Changes in frequencies and price variations on point-to-point routes: The case of easyJet

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ABSTRACT

This study analyzes how changes in flight frequencies contemporarily affect the pricing strategy of airlines. Focusing on the low-cost carrier (LCC) framework, we compare easyJet's 2012 average fares on all routes with their 2011 counterpart in the same "equivalent" week. Empirical analyses show that changes in frequency are negatively correlated with fare variations, both in monopolistic and competitive contexts. Our conjecture is that if the load factor has to be maintained within a sustainable range and the demand level can be assumed roughly constant, at least in the short period, variations in average fares should be negatively correlated with changes in frequency at the route level. Moreover, by analyzing easyJet's price discrimination dynamics, we find that an increase in weekly flights leads the airline to strategically price discriminate demand among offered flights (*between-flights discrimination*), especially in competitive situations, while reducing its ability to intertemporally price discriminate on the same flight (*within-flight discrimination*).

1. Introduction

In recent air transport literature on the determinants of airfares, flight frequency is usually included as one among several control variables. Hence, we cannot expect to reach conclusive evidence on the influence of flight frequency on prices, mainly because flight frequency occurs to be a proxy of the level of demand on different routes (notwithstanding varying degrees of competition and different passengers' preferences on departure time), so that a problem with endogeneity may arise. Indeed, some authors maintain that a higher number of flights ought to be considered as a quality attribute of the air transport service generating a product-quality competition in the airline industry, thus leading to an increase in airfares (see Borensetin, 1989; Schipper et al., 2002; Brueckner, 2004; Malighetti et al., 2009; Salanti et al., 2012; Bruecker and Luo, 2014). Conversely, others have found an opposite relationship (see, for instance, Malighetti et al., 2010; Fu et al., 2011; Alderighi et al., 2015; Moreno-Izquierdo et al., 2015).

Due to the above referred problem with endogeneity, it is quite understandable that the sign of the relationship between frequency and fares in the medium/long period and/or across different routes may be difficult to assess. However, in the short period (that is, when a flight is scheduled so that in normal circumstances all costs are fixed) *and* on a single route, any change in frequency involves a problem of indivisibility in supply

(because of the fixed number of seats on each aircraft), while the level of demand can be taken as given. In such cases a reasonable conjecture seems to be that we should observe diminishing (augmenting) fares when frequency increases (decreases) on a specific route. This amounts to say that we aim at detecting the negative correlation between flight frequency and fares on a single route, in the short period, *ceteris paribus*, and irrespective of other (more intricate) mechanisms envisaged in the current literature in order to support the same prediction[1].

Accordingly, this paper investigates the consequence of the indivisibility in supply alongside a demand constraint, focusing on the connection between the level of fares *in the event of change in frequency* over the same period of the previous year. For this purpose, we test the existence of a negative relationship between pricing and frequency by analyzing the entire offer of easyJet, the second European LCC in terms of passengers in the years of investigation (ICCSAI Fact Book 2012, 2013). This choice allows us to in-depth understand the pricing strategies of a LCC airline that, differently from other LCCs, relies on a network characterized by multi-frequency routes and has undertaken a concrete hybridazion process in the last years (Morlotti et al. 2017).[2] Specifically, we perform an in-depth investigation of this relationship studying the association with the change in prices, together with the strategic behavior of easyJet in discriminating demand among offered flights (between-flights discrimination) and, simultaneously, its capacity of differentiating prices for the same flight (within-flight discrimination). To avoid biased results, we test our conjecture controlling for numerous factors that in the past literature were found to affect the pricing strategy of an airline, from the macroeconomic perspective to the market structure in which the airline operates.

The remainder of the article is organized as follows. Section 2 reviews the literature on frequency and pricing dynamics. Section 3 describes the research design including data, methods, and descriptive statistics, while Section 4 reports the empirical analysis. Section 5 draws some conclusions and implications.

[1] We are obviously assuming that, in the short period, the level of demand is stable in most cases. In the same vein, Malighetti et al. (2014) found that, across different routes, fares per kilometer on "monopolistic" routes may be lower than on those that are more "competitive." This implies that the number of carriers serving each route depends on the level of demand for that particular pair of destinations, so that a low level of demand (signalled by a low frequency of flights) is enough to impose low fares, irrespective of the degree of competition at route level as traditionally defined.

[2] On the one hand, the airline has historically targeted passengers who are highly sensitive to price changes (leisure component), whereas, on the other hand, it has recently tried to mix its types of passengers by also targeting the most inelastic ones (business component).

2. Theoretical background

The literature on air transportation has provided unclear and mixed results about the link between frequency and pricing dynamics. On one side, a negative relation between flight frequency and airfares has been ascribed, for instance, to the scheduling behavior in oligopolistic markets where, in the presence of increasing clustering, competing airlines are required to decrease their (average per route) fares to attract further travelers (cf. Borenstein and Neitz, 1999; Salvanes et al., 2005). Moreover, the economies of density, which are credited to decrease the average cost per passenger, are presumed to go in the same direction (Caves et al., 1984; Brueckner and Spiller, 1994). In the case of LCCs, Yetiskul and Kanafani (2010) suggest that new added flights might be placed in time-day slot where the demand intensity is lower, eventually leading to a decrease in the overall average prices. Thus, setting new flights closer to those of other competitors might result in a decrease in airfares because of competition; moreover, positioning flights far from peak-hours might trigger a decrease in prices in order to stimulate demand.

On the other side, frequency is found to have a positive impact on prices (Borenstein, 1989; Malighetti et al., 2009) according to the business or leisure orientation of a route. Indeed, high (low) frequency is associated with business (leisure) markets (Borenstein, 1989), as it represents the value that business travelers place on frequent services.

Literature also focuses on how frequency may affect price dispersion and price discrimination. Mantin and Koo (2009) show how frequency has a negative and significant impact on price dispersion, but only during the last 20 days to departure, while Gaggero and Piga (2011) demonstrate how frequency generally leads to higher price dispersion in the low-cost market. Concerning price discrimination, Malighetti et al. (2009, 2010) find a negative correlation with frequency, arguing that minor discounts will be offered on routes characterized by a high level of demand.

Ultimately, measuring market concentration based on frequency (the number of flights for a specific route), scholars suggest that the entry of a new airline may increase (decrease) price dispersion in a highly (less) concentrated market (Obermeyer et al., 2013), while price discrimination is found to increase with competition (Stavins, 2001) [3].

[3] The dynamic pricing behavior of airlines has also been found to depend on the nature of airline rivalry (e.g., Brander and Zhang, 1993) or on the shortage of infrastructure (e.g., Vaze and Barnhart, 2012).

Our present conjecture is that airlines strategically modify prices and flight frequencies in response to the market demand. These three variables (i.e., prices, frequency, demand level) determine the load factor of airlines (defined as the ratio of seat kilometers sold to seat kilometers actually flown) either on average or on any single route. Without denying the problem of endogeneity among the involved variables, which surely affects the determination of their absolute time-series levels, we argue that, if the load factor has to be maintained within a sustainable range and the demand level can be assumed roughly constant, variations in average fares should be negatively correlated with the changes in frequency at the route level, at least in the short period. Therefore, considering the indivisibility issue,[4] we can intuitively infer that +(-) Δ frequency should imply -(+) Δ prices (per km).

Concerning the impact of the introduction of a new flight on price discrimination, we argue that this increase in flight frequency improves the ability of an airline to identify the share of leisure and business passengers (mix of demand) per flight in relation to their specific needs, thus implying a less need to intertemporally discriminate on each single flight as a strategy to suit passengers' various willingness to pay. This would therefore imply that +(-) Δ frequency should imply less(more) within-flight discrimination (per km). At the same time, the introduction of more flights would benefit the ability of the airline to price discriminate passengers between different flights. The offer of a new flight at noon would indeed lead a part of more leisure-oriented passengers to converge on this flight, thus reducing their demand for other flights. In this regard, we infer that +(-) Δ frequency would lead to more(less) between-flight discrimination.

3. Research design

3.1. Data and sample

To test our conjecture, we compare the 2012 average fares of easyJet on all routes with their 2011 counterpart in the same "equivalent" week (in order to control for demand seasonality), considering the possible annual changes in frequency. To do this, we relied on our own dataset of airfares of all easyJet flights between January 1, 2011 and

[4] One more/less daily (or weekly, for that matter) flight for easyJet most of the times implies 156 or 186 more/less seats offered on a certain route. A change of 5% in seat capacity on the same routes between 2011 and 2012 has occurred in only 4.9% of the cases, while in less than 1% when considering an average variation of 10%.

December 31, 2012. Airfare data represent the full prices paid by travelers, including easyJet's standard tariffs, airport charges, and other taxes or supplementary fees.[5] For each one-way trip flight, we call for the price of a single (one-way) seat starting from 90 days prior to departure to the day before departure. We check the easyJet website from 1 a.m. to 6 a.m. and collect published fares for the same routes at the same time each day. When ticket prices appear to be no longer available, we consider the associated flights as fully booked after continuously monitoring flights in order to confirm that prices become unavailable in the remaining days prior to departure.

The data were gathered from several sources: (1) unit fares and load factors were obtained from easyJet's website; (2) data on scheduled flights and airlines operating on each route were obtained from the Official Airline Guide (OAG) dataset for the corresponding periods; (3) the GDP per capita of each departing area was collected from Eurostat data (Quarterly National Accounts statistics), while the weekly variation in crude oil Brent price (in euros) at European level from the Federal Reserve Bank's economic data; and (4) distances were obtained by using Google Maps.

3.2. Methodology

To capture the impact of changes in frequency on the easyJet's pricing strategy, we consider the influence of changes in frequencies at three different extents: (1) the change in average airfares; (2) the variation in the dynamics of intertemporal price discrimination (advance booking); and (3) the change in price dispersion between 2012 and 2011. The values are calculated at week level (by aggregating all flights offered each week), where each 2012 week has been matched with its 2011 counterpart in the same "equivalent" week (year-on-year changes) in order to control for demand seasonality.

For each week *w*, $\Delta Y_{r,w}$ is equal to $Y_{r,w,2012}$-$Y_{r,w,2011}$, where $Y_{r,w}$ represents our dependent variable (see Equation 2). In the case of the average price variable, $Y_{r,w,2012}$ is the average price per kilometer applied on all easyJet flights on route *r* in week *w* in 2012. Hence, $\Delta Y_{r,w}$ stands for our delta average price (*Δ price-km*).

Concerning the other two dimensions of easyJet's pricing strategy (*Δ β; Δ price dispersion*), *β*s are firstly computed for any single flight fitting Equation (1), which stands for the optimal pricing strategy once considering the functional form of demand as

[5] The fares were non-refundable and did not include discounts for return trips.

suggested by Anjos et al. (2005), where ticket demand is a function of both the price and the time between the reservation and the departure date.

$$p_i = \frac{1}{\alpha \cdot (1 + \beta \cdot i)} \tag{1}$$

where i represents the number of days between the advance reservation and the flight date, α indicates the highest price level that may be reached during the last days before the scheduled departure date, and p_i stands for the price offered on that date. While a small α stands for a high fare for the day before departure, a small β means that the price decreases slowly as advance booking increases,[6] suggesting that there is less space for intertemporal price discrimination on individual flights (within-flight price discrimination). For our purposes, βs were then aggregated by using their average value at a week level.

Otherwise, price dispersion is defined as the standard deviation of weekly average prices *(Δ price dispersion*). This dimension complements the analysis of the change in βs by clarifying whether an increase in frequency may allow airlines to better identify the mix of demand (business vs. leisure) for each flight. In other words, this indicator aims to identify the presence of between-flights price discrimination.

The relationship between changes in flights frequency and variations in airfares is estimated by using a pooled OLS regression model with clustered standard errors at route level. A further analysis of the phenomenon is provided by using a panel data structure with yearly week-on-week variation as the longitudinal variable. Here, we adopt Mundlak's (1978) testing procedure rather than the traditional fixed effects (FE) panel model, because some of our variables have low within-route variation, and therefore, a FE model would suffer from quasi-collinearity (thus leading to an inflation of the estimated FE standard errors). In other words, we assume that the effects are random, but that the FE model is adequate to make inferences concerning the observed sample. The assumption of the procedure is that unobserved individual effects depend on the average of the other observable time-variant regressors, thus mimicking a FE estimation with averages within time. Our model therefore includes the averages over time (week w) in the set of time varying regressors.

[6] The referred price function is a hyperbola, with the price increasing as the flight date approaches. A low β value corresponds to a steady price trend as the number of advance booking days increases, whereas a high β value indicates a more significantly discounted fare, compared with the highest fare ever offered, on advance purchases.

At route level *r*, for each of the above referred price dimensions (*average price per kilometer; β; overall price dispersion*), our regression model is as follows:

$$\Delta Y_{r,w} = \sum_{z=0}^{Z} \Delta S_{z,r,w} + \sum_{j=0}^{J} \Delta X_{j,r,w} + \varepsilon_{r,w} \qquad (2)$$

where *Z* is the number of characteristics observed at a system ($\Delta S_{z,r}$), while *J* denotes the number of characteristics of each weekly route and *w* stands for the referred week. In particular, at a system level, we consider the variation of GDP related to the departure country and the overall change in the oil prices between years.

Route-level characteristics ($\Delta X_{j,r}$) include the variation between week *w* in year *t* and the comparable week *w* in *t+1* for (1) the total number of flights (*Δ Frequency*) between two connected points; (2) the market shares (measured in terms of seat capacity) offered by easyJet on the same route as a proxy of direct competition (*Δ Market share - direct*) and the market share (also measured in terms of seat capacity) offered by easyJet on alternative routes (*Δ Market share - indirect*) as an indicator of indirect competition as defined in Malighetti et al. (2015); (3) the percentage of flights during weekends defined as those departing between Fridays 2 p.m. to Mondays 10 a.m.[7] (*Δ Flight weekends*); (4) the flight's load factor (*Δ load factor)*; and (5) an indicator of differentiation in departure times (*Δ Differentiation index*) on a specific route similar to that considered in Borenstein and Netz (1999) as follows:

$$Differentiation\ Index = \sum_{h=1}^{24} S_{e_h} \cdot \left(\sum_{k=1}^{24} S_{c_k} \cdot \mathrm{MIN}(|k-h|; 24-|k-h|)\right) \qquad (3)$$

where *S* is the percentage of flights of easyJet (S_{eh}) departing at hour *h* and its competitors (S_{ck}) departing at hours *k*. This index informs about the positioning of easyJet's offer compared to that of other competitors by accounting for the pressure at each flight level in relation to both the relative positioning of competitors' offer around 24-hour clock and the number of competing alternatives. This index of departure time differentiation decreases when all competing flights tend to depart at the same time, while it increases when flights are equally spaced on the 24-hour clock.

[7] Fridays (since 2 p.m.), Mondays (up to 10 a.m.), and Sundays account for more than 15% of total seats.

Moreover, we control for (1) the average distance of flights in week *n* between the origin and destination points of each route in kilometers (*Distance*); (2) the leisure/business orientation of easyJet's routes assessed through computing the "Leisure index" as developed in Salanti et al. (2012) on easyJet's 2011 data. Specifically, based on the idea that LCCs implement intertemporal price discrimination to disentangle leisure and business passengers, the indicator is as follows:

$$L_r = \frac{\sum_i(\beta_{1-90,f,r} - \beta_{1-15,f,r})}{F}, \text{ with } f \in F \tag{4}$$

where $\beta_{1-90,f}$ and $\beta_{1-15,f}$ are dynamic price indicators computed 90 and 15 days in advance, respectively, for each flight f on route r, based on the airfare formula reported in Equation (1). The more negative the leisure index, the more the route can be defined as a "business-oriented route." A highly negative leisure index implies that, in the last days before departure, the increase in fares tend to be higher than what can be expected given the overall trend, which suggests that during the last 15 days before departure, airlines aim to address consumers with a higher willingness to pay, that is, business passengers (Salanti et al., 2012).[8] (3) The different time positioning of the Easter week between years *t* and years *t+1* by including two dummies set to 1 when flights occurred in those week for year 2011 and 2012, respectively. Table 1 reports the definition of each variable.

Table 1

Variables description.

Variable	Definition
Δ Price-km	For each route and each week, it is the difference between the weekly average price/km on all flights offered in 2012 and 2011.
Δ β	For each route and each week, it is the difference between weekly average β estimated in 2012 and 2011.

[8] Alphas (contrary to βs) are not significantly statistically different in the two sub-populations, that from 1 to 15 and that from 1 to 90 days before the departure.

Δ Price dispersion	For each route and each week, it is the difference between the standard deviation of weekly average price/km on all flights offered in 2012 and 2011.
Δ Frequency	For each route and each week, it is the difference between the weekly frequencies offered in 2012 and 2011.
Δ GDP	For each quarter and each route, it is the difference between the GDP (Mln €) of the country of departure in 2012 and 2011.
Δ Oil price	For each week, the difference between the weekly average oil prices (hundreds €) in 2012 and 2011.
Δ Market share - direct	For each route and each week, it is the difference between the market shares (measured in terms of seat capacity) offered by easyJet in 2012 and 2011 on the same route. It measures variations in direct competition.
Δ Market share - indirect	For each route and each week, it is the difference between the market shares (measured in terms of seat capacity) offered by easyJet in 2012 and 2011 on alternative routes. It measures variations in indirect competition.
Distance	Route length measured "as the crow flies" distance between origin and destination airports, in kilometers (thousands).
Δ Differentiation index	For each route and each week, it is the difference between the differentiation index computed on single easyJet's and competitors' flights in time departures offered in 2012 and 2011.
Δ Load factor	For each route and each week, it is the difference between the average number of days in advance flights offered in 2012 and 2011 that are fully booked.
Δ Flight weekends	For each route and each week, it is the difference between the percentage of flights during weekends defined as those departing between Fridays 2 p.m. to Mondays 10 a.m. in 2012 and 2011.
Leisure index	For each route, it measures the extent to which a route is leisure-oriented applying the Salanti et al.'s (2012) procedure on easyJet's 2011 data.

3.2.1.Potential endogeneity

As stated in Section 2, if *in the short period* and *on any specific route* both demand level and load factor can be assumed to be roughly constant (albeit for different reasons), then changes in route frequency cannot but be (negatively) correlated with its prices per

Km. However, because we are unable to directly observe demand level, flight frequency might be regarded as a proxy of the level of demand, which in its turn could be affected by a change in prices, so that a common problem of reverse causality might arise[9].

Along with recent contributions on air transportation pricing strategies (Morlotti et al. 2017; Mumbower et al. 2014), we deal with this potential endogeneity issue by implementing a two-stage least square instrumental variable method, acknowledging simultaneously that, unlike these authors, we are investigating the impact of frequency ("demand") on easyJet's pricing. In particular, we identify an appropriate exogenous variable that is strongly correlated with the potential endogenous regressor, ensuring that the instrument only influences the change in prices (dependent variable) through the potentially endogenous independent variable (change in frequency). Similar to Mumbower et al. (2014), for each route *r*, we employ as an instrument, easyJet's average change in frequency in all other markets *R-r* with similar length of haul (namely those registering a distance of +/- 10% compared to route *r*). Our test shows that the selected instrumental variable could be appropriate and not weak (Kleibergen–Paap Wald statistic: 30.867).[10] The instrument has been found to be highly positively correlated to the endogenous independent variable (first-stage regression of the 2SLS model: 0.460***). Pragmatically, two effects could contribute to explain this positive and significant relationship. First, easyJet's network has evolved in those years, according to an overall change of the entire European air transportation market. This is, however, not homogenous when considering short- and long-haul routes. In this regard, considering different distances allows us to properly account for the different changes in frequency characterizing specific type of routes. Indeed, the growth of short routes have been pressurized by different factors than those affecting long routes, such as the competition of high speed railways. Second, the dynamics associated with market seasonality is responsible for an overall trend of increase or decrease in the entire market offer of easyJet in each specific year. In particular, the two equations are as follows:

Stage 1:

[9] We thank the two anonymous referees for having pointed this out to us.

[10] A valid instrument is always hard to find and in practice limitations are always in place when trying to deal with the endogeneity issue in a tested relationship. We acknowledge that it would be pretentious to totally (and a-priori) exclude the existence of a relationship (even if mitigated) between the change in easyJet's prices and the variation of its frequency in all other similar markets. For instance, if easyJet's cost overall reduces, this may potentially reduce route r's price and increase other routes frequency at the same time. The use of other IV may be used to validate our findings.

$$\Delta F_{r,w} = IV_{r,w} + \sum_{z=0}^{Z} \Delta S_{z,r,w} + \sum_{j=0}^{J} \Delta X_{j,r,w} + u_{r,w} \qquad (5)$$

Stage 2:

$$\Delta P_{r,w} = \widehat{\Delta F_{r,w}} + \sum_{z=0}^{Z} \Delta S_{z,r,w} + \sum_{\substack{j=0 \\ j \neq \Delta F}}^{J} \Delta X_{j,r,w} + \varepsilon_{r,w} \qquad (6)$$

where $\Delta F_{r,w}$ stands for the change in weekly frequency of route *r*, $IV_{r,w}$ is the instrumental variable defined as the airline's average change in frequency in all other markets with similar length of haul; and $\varepsilon_{r,w}$ is the error term. In the second stage, $\Delta P_{r,w}$ is the difference in price/km on all flights offered in 2012 and 2011, while and $\widehat{\Delta F_{r,w}}$ is the predicted change in frequency from the first stage. Similar to the first stage, $u_{r,w}$ is the error term. In both stages, $\Delta X_{r,w}$ is a vector that represents a set of explanatory variables.

3.3. Descriptive statistics

Fig. 1 shows the trend of the weekly average price per week in years 2011 and 2012. The data show that the average airfares differ between years, especially starting from the 31st week, where prices were slightly higher in 2012 compared to those (weekly-matched) in 2011, up to a difference of 39% (79.3 € in 2012 vs. 57.2 € in 2011) during the 45th week.

Figure 1. Weekly trend of the weekly average price in 2011 and 2012

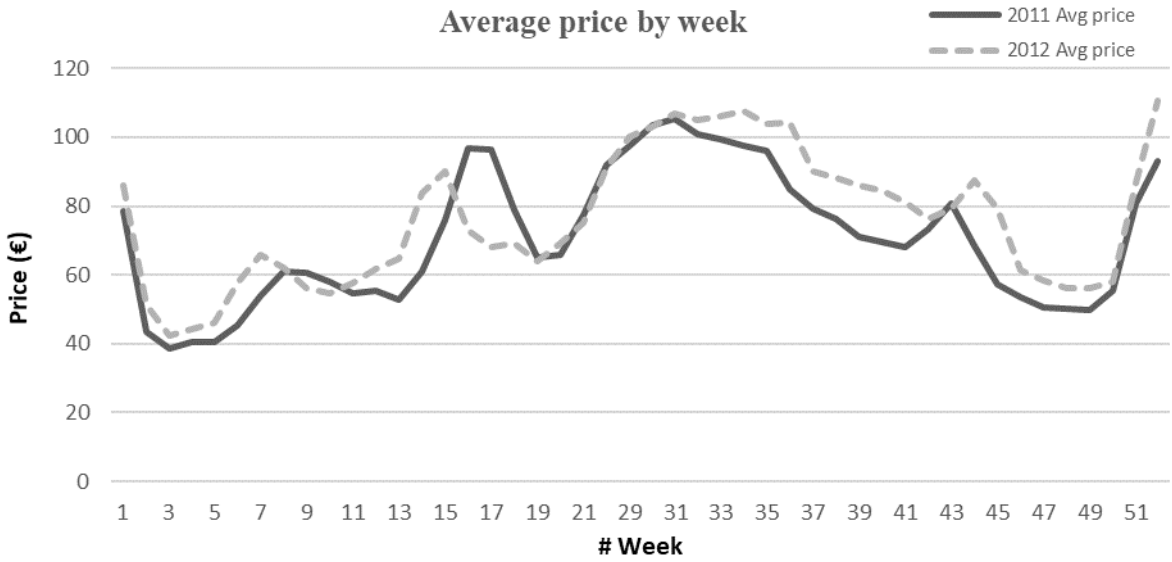


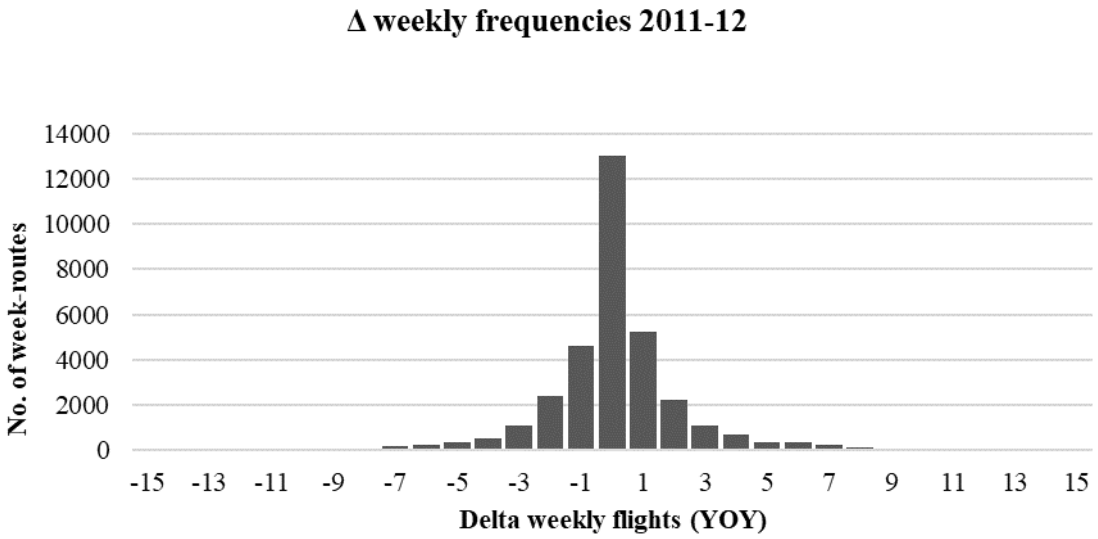
Table 2 shows the descriptive statistics of the variables in our analysis. The 2012–2011 difference of the weekly average price per kilometer has an average value of 0.004 €. While the average value of the variable representing the inter-temporal price discrimination of our sample has a negative value (-0.0005), price dispersion generally increases between 2011 and 2012 (+0.596).

Table 2 – Descriptive statistics

Variables	Obs.	Mean	S.D.
Δ Price-km	33,129	0.004	0.023
Δ β	33,129	-0.0005	0.028
Δ Price dispersion	33,129	0.596	1.647
Δ Frequency	33,129	0.105	2.311
Δ GDP	33,129	65,138	14,894
Δ Oil price	33,129	29.721	13.865
Δ Market share - direct	33,129	0.976%	11.026%
Δ Market share - indirect	33,129	1.356%	17.038%
Distance	33,129	1,206	660
Δ Differentiation index	33,129	-0.608	6.077
Δ Load factor	33,129	5.423	63.893
Δ Flight weekends	33,129	1.446%	16.504%
Leisure Index	33,129	-0.063	0.044

Δ Frequency has an average value of 0.105. Fig. 2 provides some hints on how frequency (weekly number of flights) changes between 2011 and 2012. This distribution is overall symmetric, with 39% of week-routes unchanged between years (12,985 out of 33,129), while 30% display at least a weekly change of either positive (16%: 5,254 week-routes) or negative sign (14%: 4,622 week-routes). Considering tails, up to 963 week-routes undertake a weekly increase of 6 flights, while at the opposite, we have 638 week-routes with a weekly decrease of 6 flights.

Figure 2. Differences in weekly frequencies between 2011 and 2012



Concerning route characteristics, the variation in GDP related to the country of origin has an average of 65,138 €, ranging from a minimum of 46,457 € to 86,270 €. The variation in easyJet's market shares has an average of 1% and 1.4% for direct and indirect competition, respectively, suggesting that the airline generally operates in routes with a relatively stationary market environment, whereas the decrease in the differentiation index suggests that all competing flights increasingly tend to depart at the same time. The average length of haul for easyJet routes is 1,206 km, and the leisure index varies from a minimum of -0.242 to a maximum of -0.003 for the routes of Basel-Dusseldorf and Santorini-London LGW, respectively. In 2012, easyJet offered more flights during the weekends with respect to 2011 (+1.4%), by improving also its performances in terms of load factor: the "sold out" occurs on average 5 days in advance compared to 2011.

Table 3 shows our preliminary analysis of the relationship between changes in flight frequency and variation in airfares considering different market regimes, both in 2011 and 2012, with reference to the estimated variations in the weekly average price/km (hundreds), in βs, and in price dispersion under different market conditions. More precisely, when easyJet operated under monopoly (or competition) in both years (columns 2 and 3) and when market conditions changed over time, from monopoly to competition or vice-versa (columns 4 and 5). In these last two cases, we calculate the *Δ Average price/km (hundreds)* isolating routes where easyJet reduced its market share (measured in terms of seat capacity) below 100% (competition), or where it reached a market share of 100% (monopoly) in 2012, respectively.

Table 3. Differences between weekly average price/km (hundreds), β, and overall price dispersion in 2011 and 2012 by different market conditions (monopoly vs. competition) for different change in frequencies

	All	*Monopoly*	*Competition*	*From Monopoly to Competition*	*From Competition to Monopoly*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
			PANEL A: Δ Average price/km (hundreds)		
Δ Frequency>0	0.042	0.083	0.033	-0.225	-0.006
	(100%)	*(34.6%)*	*(2.8%)*	*(4.0%)*	*(58.7%)*
Δ Frequency=0	0.467	0.465	0.481	0.222	0.472
	(100%)	*(38.9%)*	*(2.9%)*	*(2.7%)*	*(55.4%)*
Δ Frequency<0	0.791	0.868	0.745	0.508	1.027
	(100%)	*(38.2%)*	*(2.9%)*	*(2.4%)*	*(56.5%)*
			PANEL B: Δ β		
Δ Frequency>0	-0.0015	-0.0014	-0.0018	-0.0001	0.0003
Δ Frequency=0	-0.0006	-0.0013	-0.0001	0.0009	-0.0024
Δ Frequency<0	0.0008	0.0005	0.0009	0.0011	0.0035
			PANEL C: Δ Price dispersion		
Δ Frequency>0	0.618	0.533	0.679	0.645	0.440
Δ Frequency=0	0.678	0.651	0.691	0.442	1.080
Δ Frequency<0	0.461	0.475	0.460	0.441	0.280

Values in brackets represent the percentages of routes under each regime.

The results in panel A (Table 3) suggest that week-routes where frequencies decreased display a higher increase in the average price per hundreds of kilometers (0.791 €) in comparison with price variation on routes where there has been an increase in frequency (0.042 €), and double the increase on stable routes (0.467 €). The difference is even higher in the case of competitive routes (0.033 € vs. 0.745 €). When considering the change in the market structure, routes moving from a monopolistic to a competitive market, and simultaneously facing a decrease in frequency, also report an increase in the average price per kilometer, while a reduction in prices (-0.225 €) is associated with an increase in the number of flights between 2011 and 2012. Acknowledging the univariate nature of this analysis, this seems to be mainly due to the necessity of addressing the rivalry of other operators into the market. However, routes moving towards a monopolistic situation displays the highest increase in airfares (1.027 €) when frequency decreases, and, concurrently, still a slight decrease in airfares (-0.006 €) when frequency increases because of an overall increase of its offer. In both market transitions (from competition to monopoly and vice-versa), an increase in the number of flights would thus require easyJet to reformulate its pricing strategy to address both internal and external competition.

Concerning the differences in βs (panel B, Table 3), they register a decrease in correspondence to routes increasing in frequencies between 2011 and 2012. Across all the considered specifications, an increase in the number of flights is associated with a decrease in the ability to intertemporally discriminate demand (lower βs), while a decline in frequency to a growth in βs (-0.0015 vs. 0.0008). Interestingly, in the case wherein easyJet does not change frequency, it is required to less stimulate the demand ($\Delta\beta<0$), as in that period the demand itself improved overall due to exogenous factors following the global financial crisis. Moreover, in correspondence with an increase in the number of flights, the ability to discriminate demand within-flight diminishes more on routes under competition than on those under monopoly (-0.0018 vs. -0.0014). Increasing frequencies when easyJet moves from monopoly to competition is associated with a lower ability to intertemporally price discriminate (-0.001), while the opposite is true for βs (0.0003) when it moves from competition to monopoly.

Regarding price dispersion (panel C, Table 3), the results suggest that it significantly increases in association with an increase in flight frequency between 2011 and 2012 (0.618). This outcome holds across each form of market (monopoly vs. competition) and

appears to be particularly strong for routes operating under competition (0.679), even when considering the transition from monopoly to competition (0.645).

Overall, the reduction in within-flight price discrimination (smaller βs in panel B) when frequency increases is paralleled by an increase in between-flights discrimination (higher values of price dispersion in panel C). By increasing weekly flights, the airline seems to be more able to discriminate demand among offered flights (e.g., by setting starting times to better serve business or leisure travelers) so that there is less need of intertemporal discrimination on the same flight.

In the next section, using a multivariate analysis, we further investigate the linkages between an increase in frequency and changes in average prices per kilometer, βs, and overall price dispersion, controlling for several factors to drive such variations.

4. Results

4.1. Multivariate analysis

Table 4 reports the results of route-level changes in airfares in βs and in overall price dispersion as a function of route-level variations in frequency between 2011 and 2012. When easyJet's frequency increases from 2011 to 2012 on a certain route, the average price/km is found to decrease (Table 4, column 1 and 2), *ceteris paribus*. Moreover, we have some evidence that an increase in weekly average airfare per kilometer is significantly associated with an increase in the economic activity of the country of departure. With the aim of suiting various passengers' willingness to pay (Giaume and Guillou, 2004), easyJet has indeed charged more passengers flying from richer countries given their greater economic possibilities without taking the risk to scarify its market share in poorer origin areas. At a route level, the increase is instead related to a growing market share (both in direct and indirect terms) of the airline, and it is more likely to occur on routes when the percentage of flights during weekends significantly grows and/or in connection with an increase in load factors. The strategy seems that of marginally increasing profitability from fuller flights. Moreover, where the offer of easyJet becomes more differentiated in terms of time departures in 2012, the price/km rises.

Table 4. Impact of variations in flight frequency on changes in average airfares per kilometer, *β*s and price dispersion between 2011 and 2012

	Pooled-OLS 2SLS model	*Mundlak 2SLS model*	*Pooled-OLS*	*Mundlak*	*Pooled-OLS*	*Mundlak*
Variables	Δ Price-km	Δ Price-km	Δ Price Inter. discrim.	Δ Price Inter. discrim.	Δ Price dispersion	Δ Price dispersion
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Frequency	-0.008***	-0.005**	-0.000**	-0.001***	0.022***	0.011**
	(0.002)	(0.002)	(0.000)	(0.000)	(0.005)	(0.004)
Δ GDP	-0.022	0.069***	-0.291***	-0.292***	12.226***	6.410***
	(0.035)	(0.018)	(0.021)	(0.012)	(1.122)	(0.798)
Δ Oil price	-0.006	-0.002	0.013***	0.014***	-0.864***	-0.982***
	(0.003)	(0.004)	(0.001)	(0.001)	(0.106)	(0.082)
Δ Market share - direct	0.028***	0.018***	0.008**	0.006***	0.388***	0.750***
	(0.005)	(0.005)	(0.003)	(0.002)	(0.116)	(0.222)
Δ Market share - indirect	0.010***	0.009***	0.001	0.000	-0.011	-0.032
	(0.002)	(0.002)	(0.002)	(0.001)	(0.098)	(0.142)
Distance	0.002*	0.003	-0.004***	-0.005***	0.610***	0.719***
	(0.001)	(0.002)	(0.000)	(0.000)	(0.040)	(0.041)
Δ Differentiation index	-0.000	0.000***	-0.000	-0.000**	-0.002	-0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)
Δ Load factor	0.000***	0.000***	0.000***	0.000***	0.005***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
Δ Flight weekends	0.009***	0.013***	-0.003**	-0.002**	0.437***	0.101
	(0.002)	(0.002)	(0.002)	(0.001)	(0.151)	(0.068)
Leisure Index	-0.003	-0.011	-0.003	-0.006	-0.824*	-2.087***
	(0.004)	(0.007)	(0.007)	(0.005)	(0.473)	(0.574)
Easter dummies	YES	YES	YES	YES	YES	YES
Constant	-1.689***	-1.156***	-1.991***	-2.050***	42.320***	30.739***
	(0.242)	(0.163)	(0.128)	(0.074)	(5.311)	(4.884)
Observations	33,129	33,129	33,129	33,129	33,129	33,129
Nr. of routes		938		938		938
F-statistic	119.93***	6,450.95***				
R-squared			0.340	0.342	0.163	0.176

Clustered standard errors at route level are in parentheses. Significance level of 1 % (***), 5 % (**), and 10 % (*). "YES" stands for the inclusion of two dummy variables for the different time positioning of the Easter week between years t and years t+1.

All these (at first sight, seemingly incongruous) pieces of evidence can be made consistent by observing that any variation in flight frequency entails an increase, or a reduction, of the total number of offered seats on a certain route by a multiple of the number of seats of a single aircraft (in our case 156 or 180 for easyJet A319 or A320 aircrafts, respectively). Modifications in flight frequency may well be dictated by various factors, but, at the very moment in which they are effectively operated, the consequent change in supply faces a given (as it cannot but be so in the short period) demand schedule. This, in our opinion, is the key mechanism behind the observed negative

correlation between changes in flight frequencies and ensuing variations in prices per kilometer.

About the observed trends in βs, the multivariate regression analysis confirms our descriptive evidence. An increase in the number of flights is associated with a decreasing βs, that is, with diminishing intertemporal price discrimination (smaller within-flight discrimination) (Table 4, columns 3 and 4). Contrariwise, the overall price dispersion is positively associated with an increase in frequencies (Table 4, columns 5 and 6). Thus, our results suggest that, when the airline offers more frequent flights, this presumably allows it to better identify the mix of demand (business vs. leisure) for each flight. At the same time, shrinkage in intertemporal discrimination on each flight is associated with an enhanced ability to price discriminate between-flights. Overall, as two interchangeable strategies (in terms of final easyJet's objective function), easyJet decreases its effort in intertemporally price discriminating on single flights, while it tries to better disentangle business and leisure passengers by increasing its discrimination between flights (price dispersion). In other words, a change in its market positioning (due to the change in offer) suggests the presence of a compensation effect between the two strategies.[11] For example, when one more flight at noon is offered, it is likely that "leisure passengers" converge on this flight, reducing their demand for other flights less suited to the needs of such users.

As far as control variables are concerned, βs are found to grow with the increase of oil price, easyJet's market share (direct component), and load factor, while they decrease in 2012 compared to 2011 on longer routes and when GDP increases. Our findings also suggest that an increase in the percentage of flights in weekends leads to a decrease in intertemporal price discrimination. However, the overall price dispersion is found to grow across each dimension, unless in the case of an increase in oil prices, which contributes to reduce dispersion. The indirect component of easyJet's market share and the level of departure time differentiation on routes do not play a crucial role both for βs and price dispersion. To sum up, our results seem to suggest that an increase in flights in weekends is associated with a decrease in intertemporal price discrimination as new flights target

[11] Of course, when including a new flight, it is also a matter of positioning it over the 24-hour clock, considering both the offer of other competitors as well as passengers' most preferred departure time (MPDT). Travelers are indeed known to bear an additional cost in addition to the ticket price, that is, the schedule delay cost, namely the difference between their MPDT and the flight taken (Douglas and Miller, 1974). In this regard, passengers used to fly for necessity at specific times are difficult to be lured on other flights having different departure/arrival times, as the schedule delay cost would be higher compared to the potential saving arising from taking another flight with a different schedule.

more homogenous passengers, thus leading to a less need to intertemporally discriminate, along with the fact they show more similar price elasticity. This is aligned with the strategy of increasing average airfares to balance out the reduction in price discrimination and an increase in price dispersion (Mantin and Koo, 2010). Furthermore, easyJet is found to increase its ability to discriminate within each flight instead of discriminating between flights in correspondence to an increase in oil prices, being more encouraged (in economic terms) to identify the exact willingness to pay of various passengers. This is also accompanied by a related increase in overall airfares as well as price dispersion (compensation effect), especially in the presence of richer countries of origin, suggesting a higher presence of the business counterpart (Mantin and Koo, 2009).

Finally, it may be interesting to further check the influence on easyJet's dynamic pricing strategy of different market situations. Regarding this, we investigate the change in airfares, βs, and price dispersion by distinguishing routes under easyJet's monopoly and those where it operates under severe competition (for example, on the route between London Gatwick and Milan Malpensa airports, easyJet faced direct competition by British Airways and Alitalia, while indirect competition from routes between other pairs of airports in London and Milan areas), defined as routes characterized by a value of direct market share lower than the cut-off for the lower 15th percentile (0.247) in both years.

Pooled OLS regressions in Table 5 show the regression of two sub-groups: the first including routes operating under monopoly, while the second considering those operating under competition. As a remarkable difference, we found that the increase in frequency in 2012 has a significant role on within and between price discrimination, just as in the case of routes operating under competition rather than monopoly (Table 5, columns 5 nd 6). This is consistent with the fact that airlines generally address strategic pricing strategies, thus implementing both within and between price discrimination when they are under competition (Stavins 2001; Giaume and Guillou, 2004). Contrarily, under monopoly, airlines have the freedom (under each regulatory regime) to charge passengers, who in turn do not have other alternatives, without losing resources in disentangling each specific type of consumer and reorienting revenue management resources toward routes/markets with higher competitive pressure. Interestingly, the rivalry of easyJet with other airlines on the same routes appears to be accountable for compensating the decrease in within-flight discrimination with an increase in between-price discrimination.

Table 5. Impact of variations in flight frequency on changes in average airfares per kilometer, *β*s and price dispersion between 2011 and 2012, when easyJet operates as a monopolist or under competition

	Routes under monopoly			*Routes under competition*		
Variables	Δ Price-km	Δ Price Inter. discrim.	Δ Price dispersion	Δ Price-km	Δ Price Inter. discrim.	Δ Price dispersion
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Frequency	-0.016**	-0.000	-0.001	-0.011**	-0.001***	0.020***
	(0.007)	(0.000)	(0.007)	(0.005)	(0.000)	(0.007)
Δ GDP	-0.068	-0.287***	14.129***	-0.053	-0.253***	9.080***
	(0.107)	(0.030)	(1.777)	(0.105)	(0.051)	(2.818)
Δ Oil price	-0.016*	0.012***	-0.448***	-0.009	0.017***	-0.236
	(0.009)	(0.002)	(0.155)	(0.006)	(0.004)	(0.242)
Δ Market share - direct				0.210**	0.072**	1.840*
				(0.099)	(0.028)	(0.951)
Δ Market share - indirect	0.015***	-0.001	0.021	-0.001	0.002	0.122
	(0.003)	(0.002)	(0.156)	(0.005)	(0.003)	(0.087)
Distance	-0.006	-0.002*	0.601***	0.000	-0.003**	0.440***
	(0.006)	(0.001)	(0.148)	(0.003)	(0.001)	(0.079)
Δ Differentiation index	-0.000*	0.000	0.000	0.001***	-0.000***	0.007
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.008)
Δ Load factor	0.000**	0.000***	0.001***	0.000*	0.000***	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ Flight weekends	0.006	-0.002	0.246	-0.007	0.000	0.742***
	(0.006)	(0.002)	(0.292)	(0.011)	(0.004)	(0.265)
Leisure Index	-0.001	-0.004	-0.017	-0.001	-0.043*	0.705
	(0.009)	(0.008)	(0.684)	(0.017)	(0.023)	(0.791)
Easter dummies	YES	YES	YES	YES	YES	YES
Constant	-1.852***	-1.725***	33.546***	-1.542*	-2.182***	12.051
	(0.582)	(0.167)	(7.146)	(0.899)	(0.332)	(14.676)
Observations	12,367	12,367	12,367	3,097	3,097	3,097
R-squared		0.305	0.136	0.139	0.335	0.196
F-statistic	56.87***			7.17***		

Clustered standard errors at route are in parentheses. Significance level of 1 % (***), 5 % (**), and 10 % (*). "YES" stands for the inclusion of two dummy variables for the different time positioning of the Easter week between years t and years t+1.

5. Final remarks

Malighetti *et al*. (2014) intended to show that prices applied by LCCs depend on the demand size on specific routes, quite independently from the presence of competition or monopolistic position. This is so because aircraft size is usually fixed due to the homogeneity in the fleets, so that flight frequency and the number of carriers on the same route are likely to signal the level of demand for that route. Our findings show that a similar demand constraint, together with an indivisibility in supply due to the fixed

number of seats on a particular aircraft, operates when changes in flight frequency occur *on a single route* in the short period.

Indeed, comparing easyJet's 2012 average fares on all routes with their 2011 counterpart in the same "equivalent" week (in order to control for demand seasonality), and considering the year-on-year changes in frequency, we find that changes in frequency are negatively correlated with fare variations (i.e., when frequency increases, the average price per kilometer decreases and vice-versa).

Moreover, when frequency increases, β coefficient of dynamic pricing decreases as well. This suggests that, when the airline offers flights more frequently, this permits to better identify the mix of demand (business vs. leisure) for each flight, consequently requiring less intertemporal discrimination on individual flights. Not surprisingly, such a decrease in intertemporal discrimination on each flight is associated with an enhanced ability to price discriminate between-flights, especially in competitive situations.

All this suggests that LCCs' price setting strategy, namely the way they discriminate travelers, and the choice to intensify or reduce their presence in specific markets are strongly interrelated and concretely driven by the type (business or leisure) of passengers traveling on specific routes (Anderson and Wilson, 2003; Mantin and Koo, 2009).

These results may also provide valuable insights in relation to the change in LCCs' pricing strategy due to the increase or reduction of frequency in their offer (Mantin and Koo, 2009). When existing routes intensify, travelers could benefit from a reduction in airfares and in their schedule delay costs, namely the difference between their most preferred departure time and the flight actually taken (Douglas and Miller, 1974). Flight intensification increases the travel options at their disposal to reach an already served destination, thus decreasing their expected waiting time before the departure. Offering additional flights at different timing would indeed lead to less need for intertemporal price dispersion as different categories of passengers can always fit their preferences with airlines' schedule.

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