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published in Research in Transportation Economics 2019

DOI (link to publisher) 10.1016/j.retrec.2019.100741

document version Publisher's PDF, also known as Version of record

document license Article 25fa Dutch Copyright Act

Link to publication in VU Research Portal

citation for published version (APA)

van den Bogaard, J. E., & Lijesen, M. G. (2019). Pricing of imperfect substitutes: The next flight is not the same flight. *Research in Transportation Economics*, 78, 1-7. [100741]. https://doi.org/10.1016/j.retrec.2019.100741

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Research in Transportation Economics

journal homepage: www.elsevier.com/locate/retrec

Research paper

Pricing of imperfect substitutes: The next flight is not the same flight

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ARTICLE INFO

Product differentiation

JEL classification:

Keywords: Imperfect substitutes

Pricing

Airlines

D43

L93

ABSTRACT

We investigate how airfares respond to changes in the fare of adjacent flights. Using a fixed effects regression on fares from Amsterdam to Geneva, we find flights that only differ in departure times to be weak substitutes. Fare-to-fare elasticities for imperfect substitute flights of different airlines are even smaller, implying weak competition between airlines on this specific route.

If our findings hold for other routes as well, this will have implications for the analysis of price dispersion in civil aviation. It would imply that demand shocks for individual flights have small effects on prices of other flights. Demand volatility would then be likely to affect price dispersion on a route level and should be considered when analyzing price dispersion.

1. Introduction

In the economic literature on civil aviation, flights are commonly thought of as imperfect substitutes (Alderighi et al., 2015; Basso, 2008; Borenstein & Netz, 1999; Lijesen & Behrens, 2017). Characteristics that affect the level of substitution include the (perceived) quality of the airline, booking restrictions, routing of the flight and time of departure. We focus on the latter and develop and apply a method to assess the level of substitutability between flights on the same route.

Understanding the nature of imperfect substitutes and its consequences for pricing is important for several reasons. First, the level of substitutability partly determines the boundaries of the relevant market (see e.g. Lijesen & Behrens, 2017), which is valuable information both for policy makers and for academics looking to assess (changes in) the level of competition. Second, the level of substitutability has an impact on price dispersion. If goods are strong substitutes, demand shocks are more likely to spread over several goods and hence cause smaller price shocks. Understanding the consequences of substitutability on pricing can therefore contribute in resolving the long-lasting debate on the impact of competition on price dispersion (Borenstein & Rose, 1994; Gerardi and Shapiro, 2009; Dai, Liu, & Serfes, 2014; Chandra & Lederman, 2016, to name but a few influential papers in this debate).

Flights from different airlines are often imperfect substitutes, as the characteristics of airlines are likely to be different. These differences range from clearly measurable features such as seat pitch to subjective judgements about quality. Most authors either use dummy variables (or fixed effects) for every airline in the analysis or run separate analyses for each airline. Booking restrictions, such as the Saturday night stayover, used to be an important source of product heterogeneity (see e.g. Stavins, 2001). The importance of these restrictions is decreasing for short haul flights with the rise of the low-cost carrier business model, as Alderighi et al. (2015) show.

Routing is also an important product characteristic. It is commonly assumed that airlines compete on the level of city pairs, although several authors distinguish additional factors that should be considered. Lijesen (2004) shows that indirect flights are imperfect substitutes to direct flights between the same cities. Many authors (e.g. Dai et al., 2014; Gerardi and Shapiro, 2009) ignore this issue by focusing on direct flights (and hence ignore the presence of the close substitute) or by limiting the analysis to flights where indirect flights are hardly a viable alternative (e.g. Chandra & Lederman, 2016; Lijesen & Behrens, 2017).

Another routing issue is that some cities have multiple airports, or, more general, that some airports are close enough to be imperfect substitutes. This issue of competition between nearby airports has been extensively treated on a case-by-case basis (examples include Jun and Van Dender, 2009 and Pels, Nijkamp, & Rietveld, 2000). Lijesen and Behrens (2017) analyze the extent to which alternative city- or airportpairs impact airline competition and find that the relevant market for a flight extends well beyond the city-pair level.

The impact of departure time on product homogeneity is implicitly

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https://doi.org/10.1016/j.retrec.2019.100741

Received 24 January 2019; Received in revised form 19 June 2019; Accepted 29 August 2019 Available online 26 September 2019 0739-8859/ © 2019 Elsevier Ltd. All rights reserved. present in the spatial competition literature (e.g. Borenstein & Netz, 1999; Salvanes et al., 2005), and the subject is briefly touched upon in Gaggero, and Piga (2011). Our paper is the first to explicitly study the impact of departure timing on the level of product homogeneity.

The remainder of the paper is organized as follows. Section 2 sets up a theoretical framework to explore the implications of price responses, followed by a translation to our empirical specification. Section 4 provides an overview of the data and we present our empirical results in section 5. The final section provides conclusions and a discussion.

2. Theoretical framework

Airline pricing is a complex interaction of peak load pricing with stochastic demand and strategic interactions between competitors. According to people working in the field, some airlines have highly advanced pricing schemes, responding to all sorts of changes, whereas others set fixed fares for certain numbers of chairs (fare buckets). On some routes, airlines have been observed to match the price of competing flights. All these approaches have in common that a positive demand shock leads to a price increase for the flight that experiences the demand shock. Prices of flights on the same route (but different departure times) are likely to increase as well. This may occur either as a direct response to the price increase, or as a result of passengers looking for alternatives for their preferred flight that has now increased in price.

Consider a market where n imperfect substitutes are supplied. We assume that the individual supply curve for every good has a strictly positive slope. The demand for good i can be described by:

$$q_i = q(p_i, p_i, a_i) \tag{1}$$

where *p*'s reflect prices, and *a_i* denotes an exogenous and independent demand shifter for good *i*, with $\frac{\partial q_i}{\partial a_i} > 0 \forall i$ and $\frac{\partial a_i}{\partial a_{-i}} = 0.^1$ Subscript '-i' refers to all other goods than good *i*. Imperfect substitution implies that:

$$0 < \frac{\partial q_i}{\partial p_{-i}} < -\frac{\partial q_i}{\partial p_i} \tag{2}$$

Given the upward sloping supply curve, it is rational to increase the price of a good in response to an exogenous increase in demand. This in turn means that an exogenous increase in demand for good i increases demand for all other goods through the associated price increase. Hence, we have that a demand shock in good i impacts the prices of all goods:

$$\frac{\partial p_{-i}}{\partial a_i} = \frac{\partial p_{-i}}{\partial p_i} \frac{\partial p_i}{\partial a_i} > 0 \tag{3}$$

Where $0 < \frac{\partial p_{-i}}{\partial p_i} < 1$ reflects the price response of other goods on a price change in good *i*. The term 'response' intuitively relates to the game theoretic concept of a best response and is indeed consistent with such a response in equilibrium. The relationship described by equation (3) is very general and extends beyond game theoretic interactions.

The mechanism described above can be illustrated by a graph of a market where two imperfect substitutes are supplied. The graph shows all curves as linear for ease of interpretation, but this does not drive the result. The use of demand and supply curves suggest a competitive market. A similar graphical representation can be made using marginal costs and marginal benefits curves to cover monopoly and oligopoly markets.

In practice, we often cannot observe the size of demand shocks or

the slopes of supply and demand curves. Prices, on the other hand, are often directly observable, especially for goods that are sold online. Observed prices' responses provide information on the substitutability of the goods. It can be seen from Fig. 1 that the level of substitutability affects the impact of a demand shift of good i on the prices of other goods. Both from Fig. 1 and from the formal analysis in Appendix A, we note that the price response is positively related to the level of substitutability. The steeper (i.e. inelastic) the supply curve is relative to the demand curve, the more precise the measure is. For perfectly inelastic supply (of good j), the price response is a perfect measure of the level of substitutability.

3. Empirical specification

3.1. Setup and case selection

Flights on a specific itinerary fit our framework quite well; they are clearly imperfect substitutes and, since capacity is fixed in the short run, an upward sloping supply curve is ensured. More importantly, airlines actively adjust prices to changes in demand, and consumers can observe prices very well, so that all substitutes are taken into account. In order to identify how departure timing affects the level of product substitutability, we need to correct for other causes of product homogeneity and other substitutes. Rather than trying to take into account these causes and running the risk of poorly specifying the effects or incorrectly proxy the characteristics, we choose to select a single route and analyze the data on the lowest feasible level of aggregation. The route selection is then based on the lack of importance of other imperfect substitutes, that may affect our analysis and lead to a potential omitted variable bias.

The selected route, Amsterdam-Geneva, fits our purpose very well. It is a relatively densely travelled route, served by a network carrier (KLM) and a low-cost carrier (EasyJet). They have both been operating on this route for many years, without entry or exit of other airlines. Several flights are available every day, implying that we can observe several imperfect substitutes. The flying time between Amsterdam and Geneva varies between 1 h and 30 min and 1 h and 40 min.

Other imperfect substitutes are relatively unimportant. Travel time by land modes takes at least four times as long. Several more or less adjacent flight routes are available; Lyon (98 km from Geneva) is served from Amsterdam airport and flights depart from Dusseldorf (179 km from Amsterdam) and Brussels (158 km) to Geneva and Lyon. Based on the distance decay function and parameter values used by Lijesen and Behrens (2017), only Amsterdam-Lyon might be a viable alternative. Due to the geographic situation, the landside travel time from Lyon airport to Geneva is 1 h and 35 min, which is about as long as the flight time itself. This would hardly count as a reasonable alternative to most travelers.² Indirect flights are also available, with total flight times starting at 3 h and 25 min, i.e. twice as long as the direct flight. This, again, will not be considered by the majority of travelers.

3.2. Empirical specification

We aim to estimate price responses, i.e. $\frac{\delta p_{-i}}{\delta p_i}$, as used in equation (3) in section 2. As Fig. 1 suggests, this value provides information on the level of substitutability of two goods. It measures the price impact of a demand shock on good *i* on the prices of other goods relative to the effect on the price of good *i* itself. Demand for flights from a specific carrier on a specific time of day is often quite volatile, i.e. many demand shifts occur. The demand shifts are not observed, but price

¹ Note that the assumption of independent demand shocks might not always hold, as demand shocks may stretch out over a longer period of time, e.g. because of a longer lasting event. We expect positive dependence to be more likely in practice than negative dependence. In that case our results provide an overestimation of the actual substitutability, implying that our qualitative conclusions still hold.

² Apart from additional travel time, passengers would also have the additional costs of having to rent a car. Public transport options are much slower, with the exception of the direct Oui-connection, which has a frequency of 1 per day. Geneva airport on the other hand has a frequent 7-min connection to the city.



Fig. 1. Graphical representation of a positive demand shock.

responses are, and they form the backbone of our empirical analysis. Apart from price responses, we need to take several other aspects into account. First of all, we need to account for flights being sold out. Second, we need to correct for all observable factors that affect airfares in order to estimate the relationship between fares with as little bias as possible.

If a flight is sold out, we no longer observe its price, but the fact that it is sold out can be observed.³ If a flight is sold out, two remarks are in order. First, the demand for the sold-out flight was high, implying that (unobserved) prices for the last few seats were probably high. Second, the flight is no longer for sale, implying that close substitutes gain market power. Both effects lead to a higher price for close substitutes. We add sold-out dummies for adjacent flights to capture the effect on fare.

Numerous research papers have tried to pinpoint the factors that are responsible for differences in airfares. The time between booking and departure is consistently shown to impact air fare levels (see e.g. Bilotkach, Gorodnichenko, & Talavera, 2010; Button & Vega, 2010; Pels & Rietveld, 2004; Piga & Bachis, 2007). We therefore add this variable to our analysis as well. Moreover, we use a fixed effects estimation, at the level of individual flights (i.e. the combination flight number and date), thus capturing all differences in fare levels between individual flights.

The considerations above lead to the following equation to be estimated, where we use a log-log transformation in order to be able to interpret the coefficients as elasticities:

$$Ln(P_{i,j,t}) = \alpha_0 dt d_{i,j,t} + \sum_{x=1}^{6} \alpha_{p,j,j,x} \ln(P_{i+x,j,t}) + \sum_{x=-6}^{-1} \alpha_{p,j,j,x} \ln (P_{i+x,j,t}) + \sum_{x=-6}^{6} \alpha_{p,j,-j,x} \ln (P_{i+x,-j,t}) + \sum_{x=-6}^{1} \alpha_{p,j,-j,x} \ln (P_{i+x,-j,t}) + \sum_{x=-6}^{6} \alpha_{s,j,j,x} \ln (S_{i+x,j,t}) + \sum_{x=-6}^{-1} \alpha_{s,j,j,x} \ln (S_{i+x,j,t}) + \sum_{x=1}^{6} \alpha_{s,j,-j,x} \ln (S_{i+x,-j,t}) + \sum_{x=-6}^{1} \alpha_{s,j,-j,x} \ln (S_{i+x,-j,t}) + \varepsilon_{i+1} + \varepsilon_{i,j,t}$$
(4)

Where subscripts *i* denote individual flights, operated either by airline *j* or airline –*j*. *P*'s, both in variable names and parameter subscripts, relate to prices, and similarly *S*'s denote that a flight is sold out. The summations over *x* denote the six flights departing before and after flight *i*, for both airlines and *dtd* is a counter for the number of days to departure.⁴ Fixed effects are captured in ε_{i} , and $\varepsilon_{i,j,t}$ is a normally distributed error term with zero mean.⁵

 $^{^3}$ Sold out flights are reported as sold out on EasyJet's website, but not on KLM's website. However, by comparing the schedule and flights on offer, a sold-out KLM-flight can still be identified.

⁴ Six flights earlier and later implies 24 h earlier and later for KLM. EasyJet has a lower frequency on the route and hence the time span is a bit longer.

⁵ Our theoretical framework is based on a demand shock for one good. If multiple demand shocks occur at the same time, it would matter whether these shocks are systematically related or not. If not, the error term captures the effect of the flight's own demand shock on the flight's price and the response to demand shocks on other flights are captured in the alphas in equation (4). In that case, the alphas are unbiased parameters. Only if demand shocks are systematically related, a bias might occur. See footnote 1 for a further discussion.

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Table 1

Descriptive statistics of fares by airline, day of departure and departure time.

	Mon	Tue	Wed	Thu	Fri	Sat	Sun
KLM, N	4779	4980	5097	4529	4525	4630	4593
Mean	207	160	155	164	161	192	257
Median	137	108	97	97	98	110	220
Sd	146	116	113	124	119	152	164
Min	96	96	96	96	96	96	96
Max	660	660	660	660	660	660	660
EasyJet, N	2398	1667	1701	2264	2963	1569	1547
Mean	109	68	62	73	71	79	179
Median	101	63	50	60	56	69	161
Sd	49	28	30	39	40	39	61
Min	35	35	33	34	34	33	69
Max	307	230	273	312	332	246	430
	7:00	9:40	12:20	15:15	17:10		21:00
KLM, N	5589	5483	5532	5477	5505		5547
Mean	162	189	187	170	205		196
Median	98	112	108	98	135		111
Sd	119	138	144	122	153		148
Min	96	96	96	96	96		96
Max	660	660	660	660	660		660
	7:25–7:30	8:45-9:00	13:35–14:20	14:45-15:20	17:20-17:40	18:45	20:35-21:30
EasyJet, N	2657	647	742	2812	4007	657	2587
Mean	79	61	103	90	83	66	117
Median	67	56	91	65	69	57	106
Sd	42	23	42	64	46	34	68
Min	34	35	50	33	35	35	35
Max	332	137	242	430	312	192	398

4. Data

We apply the framework above to the airline route Amsterdam – Geneva. Airfare data were collected from booking sites on a daily basis between February 14, 2017 and May 30, 2017 within the time interval of 10 p.m. and midnight. We collected single trip fares to avoid any influence of booking restrictions. Data were recorded for all flights departing between February 15, 2017 and May 31, 2017. A unique flight number is assigned to every flight observed, running in chronological order.⁶ Note that this is not the same as a flight number assigned by an airline (which is only unique on a given day). Every unique combination of a specific flight and a specific collection date make an observation. Each observation contains information on the airline, the observation date, the departure date, departure time and day of the week and the price of the ticket. Table 1 below shows descriptive statistics for the economy class airfare by airline and departure day.

The number of observations per day for KLM ranges between 4525 for Fridays and 5097 for Wednesdays and for EasyJet between 1547 (Sundays) and 2963 (Fridays). These differences reflect the differences in both the number of flights (6 per day for KLM, and 2 to 4 per day for EasyJet) and the number of sold out flights. The observations by departure time are grouped for EasyJet, as they don't fly on the exact same time every day. The mean fare of all days and departure times is higher than the median fare, hinting at a skewness to the right, which is consistent with prices increasing steeply once capacity is nearly reached. Flights on Mondays and Sundays are notably more expensive than midweek flights for both airlines (indicating higher willingness to pay when nearing the work week), and Saturdays are in between. Fare differences by departure time are smaller than those by day of the week and do not show any obvious pattern. Overall, average and median fares are considerably lower for EasyJet than for KLM.

Based on the raw dataset, we constructed variables relating the flights to each other, such as the airfare for the previous 6 and next 6 flights of both airlines, a sold-out dummy variable (again for the previous 6 and next 6 flights of both airlines), the number of days to departure and dummy variables for all weekdays, departure times and months. Ultimately, the data set contained 31,745 observations for KLM and 13,476 observations for EasyJet flights and 155 variables.

5. Empirical results

Table 2 below presents the results of the empirical analysis for both airlines. Since both the dependent variable and the independent price variables are in logs, the parameters can be interpreted as elasticities. The overall picture that emerges is that prices are positively related for adjacent (in terms of departure time) flights, with the effect being stronger for flights of the same airline. Both make sense in terms of our theoretical framework, as both the different departure times and the airlines' perceived quality are expected to increase the difference between the goods. The effect of adjacent prices is nearly symmetric, especially for flights of the same airline. The effect decreases if flights are further away, indicating that flights become closer substitutes if

⁶ The first departing EasyJet flight on February 15, 2017 was assigned number 1 whereas the last EasyJet flight on May 31, 2017 was assigned number 266, thus accounting for 266 EasyJet flights in that time frame on that route. In the same time frame KLM had 632 flights, thus numbered 1 to 632.

Table 2

Fixed effect regression result for ln(price).

	ln(price) KLM		ln(price) EZY	
	Parameter	Std error	Parameter	Std error
Days to Departure	-0.001***	-0.0001	-0.0002**	-0.0001
ln(price) of other flights				
KLM-6	0.088***	0.005	-0.024***	-0.005
KLM-5	0.028***	0.006	0.020***	0.006
KLM-4	-0.037***	-0.005	0.025***	0.006
KLM-3	0.044***	0.006	-0.025***	-0.006
KLM-2	0.092***	0.006	-0.004	-0.006
KLM-1	0.233***	0.005	0.042***	0.006
KLM + 1	0.242***	0.005	0.018***	0.006
KLM + 2	0.096***	0.006	-0.022^{***}	-0.006
KLM+3	0.047***	0.006	0.019***	0.005
KLM+4	-0.029***	-0.006	0.040***	0.006
KLM + 5	0.033***	0.006	0.009	0.006
KLM+6	0.090***	0.005	-0.033***	-0.005
EZY-6	0.013*	0.007	0.013*	0.007
EZY-5	-0.020**	-0.008	0.043***	0.008
EZY-4	-0.005	-0.008	0.014*	0.008
EZY-3	-0.020**	-0.008	-0.001	-0.008
EZY-2	0.023***	0.008	0.091***	0.008
EZY-1	0.028***	0.008	0.228***	0.008
EZY+1	0.051***	0.008	0.229***	0.008
EZY+2	-0.025***	-0.008	0.096***	0.009
EZY+3	0.014	0.009	-0.019**	-0.009
EZY+4	0.001	0.009	0.015*	0.009
EZY+5	0.021**	0.009	0.047***	0.009
EZY+6	-0.003	-0.009	0.025***	0.008
Other flights sold out				
KLM-6	0.550***	0.033	-0.174***	-0.032
KLM-5	0.225***	0.036	0.118***	0.039
KLM-4	-0.209***	-0.036	0.120***	0.038
KLM-3	0.275***	0.036	-0.141^{***}	-0.04
KLM-2	0.569***	0.036	-0.046	-0.036
KLM-1	1.492***	0.036	0.231***	0.038
KLM + 1	1.572***	0.036	0.157***	0.038
KLM+2	0.597***	0.037	-0.111***	-0.037
KLM + 3	0.268***	0.037	0.097***	0.036
KLM+4	-0.261***	0.037	0.341***	0.038
KLM + 5	0.302***	0.037	0.018	0.039
KLM+6	0.548***	0.035	-0.223^{***}	-0.036
EZY-6	0.063	0.038	0.092**	0.039
EZY-5	-0.069	-0.043	0.240***	0.043
EZY-4	-0.07	-0.044	0.093**	0.044
EZY-3	-0.098**	-0.045	-0.03	-0.045
EZY-2	0.075*	0.045	0.457***	0.045
EZY-1	0.179***	0.044	1.250***	0.044
EZY + 1	0.295***	0.046	1.234***	0.047
EZY+2	-0.177***	-0.047	0.496***	0.048
EZY+3	0.043	0.047	-0.126^{***}	-0.048
EZY+4	-0.042	0.049	0.157***	0.048
EZY+5	0.131***	0.049	0.226***	0.049
EZY+6	0.002	0.049	0.095**	0.047
Observations		31,745		13,476
Adjusted R2		0.723		0.566
-				

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

departure times are closer and vice versa. The impact of KLM's + 6 and - 6 flights on KLM's own flight are rather strongly positive. These are flights that fly exactly 24 h earlier or later. This might suggest that, for some travelers, departing a day earlier or later on the same time of day may be a better option than departing on a different time of day on the same day.

For ease of interpretation, we plot the parameters against the time difference between flights in Fig. 2. The general image that emerges shows that KLM flights affect other KLM fights that differ up to 12 h in departure time. The impact holds both for fares and for sold-out flights and decreases rather rapidly if the difference in departure times increases. The impact of EasyJet fares and sold-out flights on KLM's fares is rather obvious (and similar in size) for the flights directly adjacent, but the picture becomes less clear for flights further apart. Similar findings hold for the impact on EasyJet's fares. The main difference between the left-hand side and right-hand side of the figure is that the impact of EasyJet's own fares and sold-out flights seems to spread out over a longer period of time. It is not clear from our results whether this is caused by the difference in timing of flights or by something else.⁷

Our results show that the price of a flight responds to nearby flights, but less so to flights further apart timewise. Moreover, the response to fares of own flights is stronger than the response to flights of the other airline. The latter makes perfect sense, as KLM and EasyJet can be considered as imperfect substitutes, regardless of their departure times. Our results are remarkably –although not perfectly- symmetric in terms of earlier versus later flights. The response to other flights being sold out, roughly follows the same patterns.

The strongest price responses in our results are below 0.25, which is low compared to an expected value of unity for perfect substitutes. This suggests that departure time is likely to be a strong driver of product heterogeneity and that two otherwise exactly similar flights can be weak substitutes by their departure time alone.

6. Conclusions and discussion

We have empirically established how the fares of flights (on the route Amsterdam to Geneva) respond to changes in the fares of earlier and later flights. These fares are related, but the price-to-price elasticities do not exceed 0.25, suggesting that adjacent flights are rather weak substitutes. The elasticities for adjacent flights of different airlines are even smaller, implying that competition between airlines is rather weak, even if they offer very similar flights.

Our findings (on this route) suggest that the traditional view that two airlines operating on the exact same route engage in strong competition, needs rethinking. Price responses to price changes of other airlines are very low, and even price responses to a competitor's flight selling out are rather limited. This suggests that, on the route analyzed in this paper, airlines have quite some freedom in setting fares without provoking a competitive response.

Moreover, our findings may have implications for the ongoing debate on price dispersion in civil aviation and its relationship with competition. Our results suggest that arbitrage between flights (even of the same airline) is limited on the route investigated in this paper. If this holds for other routes as well, it implies that demand shocks at the level of individual flights can cause strong price responses that only partly spread over to other flights. Given that price dispersion is often measured at the airline-route level, this implies two things. First, demand shocks for individual flights contribute to price dispersion and are not arbitraged away easily. Secondly, flights with differently valued departure times (but similar capacity) cause price dispersion between flights of the same airline, even if no demand shocks occur. The above implies that to fully understand and correctly analyze price dispersion, researchers may also want to consider measures for demand volatility and the presence of flights leaving on different (more or less popular) times of the day.

We note that our empirical analysis is based on a single city pair.

 $^{^{7}}$ One would expect closer flights to be stronger substitutes and hence that elasticities decrease when flights are further apart, which is exactly what we find. Given this finding, there seems to be no merit to looking at flights that are even further apart.

Elasticity with respect to price of KLM-flight



Elasticity with respect to price of EZY-flight





Impact of sold out flight on In(price of KLM-flight)

Impact of sold out flight on In(price of EZY-flight)

specific arrival times. Moreover, it would be interesting to see whether

firms respond stronger to each other if the airlines competing on that

route are more similar (e.g. both low cost airlines or both network

Fig. 2. Graphical representation of parameters by difference in departure time (hours).

Obviously, other city pairs may provide different results, and future research should certainly focus on identifying and explaining these differences. One can imagine that substitutability depends on factors like the share of business travelers, as these are more likely to value

Appendix A. Relationship between price response and substitutability

Consider a situation where two imperfect substitutes (i and i) are offered. Both goods have a downward sloping demand curve and an upward sloping supply curve. We start from the observation that the price of good *i* has increased as a result of some exogenous development. The impact of the price increase of good i on the demand for good j is:

carriers).

$$dq_j^D = \frac{\partial q_j^D}{\partial p_i} dp_i \tag{A.1}$$

where $\frac{\partial q_j^D}{\partial p_i} > 0$ is the (local) slope of the demand for good j with respect to the price of good i and dq_j^D is the shift of the demand curve of good j (as a function of good j, as depicted in the lower left quadrant of Fig. 1).8 The shift of demand curve leads to a smaller (or equal if demand is inelastic) increase in equilibrium output, θ . This increase can be found by equating two expressions for the change in equilibrium price and solving the equation for θ .

$$\frac{\partial p_j^S}{\partial q_j}\theta = \frac{\partial p_j^D}{\partial q_j} \left(\theta - dq_j^D\right) \tag{A.2}$$

rewriting yields:

$$\Theta = \frac{\frac{\partial p_j^D}{\partial q_j}}{\frac{\partial p_j^D}{\partial q_j} - \frac{\partial p_j^S}{\partial q_j}} dq_j^D \tag{A.3}$$

From (A.3), we can calculate the price change:

⁸ We use linear slopes throughout this analysis, assuming that changes are sufficiently small to approximate the effect by a local linearization of the slopes.

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$$dp_{j} = \frac{\partial p_{j}^{S}}{\partial q_{j}} \theta = \frac{\frac{\partial p_{j}^{S}}{\partial q_{j}} \frac{\partial p_{j}^{D}}{\partial q_{j}}}{\frac{\partial p_{j}^{D}}{\partial q_{j}} - \frac{\partial p_{j}^{S}}{\partial q_{j}}} dq_{j}^{D}$$

Substituting (a.1) into (A.4) yields:

$$dp_{j} = rac{rac{\partial p_{j}^{S}}{\partial q_{j}}rac{\partial p_{j}^{D}}{\partial q_{j}}}{rac{\partial p_{j}^{D}}{\partial q_{j}} - rac{\partial p_{j}^{S}}{\partial q_{j}}}rac{\partial q_{j}^{D}}{\partial p_{i}}dp_{i}$$

Now note that $\frac{\partial q_j^D}{\partial p_l} = -\gamma_{ij} \frac{\partial q_j^D}{\partial p_j}$, where $0 < \gamma_{ji} < 1$ denotes the level of substitutability between the goods. We also note that $\frac{\partial q_j^D}{\partial p_j}$ is the inverse of $\frac{\partial p_j^D}{\partial q_j}$. Using these observations, we arrive at:

(A.4)

(A.5)

 $\frac{dp_{j}}{dp_{i}} = -\gamma_{ij} \frac{\frac{\partial p_{j}^{S}}{\partial q_{j}} \frac{\partial p_{j}^{D}}{\partial q_{j}}}{\frac{\partial p_{j}}{\partial q_{j}} - \frac{\partial p_{j}^{S}}{\partial q_{j}}} \frac{\partial q_{j}^{D}}{\partial p_{j}} = \gamma_{ij} \frac{\frac{\partial p_{j}^{S}}{\partial q_{j}}}{\frac{\partial p_{j}^{S}}{\partial q_{j}} - \frac{\partial p_{j}^{D}}{\partial q_{j}}}$ (A.6) shows that the price response is positively related to the level of substitutability. The steeper (i.e. inelastic) the supply curve is relative to the demand curve, the more precise the measure is. For perfectly inelastic supply, the price response is a perfect measure of the level of substitutability.

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