Type	Departure date	
Bari - Rome, and return	Same day return, business	10 November 2015;	3 December 2015;
		15 December 2015;	2 February 2016;
		19 May 2016;	7 June 2016.
Rome - Bari, and return	Long weekend, leisure	4 to 8 December 2015;	2 to 5 June 2016.
Rome - Bari, and return	Short weekend, leisure	12 to 14 February 2016;	29 April to 1 May 2016.
Venice - Rome, and return	Same day return, leisure	10 November 2015;	3 December 2015;
		15 December 2015;	7 June 2016.
Rome - Venice, and return	Long weekend, leisure	2 to 5 June 2016.	
	Short weekend, leisure	11 to 13 December 2015;	29 April to 1 May 2016.
Milan - Rome, and return	Same day return, leisure	10 November 2015;	3 December 2015;
		15 December 2015;	19 May 2016.
Rome - Milan, and return	Same day return, leisure	10 November 2015;	3 December 2015;
		15 December 2015;	19 May 2016.
Milan - Rome, and return	Long weekend, leisure	2 to 5 June 2016.	

We identify train rides that are in competition with flights as those departing up to one hour before the flights and arriving up to one hour later. This was slightly relaxed for the Rome-Bari city-pair, where the number of transport services is lower than other city-pair markets (see Table 2). The same applies to competition among airlines, since the number of flights of the low-cost airline Ryanair is lower than to those of full-service airline Alitalia.

Table 4 shows the average absolute difference, in minutes, among the departing times of competing transport services, distinguishing between the transport modes.

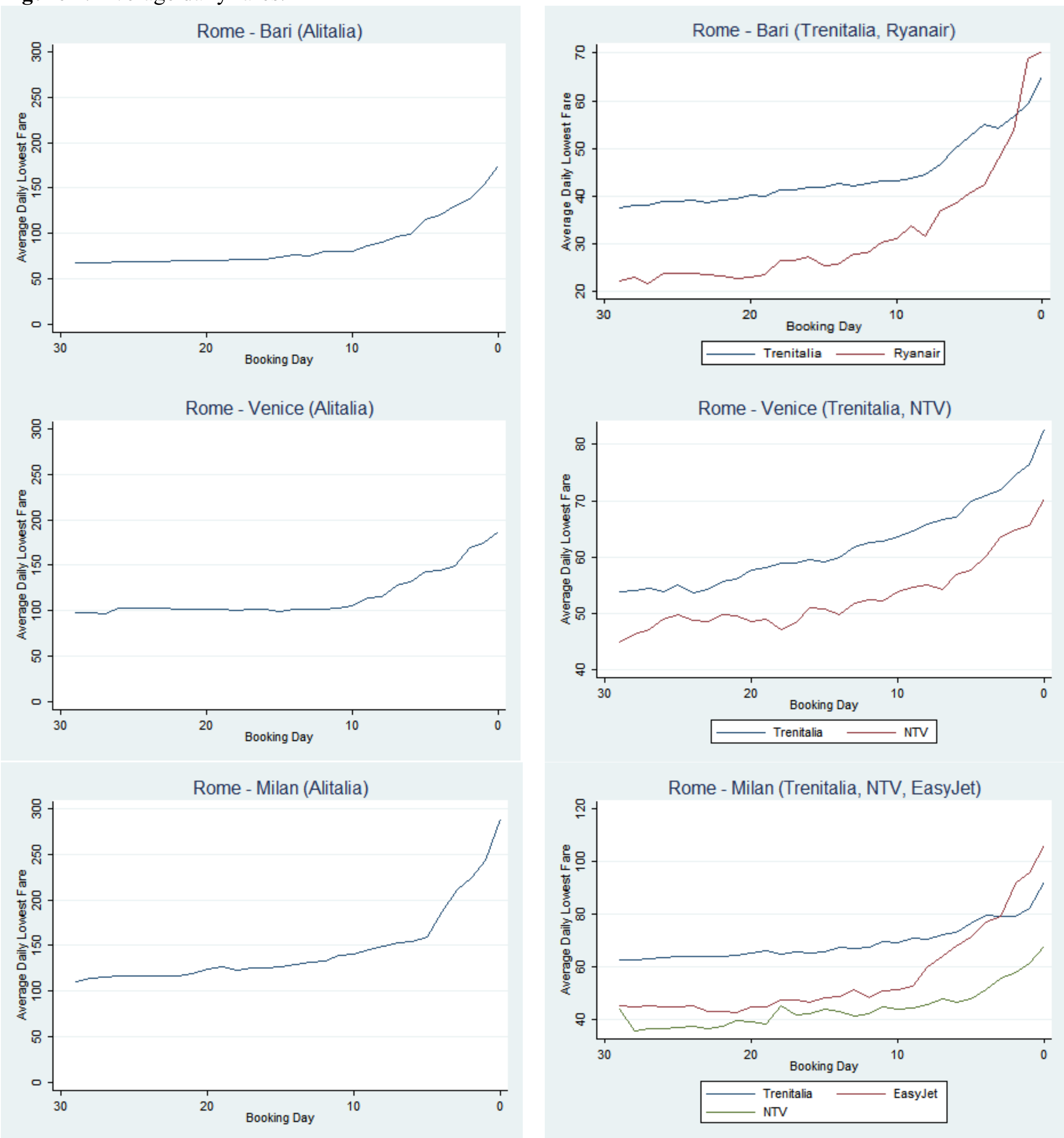
Table 4. Average absolute difference between departing time of competing transport services (in minutes).

City-pair	Difference between departing time		
	Air/Air	Rail/Rail	Air/Rail
Rome - Bari	105		107
Bari - Rome	89		64
Rome - Venice		68	52
Venice - Rome		56	53
Rome - Milan	84	19	36
Milan - Rome	59	27	39

These figures can be interpreted as a supplementary measure of intra- and inter-modal competition. Indeed, the lower is the difference among departing times, the greater is the degree of substitution of transport services, thus the greater is the degree of competition. It appears that the Rome Milan city-pair has the greatest degree of competition, while the Rome-Bari city-pair has the lowest.

The average daily fares over the booking days of transport companies are shown in Figure 1. Alitalia's fares are presented separately from fares of the other companies. This is done to better appreciate the inter-temporal profile of fares, since the flag airline sets relatively higher fares compared to the other transport companies.

Figure 1. Average daily fares.



The inter-temporal profiles of fares of Alitalia and Trenitalia are smoother compared to the profiles of the other transport companies that, instead, exhibits some high-low price movements. The price differences across companies are also shown by descriptive statistics reported in Table 5.

Table 5. Descriptive statistics for the average lowest fares.

City-pair	Company	Mean	Std. Dev.	Min	Max
Rome - Bari	*Alitalia*	116.03	24.91	96.34	186.32
	Ryanair	33.24	13.06	22.38	73.05
	Trenitalia	44.06	7.72	36.66	66.27
Rome - Venice	*Alitalia*	92.43	34.38	68.22	203.76
	Trenitalia	62.12	7.50	53.60	82.79
	NTV	53.03	6.23	44.86	70.39
Rome - Milan	*Alitalia*	147.83	40.76	110.93	282.81
	EasyJet	59.39	16.84	45.52	109.07
	Trenitalia	70.89	6.49	63.75	92.12
	NTV	45.64	6.94	37.48	67.58

Figure 2, 3 and 4 shows the average daily change of fares by transport companies on the considered city-pairs.

Figure 2. Average daily change of fares on Rome-Bari.

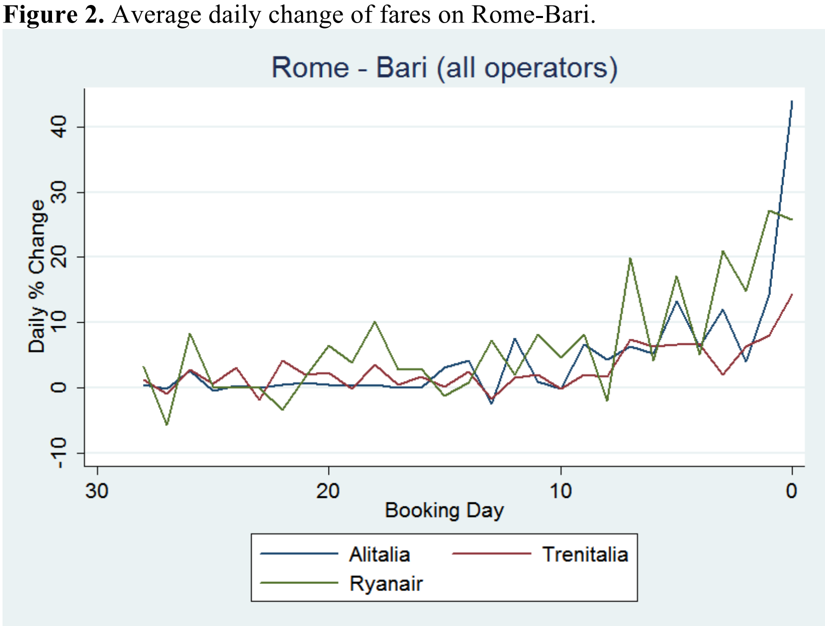


Figure 3. Average daily change of fares on Rome-Venice.

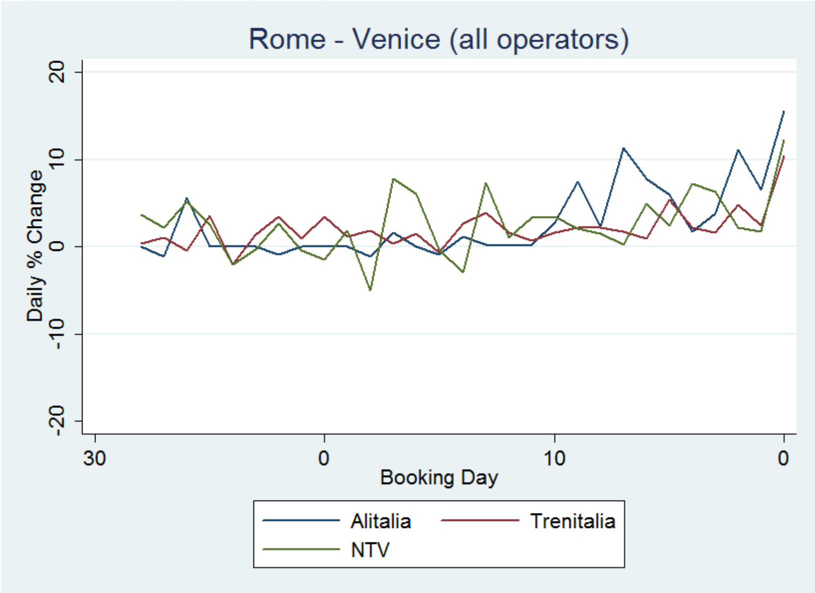
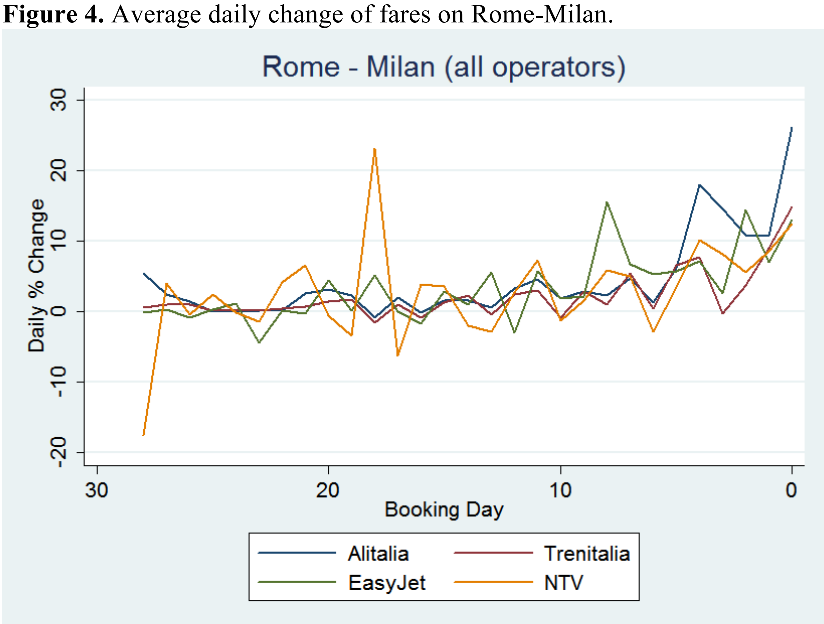


Figure 4. Average daily change of fares on Rome-Milan.



On the Rome-Bari city-pair, Ryanair is the company showing, on average, more frequent and wider price changes over the booking days. Alitalia's price changes are modest until, around, one week before departure, becoming henceforth wider than Ryanair. Instead, Trenitalia shows contained price changes over the period.

On the Rome-Venice city-pair, NTV exhibits, on average, more frequent and wider price changes over the booking days. As before, Alitalia's price changes are modest until one week before departure, becoming wider in the last week, whereas Trenitalia shows minor price changes over the period.

On the Rome-Milano city-pair, price changes by Alitalia and Trenitalia move almost identically over the booking days, except for the last week in which they diverge. EasyJet and NTV show the broader price changes.

The discussion above is useful to get an idea on how price changes evolve over time. However, the causal relationships can be inferred only from the results of PVAR estimations.

6. Results

Before presenting estimation results, we discuss some issues regarding the lag selection and the stability condition.

In Table 6 we show the results of the lag selection procedure using the MMSC BIC.

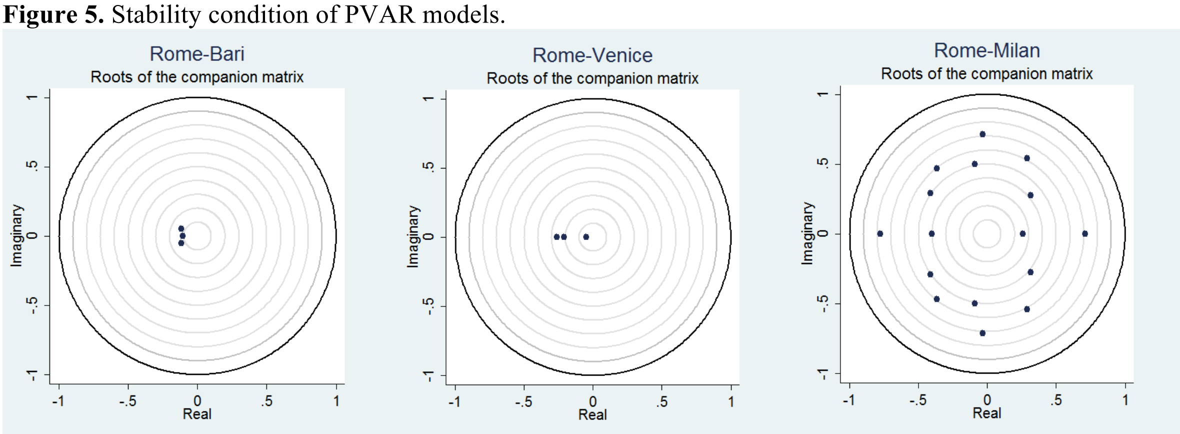
Table 6. Lag selection.

	MMSC BIC		
	Rome - Bari	**Rome - Venice**	**Rome - Milan**
lag - 1	-108.5157	-75.11489	469.0325
lag - 2	-77.21404	-62.10484	268.3489
lag - 3	-29.13968	-22.84409	283.591
lag - 4	-55.80221	-46.92608	-31.5806

Looking at the lowest value of MMSC BIC, the optimal number of lags for Rome-Bari and Rome-Venice city-pairs is one, whereas the optimal number of lags for Rome-Milan city-pair is four.

The stability condition of PVAR models is verified if the modulus of each eigenvalue of the companion matrix is strictly less than one.[9] The stability implies that the PVAR is invertible, has an infinite-order vector moving-average representation, providing known interpretation to the impulse-response functions (IRFs). Figure 5 shows that the stability condition is satisfied since all the eigenvalues lie inside the unit circle.

Figure 5. Stability condition of PVAR models.



[9] See Hamilton (1994) and Lutkepohl (2005).

From Table 7(a) to Table 7(c), we present the results for estimations together with the Granger causality.[10] The Granger causality tests for the joint significance of lagged variables. When only the first lag is introduced in the equation, the p-value associated to the related coefficient shows itself the Granger causality.

Starting from Table 7(a), we show the first set of estimates on the Rome-Bari city-pair market.

Table 7(a). Estimation results of PVAR model on the Rome-Bari city-pair market.

Dependent variable: daily change of the lowest fare	**Lagged dependent variable (t-1)**	*Coefficient*	*p-value*	*Granger Test (p-value)*
Alitalia	*Alitalia*	-0.054	0.411	
	Trenitalia	0.173	0.003	8.675 (0.003)
	Ryanair	0.002	0.923	0.009 (0.923)
Trenitalia	*Alitalia*	-0.037	0.105	2.623 (0.105)
	Trenitalia	-0.177	0.001	
	Ryanair	0.002	0.839	0.041 (0.839)
Ryanair	*Alitalia*	-0.019	0.692	0.157 (0.692)
	Trenitalia	0.018	0.637	0.223 (0.637)
	Ryanair	-0.102	0.002	
N. observations	1,932			
N. panels	71			

Booking day dummies are always included but not reported.

It emerges a *unidirectional and positive causality* between Alitalia and Trenitalia. A price change by Trenitalia Granger-causes a price change by Alitalia in the following period in the *same* direction. This is the evidence of price leadership, where the *leader* is Trenitalia and the *follower* is Alitalia. The price changes of Ryanair are neither influenced by influence other companies.

This finding is very interesting since the leader-follower relationship occurs between a railway company and an airline company. This might suggest that the two companies compete for the same consumer segment, with Alitalia adapting to the pricing behaviour of Trenitalia.

In Table 7(b), we report the second set of estimates on the Rome-Venice city-pair.

[10] We use the Stata package developed by Abrigo and Love (2015) to estimate PVAR models and to implement Granger causality tests and optimal model (lag) selection.

Table 7(b). Estimation results of PVAR model on the Rome-Venice.

Dependent variable: daily change of the lowest fare	**Lagged Dependent variable (t-1)**	*Coefficient*	*p-value*	*Granger Test (p-value)*
Alitalia	*Alitalia*	-0.040	0.313	
	Trenitalia	0.006	0.859	0.031 (0.859)
	NTV	0.047	0.038	4.299 (0.038)
Trenitalia	*Alitalia*	-0.023	0.178	1.818 (0.178)
	Trenitalia	-0.182	0.001	
	NTV	-0.031	0.02	5.379 (0.020)
NTV	*Alitalia*	-0.033	0.063	3.468 (0.063)
	Trenitalia	0.096	0.019	5.49 (0.019)
	NTV	-0.301	0.000	
N. observations	2,365			
N. panels	88			

Booking day dummies are always included but not reported.

On this city-pair, we find no evidence of price leadership. The results indicate two *bidirectional causalities with opposite signs* between Alitalia and NTV and between Trenitalia and NTV.

First, a price change by NTV Granger-causes a price change by Alitalia in the following period in the *same* direction. Moreover, a price change by Alitalia Granger-causes a price change by NTV in the following period in the *opposite* direction. While Alitalia seems to adapt its pricing to NTV's changes, on the other side NTV differentiates its pricing from Alitalia.

Second, a price change by NTV Granger-causes a price change by Trenitalia in the following period in the *opposite* direction, but a price change by Trenitalia Granger-causes a price change by NTV in the following period in the *same* direction. In this case, NTV modifies its pricing following Trenitalia's changes, whereas Trenitalia differentiates its pricing strategy from NTV.

NTV, the new comer, appear to be influenced both rival companies, although in different ways. Its pricing moves in the same direction of the railway's pricing, whilst it deviates from the airline's pricing. At the same time, the new comer's pricing influences competitors' pricing.

All in all, the Rome-Venice city-pair market appears quite dynamic, with strong strategic interdependencies among players, but none of them is price leader.

In Table 7(c) we present the estimations on the Rome-Milan city-pair market. In this case, two analysis are carried. The first on the full sample of transport services provided, the second on restricted sample of transport services provided during peak hours.[11] As explained before,

[11] For airlines, we consider peak-hours flights those departing from the early morning until 8:30 and from 18:00 to 21:00. For rail operators, we consider peak-hours services those running from the early morning until 8:00 and from 17:00 to 20:00.

this is intended for verifying whether the strategic interaction between transport companies changes when the demand for travel is relatively higher.

The estimations on the full sample reveal two *unidirectional and positive causalities* that would interpreted as the evidence of price leadership. One involves the two airline companies while the other involves the two railway companies.

First, a price change by Alitalia Granger-causes a price change by EasyJet in the following period in the *same* direction, but the opposite does not occur. In the specific, the coefficient of the forth lag of is positive and significant, while coefficients of the third to the first lags are not significant. This entails that the reaction of EasyJet to Alitalia's price change does not occur almost immediately but it takes a few days.

Second, a price change by Trenitalia Granger-causes a price change by NTV in the following period in the *same* direction, but the opposite does not occur. The coefficients of the third and fourth lags are positive and significant, while coefficients of the second and first lags are not.

Moreover, there are two other intermodal strategic interactions. There is a *bidirectional and negative causality* between EasyJet and NTV. A price change by EasyJet Granger-causes a price change in the *opposite direction* by NTV in the following period, but also the vice versa happens. Between the two companies there is a strong, non-collusive, oligopolistic competition. Moreover, there is a *bidirectional causality of opposite signs* between EasyJet and Trenitalia. First, a price change by Trenitalia Granger-causes a price change by EasyJet in the following period in the *opposite* direction. However, a price change by EasyJet Granger-causes a price change by Trenitalia in the following period in the *same* direction.

Interpreting these findings as a whole, the clearer leader-follower relation is between Alitalia and EasyJet. In fact, between Trenitalia, NTV and EasyJet there is a triangular relationship. Trenitalia influences NTV, which influences and is influenced by EasyJet that, in turn, influences Trenitalia. Alitalia seems the be the only one that influences directly and indirectly competitors' pricing behaviour, but it is influenced by none of them.

Estimations on the subsample of transport services provided during peak hours show that EasyJet, Trenitalia and NTV are influenced by *all* competitors' pricing behaviour. Particularly, Alitalia's price changes have a *positive* influence on all competitors' price changes, whereas it is only weakly positive influenced by EasyJet, since the coefficient of the third lag of EasyJet's price change is weakly different from zero. We can consider Alitalia as the price leader during peak hours.

All in all, the results highlight the role of leader played by Alitalia in setting prices on the Rome-Milan city-pair markets. The fact that Alitalia's fares are considerably higher than those of competitors (see Table 5) strengthens the intuition that the flag carrier is not influence by competitors' pricing behaviour.

Table 8(c). Estimation results of PVAR model on the Rome-Milan.

Dependent variable: daily change of the lowest fare	**Lagged dependent variable (t-1 to t-4)**	**Full Sample**			**Peak hours**		
		Coefficient	*p-value*	*Granger Test (p-value)*	*Coefficient*	*p-value*	*Granger Test (p-value)*
Alitalia	*Alitalia*	-0.157	0.000		-0.113	0.041	
		-0.090	0.017		-0.039	0.449	
		0.085	0.010		0.033	0.464	
		-0.068	0.003		-0.015	0.636	
	EasyJet	0.038	0.334	4.416 (0.353)	-0.035	0.495	10.53 (0.032)
		0.072	0.079		0.040	0.471	
		0.080	0.073		0.125	0.053	
		0.007	0.853		-0.079	0.132	
	Trenitalia	-0.044	0.218	4.12 (0.390)	-0.053	0.407	5.237 (0.264)
		-0.028	0.417		-0.054	0.329	
		-0.067	0.100		-0.116	0.062	
		-0.057	0.177		-0.126	0.043	
	NTV	-0.010	0.452	6.456 (0.168)	-0.044	0.059	5.378 (0.251)
		0.007	0.587		-0.009	0.575	
		0.046	0.012		0.025	0.425	
		0.005	0.653		-0.025	0.083	
EasyJet	*Alitalia*	-0.015	0.184	9.993 (0.041)	0.005	0.684	22.855 (0.000)
		-0.002	0.904		0.064	0.000	
		-0.007	0.525		0.032	0.071	
		0.023	0.046		0.039	0.006	
	EasyJet	-0.118	0.000		-0.210	0.000	
		0.100	0.000		0.044	0.124	
		0.047	0.119		0.030	0.261	
		0.285	0.000		0.354	0.000	
	Trenitalia	-0.024	0.032	65.319 (0.000)	-0.014	0.488	32.997 (0.000)
		-0.048	0.000		-0.056	0.002	
		-0.099	0.000		-0.104	0.000	
		-0.021	0.096		-0.053	0.002	
	NTV	-0.021	0.002	73.686 (0.000)	-0.033	0.000	52.333 (0.000)
		-0.046	0.000		-0.063	0.000	
		-0.056	0.000		-0.047	0.000	
		-0.029	0.000		-0.030	0.001	
Trenitalia	*Alitalia*	0.027	0.214	4.934 (0.294)	0.091	0.005	17.903 (0.001)
		0.052	0.031		0.143	0.000	
		0.016	0.477		0.002	0.948	
		0.012	0.483		0.047	0.062	
	EasyJet	0.026	0.423	15.143 (0.004)	-0.019	0.689	22.319 (0.000)
		0.090	0.010		0.151	0.003	
		0.140	0.000		0.211	0.001	
		0.084	0.012		0.164	0.007	
	Trenitalia	-0.300	0.000		-0.399	0.000	
		-0.228	0.000		-0.407	0.000	
		-0.084	0.052		-0.281	0.000	
		0.012	0.838		-0.082	0.370	
	NTV	0.011	0.502	2.861 (0.581)	0.027	0.258	12.850 (0.012)
		0.021	0.233		-0.016	0.551	
		0.020	0.349		0.078	0.002	
		0.021	0.173		0.023	0.307	
NTV	*Alitalia*	0.012	0.568	5.967 (0.202)	0.039	0.185	9.561 (0.048)
		-0.011	0.656		0.043	0.247	
		0.000	0.987		-0.027	0.433	
		0.037	0.042		0.045	0.077	
	EasyJet	-0.042	0.333	50.154 (0.000)	-0.171	0.017	28.551 (0.000)
		-0.048	0.302		-0.105	0.133	
		-0.144	0.001		-0.267	0.000	
		0.164	0.005		-0.012	0.856	
	Trenitalia	0.036	0.162	11.474 (0.022)	0.121	0.002	10.222 (0.037)
		-0.031	0.277		0.031	0.462	
		0.060	0.074		0.057	0.198	
		0.052	0.049		0.046	0.240	
	NTV	-0.225	0.000		-0.195	0.000	
		-0.135	0.000		-0.108	0.000	
		-0.136	0.000		-0.151	0.000	
		-0.086	0.000		-0.089	0.004	
N. observations		4739			2477		
N. panels		220			113		

Booking day dummies are always included but not reported.

7. Conclusions

In this paper, we empirically explore the strategic interaction in price setting in the passenger transport market to uncover the existence of price leadership. This market is well suited to the research purpose given its oligopolistic structure, with pricing being one of the principal elements of competition among transport companies. Moreover, the selected Italian city-pair markets differ from one another with respect to the number of competing companies and to the degree of substitutability of the transport services offered. We exploit this heterogeneity to study the price leadership in different competitive environments.

The contribution of our work is threefold. First, we contribute to the empirical research on price leadership that currently is quite limited. Second, we contribute to the literature on pricing strategies in the transport industry. Although this research field is widely explored, there is no paper that studies the leader-follower relationship. Third, the PVAR model is used as an econometric tool to address microeconomic topic, whereas this methodology is mostly used to analyse the interdependence among series of macroeconomic and financial variables, while the application to microeconomic variables is rather scarce.

Our results provide evidence of the existence of price leadership in two of the three city-pair markets observed. Interestingly, the strategic interaction occurs also among companies of different transport modes. We do not find a result that is common to all the observed markets. On the contrary, results differ across city-pair markets, indicating the one company can be a leader on a given city-pair market and a follower on another. The heterogeneity of the results can be explained by the different competitive environments that describe each city-pair market. All in all, what emerges is that the role of leader is held on a city-pair market by Trenitalia and on another city-pair market by Alitalia, both incumbent companies in the rail sector and in the air sector, respectively.

References

Abrigo, M. R., Love, I. 2015. Estimation of panel vector autoregression in Stata: A package of programs.

Alderighi, M., Piga, C.A. 2010. On-line Booking and Revenue Management: Evidence from a Low-Cost Airline. *Review of Economic Analysis*, 2(3): 272-286.

Andrews, D.W.K., Lu. B. 2001. Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *Journal of Econometrics*, 101: 123-164.

Arellano, M., Bover, O. 1995. Another look at the instrumental-variable estimation of error-components models. *Journal of Econometrics* 68: 29-52.

Atkinson, B. 2009. Retail Gasoline Price Cycles: Evidence from Guelph, Ontario Using Bi-Hourly, Station-Specific Retail Price Data. *Energy Journal*, 30(1): 85-109.

Bergantino, A. S., Capozza, C., Capurso, M. 2015. The impact of open access on intra-and inter-modal rail competition. A national level analysis in Italy. *Transport Policy*, 39, 77-86.

Bergantino, A.S. 2015. Incumbents and new entrants. In *Rail Economics, Policy and Regulation in Europe*, Finger M., Messulam P. (ed.), Edward Elgar, London.

Bergantino, A.S., Capozza, C. 2015a. Airline Pricing Behavior under Limited Inter-modal Competition. *Economic Inquiry*, 53(1): 700–713.

Bergantino, A. S., Capozza, C. 2015b. One price for all? Price discrimination and market captivity: Evidence from the Italian city-pair markets. *Transportation Research Part A: Policy and Practice*, 75: 231-244.

Blundell, R., Bond, S. 1998. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87: 11-143.

Borenstein, S. 1989. Hubs and high fares: dominance and market power in the US airline industry. *RAND Journal of Economics*, 20(3): 344-365.

Borenstein, S., Rose, N.L. 1994. Competition and price dispersion in the US airline industry. *Journal of Political Economy*, 102(4): 653-683.

Brueckner, J.K., Lee, D. Singer, E.S. 2013. Airline competition and domestic US airfares: A comprehensive reappraisal. *Economics of Transportation*, 2(1): 1-17.

Button, K. 2012. Is there any economic justification for high-speed railways in the United States? *Journal of Transport Geography*, 22: 300-302.

Canova, F., Ciccarelli, M. 2013. Panel Vector Autoregressive Models: A Survey. In Thomas B. Fomby, T.B., Kilian, L., Murphy, A. (ed.) *VAR Models in Macroeconomics – New Developments and Applications: Essays in Honor of Christopher A. Sims (Advances in Econometrics, Volume 32)*, Emerald Group Publishing Limited, pp.205 - 246

Capozza, C. 2016. The effect of rail travel time on airline fares: first evidence from the Italian passenger market. *Economics of Transportation*, 6: 18-24.

Cooper, D. 1997. Barometric price leadership. *International Journal of Industrial Organization*, 15: 301-325.

Deneckere, R., Kovenock, D. 1992. Price leadership. Review of Economic Studies, 59: 143-162.

Deng, C., Ma, Y., Chiang, Y. M. 2009. The Dynamic Behavior of Chinese Housing Prices. *International Real Estate Review*, 12(2): 121-134.

Eckert, A. 2003. Retail price cycles and the presence of small firms. *Journal of Industrial*

Organization, 21: 151-170.

Enders, W. 2008. *Applied econometric time series*. John Wiley & Sons.

Gaggero, A.A., Piga, C.A. 2010. Airline competition in the British Isles. *Transportation Research Part E: Logistics and Transportation Review*, 46(2): 270-279.

Gaggero, A.A., Piga C.A. 2011. Airline Market Power and Inter-temporal Price Dispersion. *Journal of Industrial Economics*, 59(4): 552-577.

Granger, C.W.J. 1969. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica* 37: 424-438.

Graubner, M., Koller, I., Salhofer, K., Balmann, A. 2011. Cooperative versus non-cooperative spatial competition for milk. *European Review of Agricultural Economics*, 38(1): 99-118.

Hamilton, J.D. 1994. *Time Series Analysis*. Princeton, NJ: Princeton University Press.

Hannah, L., Kim, K.H., Mills, E.S. 1993. Land use controls and housing prices in Korea. *Urban Studies*, 30(1): 147-156.

Holtz-Eakin, D., Newey, W., Rosen, H. S. 1988. Estimating vector autoregressions with panel data. *Econometrica*, 56(6): 1371-1395.

Ishibashi, I. 2008. Collusive price leadership with capacity constraints. *International Journal of Industrial Organization*, 26(3): 704-715.

Kauffman, R.J., Wood, C.A. 2007. Follow the leader: price change timing in internet-based selling. *Managerial and Decision Economics*, 28(7): 679-700.

Lewis, M.S. 2012. Price leadership and coordination in retail gasoline markets with price cycles. *International Journal of Industrial Organization*, 30(4): 342-351.

Lutkepohl, H. 2005. *New Introduction to Multiple Time Series Analysis*. Berlin: Springer-Verlag.

Maskin, E., Tirole, J. 1988. A theory of dynamic oligopoly II: price competition, kinked demand curves and Edgeworth cycles. *Econometrica*, 56: 571–599.

Miller, N., Peng, L. 2006. Exploring metropolitan housing price volatility. *Journal of Real Estate Finance and Economics*, 33(1): 5-18.

Mouraviev, I., Rey, P. 2011. Collusion and leadership. *International Journal of Industrial Organization*, 29(6): 705-717.

Noel, M. 2007. Edgeworth Price Cycles: Evidence from the Toronto Retail Gasoline Market. *Journal of Industrial Economics*, 55(1): 69–92.

Noel, M. 2008. Edgeworth price cycles and focal prices: computational dynamic Markov equilibria. *Journal of Economics and Management Strategy*, 17: 345–377.

Orlov, E. 2011. How Does the Internet Influence Price Dispersion? Evidence from the Airline Industry. *Journal of Industrial Economics*, 59(1): 21-37.

Perennes, P. 2014. Intermodal competition: studying the pricing strategy of the French rail monopoly. Transport Research Arena 2014, Paris, France <hal-01272287>.

Revoredo□Giha, C., Renwick, A. 2012. Retailers price behavior in the UK fresh fruit and vegetable market. *Agribusiness*, 28(4): 451-468.

Rotemberg, J.J., Saloner, G. 1990. Collusive price leadership. *Journal of Industrial Economics*, 39: 93-111.

Seaton, J.S., Waterson, M. 2013. Identifying and characterising price leadership in British supermarkets. *International Journal of Industrial Organization*, 31(5): 392-403.

Sengupta, A., Wiggins, S.N. 2014. Airline pricing, price dispersion, and ticket characteristics on and off the internet. *American Economic Journal: Economic Policy*, 6(1): 272-307.

Stavins, J. 2001. Price Discrimination in the Airline Market: The Effect of Market Concentration. *Review of Economics and Statistics*, 83(1): 200-202.

Wei, F., Chen, J., Zhang, L. 2014. Demand shocks, airline pricing, and high-speed rail substitution: Evidence from the Chinese market. Working paper, Sichuan Agricultural University, China.