Measuring competition intensity; an application to air/hsr transport markets[☆]

Christiaan Behrens[a,b,*], Mark Lijesen[b]

[a] *Tinbergen Institute, Gustav Mahlerplein 117, 1082 MS Amsterdam, The Netherlands*
[b] *Department of Spatial Economics, VU University Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands*

Abstract

We develop a method to measure the intensity of competition between firms. Our method, which we call the Best Response Measure (BRM), is related to the conduct parameter method, but avoids the main problems associated with that method. The BRM relies on a very general framework and limited data requirements. Moreover, we show that it provides valuable information in determining the relevant market. We illustrate how the BRM can be used in markets with imperfect substitutes and apply the method to aviation markets in the North Sea area. This also enables us to establish to what extent the high speed rail link between London and the European mainland affects the supply by air carriers.

Keywords: inter- and intramodal competition, aviation, spatial networks, high-speed rail

JEL codes: D22, D43, L10, L93, R41

[☆]This research is supported by Advanced ERC Grant OPTION # 246969.

[*]Corresponding author. Fax +31 20 5986004, phone +31 20 5984847.

Email addresses: c.l.behrens@vu.nl (Christiaan Behrens), m.g.lijesen@vu.nl (Mark Lijesen)

1. Introduction

Measuring the competitiveness of a market is of great importance in competition policy and merger control. As early as halfway the previous century, economists have tried to find aggregate measures that can provide information on the competitiveness of a market. Several measures have been developed and used, of which the Hirschmann-Herfindahl index (HHI) is without doubt the most popular, due to its straightforward interpretation and light data requirements. The measurement of competition is not without problems however. Both the HHI and other competition measures are based on assumptions that limit their validity to specific cases. Moreover, all measures rely heavily on the definition of the relevant market, which is often problematic as well.

The commonly used concentration index HHI was formally linked to profitability by Cowling and Waterson (1976). They showed the HHI to be proportionate to the Lerner index (price cost margin) in the case of a symmetric Cournot model. Many studies (see Schmalensee (1989) for an overview) failed to empirically establish this relationship. The conduct parameter method (CPM) does not require strict assumptions on the type of model to establish the relationship with the Lerner index and became rather popular in the 1980s (see Bresnahan (1989) for an overview) and 1990s. It requires more data than the HHI, as well as some empirical work, which might be a hurdle for some to use it. Moreover, as shown by Corts (1999), the simultaneous estimation of a demand and cost functions may lead to incorrect results. The relative profit differences measure (RPD, Boone (2008)) measures change in the competitiveness of the market by changes in relative profits of firms with different profit levels. The measure can be used for many types of markets, but it is sensitive to changes in efficiency levels.

We contribute to the literature by developing a measure that is as intuitive as market concentration measures and has the same limited level of data requirements. Based on a very limited set of non-restrictive assumptions, it will pick up the intensity of competition, whether it follows from observed or unobserved aspects of product differentiation, differences in firm's beliefs or information; costs or quality differences. The measure is directly applicable to almost any type of market or model, can be applied at various levels of aggregation and its interpretation is consistent over time and markets. An important strength of our framework is that the impact of imperfect substitutes is endogenously determined. This way our framework also provides valuable information that may help regulators in determining the relevant market.

Our measure follows the intuition embedded in game theoretical models, without having to specify the model in much detail. We show that firms' best responses are related both to the profitability of the firms as well as the dead weight loss due to imperfect competition. We therefore develop a measure based on best responses, and hence label it the best response measure (BRM). We introduce the concept of quasi equilibrium, where all firms are assumed to play their best response and one firm is considered to play an unobserved strategy. This allows us to determine the slope of the best response functions in (quasi) equilibrium. Best responses are determined at the level of pairs of firm-product combinations, allowing in principal to obtain firm-pair specific responses. Firms that do not respond to each other, can be considered as not being in each other's relevant market. By means of illustration, we apply the general framework to a Cournot oligopoly with exogenous horizontal product differentiation. Interestingly, we find that the BRM for a symmetric Cournot oligopoly equals the inverse of the number of firms, which can serve as a useful benchmark.

We apply our measure to short haul airline markets in Europe. These markets provide several challenges that put our measure to a serious test. Unlike in the US, publicly available data is very limited for European airline markets. Airline markets exhibit both observed and unobserved product differentiation, both in terms of the airports that airlines fly from and in terms of the level of service. Moreover, cost differences are likely to be present and the behavior of some of the airlines (i.e. the network carriers) is likely to be affected by their network structure. Specifically in our study area, the high speed rail forms an influential substitute that should also be taken into account.

We estimate a hurdle model for airline-route output levels, consisting of a logit model for the decision whether to fly a certain route and a count model for the number of seats offered. We account for product differentiation by distinguishing between types of airlines, as well as through the distance between airports on both sides of the route. Earlier studies (Brander and Zhang (1990); Oum et al. (1993); Fischer and Kamerschen (2003)) applying the conduct parameter method to aviation find that airline conduct resembles Cournot behavior in duopoluy routes in the US. Fageda (2006) finds that competition in Spanish aviation is less competitive, as he also takes monopoly routes into account. None of these studies accounts for the possibility that airport pairs may be imperfect substitutes. We do take this into account and find that the vast majority of airline markets in our sample is less competitive than a homogeneous Cournot duopoly but more competitive than a monopoly.

Disaggregated results from our analysis also provide us with information on the geographic boundaries of the relevant market. In aviation, these are normally approximated by the catchment areas of airports, (generally defined as circle around an airport, see e.g. Marcucci and Gatta (2011), a more refined approach is developed by Lieshout (2012)). Apart from the geographical aspect, our results also take into account current output levels and the possibility that airlines of a different signature may have a stronger or weaker response. A special case of the relevant market definition is that of the high speed rail. Existing empirical evidence on rail-air interdependence is route specific (Gonzalez-Savignat (2004), Park and Ha (2006), and Behrens and Pels (2012)) or lacks theoretical support (Dobruszkes et al., 2014). Our results suggest that the impact of a change in capacity on a the high speed rail link between London and Brussels has a wider geographical scope.

The remainder of this paper is organized as follows. Section 2 discusses commonly used competition indicators and the problems associated with them. We develop the theoretical framework in section 3. The empirical setting is outlined in section 4. We present and discuss our empirical results in section 5. In section 6 we present the computed indicators, followed by a conclusion in section 7.

2. Competition indicators

All commonly used competition indicators are in some way linked to industry profitability, implying that they measure more or less the same thing. Nevertheless, Carbó et al. (2009) find only weak cross-country correlations between a set of profit and competition indicators, based on data from the same set of European banks.[1] These, and similar results makes one question the validity of the assumptions that link competition indicators to profitability. In this section, we will discuss the most common indicators to measure the level or intensity of competition and the problems they run into.

Concentration measures, such as the HHI, the Gini-coefficient and market shares of the largest firms, provide easy-to-measure and highly intuitive measures of competitiveness and have been very popular among regulators for decades. The indicators measure concentration rather than competition, but the HHI has been formally linked to the Lerner index by Cowling and Waterson (1976) for a symmetric Cournot oligopoly, establishing that more concentrated markets are less competitive. If cost or quality differences between firms exist, concentration may however be the outcome of the competitive process. Consider a Cournot duopoly with homogeneous goods and cost differences. The low cost firm will have a higher market share and hence the HHI will be larger than 0.5. In this static example, the HHI correctly approximates industry profitability. Suppose however, that the intensity of competition increases. The market share of the low cost firm increases, as does the HHI. The increase of the HHI suggests that competition has become less intense, whereas the opposite has occurred.

[1]See Schmalensee (1989) for an overview of similar findings in earlier literature.

One can think of many cases where the HHI certainly or maybe provides an incorrect image of the intensity of competition. Only in the case of a homogeneous goods Cournot market, the link between concentration and profitability is guaranteed.

Another approach that has been popular with regulators and academics for quite some time is the conduct parameter method (CPM), which was used extensively in the 1980s and 1990s (see Bresnahan (1989) for an overview). Like the HHI, this measure is linked to the Lerner index (it is also referred to as the elasticty adjusted price-cost margin), but the assumptions that establish this link are less restrictive. The measure is established empirically by simultaneous estimation of the industry's cost function and demand function. Estimating these functions may lead to a loss of information, especially if firms set different prices or have different cost levels. Moreover, Corts (1999) shows that the conduct parameter method can lead to mis-measurement, as a result of incomplete information when simultaneously estimating the cost- and conduct parameters.

The relative profit differences (RPD) measure (Boone, 2008) is a fairly new addition to the collection of competition indicators. Consider three firms ranked by their level of efficiency. The RPD is then defined as the profit difference between the first and third firm, divided by the profit difference between the second and third firm. An increase in competition will lead to an increase in the RPD as long as it reallocates output from less efficient firms to more efficient firms. This holds for a great number of markets and models, giving the measure a wide validity. The RPD measure may also lead to misleading results however. Rather than being exogenous, the efficiency levels of firms may be an outcome of the competitive process. If, for example, an increase in competition leads to an increase of efficiency levels, the RPD might provide an incorrect conclusion on the development of competition. This is especially the case if the least efficient firms improve their efficiency more than the most efficient firm does. Other factors might influence the result as well. Suppose that, in a horizontally differentiated market, consumer preferences change. This would cause a change in relative profits without any relationship with the intensity of competition.

One of the reasons that the HHI became so popular is probably that it only requires market shares to be computed, which are fairly easy to come by. The CPM requires more data, as both the demand and cost functions need to be estimated. At the minimum, this requires total costs, prices and outputs. Several control variables (e.g. demand and cost shifters) might be needed too. If the good is produced by multiproduct firms, estimating the cost function will require even more data. The RPD requires similar data, but can be applied to a smaller number of firms, provided that each firm sells only one product. For multi-product firms, identifying efficiency levels for firms will require more data and additional analysis.

In the following section, we will construct a measure that does not suffer from the problems described above. Additionally, our measure does not require the researcher to define the relevant market ex ante, as it follows naturally from the analysis.

3. Theoretical Framework

3.1. The general model

The aim of this section is to derive a measure that unambiguously reflects the intensity of competition in a market, using only a small number of widely accepted assumptions. The development of that measure runs along similar lines as the development of the conduct parameter, but we avoid the problems mentioned in the previous section by focusing on best responses rather than attempting to estimate an elasticity-adjusted Lerner index.

Consider an industry where n profit maximizing firms face a downward sloping aggregate demand curve and have non-negative marginal costs. Furthermore, we assume that the level of demand is positive if price equals marginal costs. U nder these very general assumptions, the welfare loss due to market power results directly from aggregate output being below its optimal level. This implies that any measure that correctly expresses the difference between the actual output in a market and the welfare maximizing level of output, provides an adequate measure for the welfare loss due to market power, on which we will base our measure for the intensity of competition.

Every individual firm j maximizes profits and hence equals marginal costs, $c_j'(q_j)$, to marginal revenues:

$$p_j(Q) + \frac{\partial p_j(Q)}{\partial q_j} q_j = c_j'(q_j) \tag{1}$$

where q_j denotes firm j's output, $Q = \sum_j q_j$ denotes market output and $p_j(Q)$ resembles the inverse of the demand relationship $Q(p_j)$ that firm j faces. Reshuffling and multiplying both sides by $\frac{\partial Q(p_j)}{\partial p_j}$ yields the impact on (aggregate) output associated with the price cost margin of firm j:

$$\frac{\partial Q(p_j)}{\partial p_j}\big(p(Q) - c_j'(q_j)\big) = -\frac{dQ}{dq_j} q_j, \tag{2}$$

Where the right hand side equals the market response to any change in firm j's output times firm j's output level. Since $Q = q_j + \sum_{i \neq j} q_i$, we can express the market response as:

$$\frac{dQ}{dq_j} = 1 + \sum_{i \neq j} \frac{dq_i^*}{dq_j} \tag{3}$$

Where q_i^* reflects the (Nash) equilibrium output of firm i. Given the characteristics of the Nash equilibrium, the observed behavior of every firm is its best response to the other firms' actions. However, if we were to derive the equilibrium analytically, we could not determine the value of dQ/dq_j, since equilibrium outcomes of a Nash game do not contain decision variables of other players. To work around this issue, we assume that firm j follows a strategy that is unobserved by both the researcher and the other firms. Hence, this strategy will be treated as exogenous in the model. The strategy of firm j might still be the best response to the other firms' actions, or it might be based on different strategies, other objectives, or differences in information and so on. The other firms are assumed to play a best response, both to firm j's observed output and to each other's strategies. Solving the model, while assuming firm j's strategy to be exogenous, yields a quasi equilibrium that allows us to determine the value of dQ/dq_j.

Summation of (2) over all firms provides the total effect, i.e. the difference between the actual and the optimal aggregate output levels. We drop the minus for ease of interpretation and, in order to compare the indicator over markets and over time, divide the total effect by total industry output. This leads to our (inverse) measure of competition, the best response measure (BRM):

$$BRM = \sum_j \frac{dQ}{dq_j}\frac{q_j}{Q}, \tag{4}$$

which is the sum of the elasticities of market responses to any firm's change in output, as well as a weighted average of the individual measure $\frac{dQ}{dq_j}$. Note that in a competitive market (as well as in a Bertrand oligopoly market), $\frac{\partial Q}{\partial q_i} = 0 \forall i$ whereas it takes a unity value in the case of a monopoly. In a homogeneous symmetric Cournot market, the outcome would be $\frac{1}{n}$, as we will show later on. This implies that the BRM has a very straightforward interpretation: The market is as competitive as a symmetric Cournot market with $\frac{1}{BRM}$ firms would be. By coincidence, the often used HHI has the same interpretation, albeit that the HHI measures concentration rather than competitiveness.

The framework above is clearly related to the framework of the conduct parameter method.[2] In fact, under the assumption that firms have equal costs and outputs, (2) may be rewritten to the elasticity adjusted Lerner index (Bresnahan, 1989). We feel that this assumption would however sincerely limit the generality of our approach. Moreover, we note that our measure does not require information on the industry's demand function, thus avoiding the problem of mismeasurement in the simultaneous estimation, as discussed by Corts (1999).

[2]See Bresnahan (1989) for a review of papers using this method.

3.2. An illustration: Cournot with horizontal product differentiation

So far, we didn't specify a cause for differences in the intensity of competition. Although we feel that knowing these causes is useful in understanding the nature of market power, they are not crucial for measuring the intensity of competition. We will however further illustrate our framework, using a model where horizontal product differentiation lowers the intensity of competition in a Cournot framework. Consider an n-firm oligopoly, where firms i and j produce their own variant of a good and the remaining $n-2$ identical firms produce a third variant. The following inverse demand function for good i is assumed to hold:

$$p_i = \alpha_i - \beta_i q_i - \gamma_{ij} q_j - \sum_{k \neq i, k \neq j} \gamma_{ik} q_k. \tag{5}$$

with parameters α_i and β_i strictly positive and $\gamma_{ij} = \gamma_{ji}$. For $\gamma_{ij} > 0$, goods i and j are substitutes. The parameters provide information on the degree of substitutability. If $\alpha_i = \alpha_j$ and $\beta_i = \beta_j = \gamma_{ij}$, goods i and j are perfect substitutes. For $\beta_i \beta_j > \gamma_{ij}^2 > 0$, goods are imperfect substitutes.

Firms maximize profits by setting quantities and have linear cost functions. From the first order condition of firm i's profit maximization problem, we can derive firm i's best response function in output:

$$q_i = \frac{\alpha_i - c_i - \gamma_{ij} q_j}{2\beta_i} - (n-2)\frac{\gamma_{ik}}{2\beta_i} q_k. \tag{6}$$

Treating firm j's output as exogenous as discussed earlier and deriving similar best responses for all firms k, we find the quasi equilibrium output for firm i by solving the system of $n-1$ equations (see Appendix C). The slope of the quasi equilibrium output of firm i with respect to q_j is equal to:

$$\frac{dq_i^*}{dq_j} = \frac{-\gamma_{ij}}{2\beta_i} \frac{(n-1)2\beta_i\beta_k}{(n-1)2\beta_i\beta_k - (n-2)\gamma_{ik}^2} + \frac{(n-2)\gamma_{ik}\gamma_{kj}}{(n-1)2\beta_i\beta_k - (n-2)\gamma_{ik}^2}. \tag{7}$$

The slope of the best response of firm in quasi equilibrium, as represented by (7) coincides with the same term on the right hand side in (3) and quantifies the intensity of competition between firms i and j. A further exploration of the properties of this slope is provided in Appendix C, here we limit ourselves to noting that the case of full symmetry (i.e. all β's and γ's equal) yields the outcome of $-1/n$. Substituting that result in 3 yields a value of $1/n$ for the BRM, the outcome of a symmetric Cournot oligopoly with homogeneous products, ranging from 1/2 in duopoly to 0 if the number of firms is very large.

4. Empirical Setting

4.1. Aviation in the North Sea area

We test our theoretical framework by examining the aviation industry, in particular, we analyze flights between the United Kingdom on the one hand and Belgium, France, Germany, The Netherlands, and Switzerland on the other hand.[3] Figure 1 provides a map of our study area and the airports in our sample. Civil aviation markets provide a great opportunity to illustrate our framework, as capacity decisions reflect strategic choices in a quantity game.[4] Moreover, product differentiation is a common feature of civil aviation, both in terms of branding and product quality and in terms of access to the nodes in the network. Other factors that might influence the intensity of competition in aviation are cost differences, imperfect information, conjectural variations, airport capacity restrictions and the place that a specific link may have in the broader network of an airline. Furthermore, imperfect substitutes are available, in the form of high speed rail, conventional rail or road transport.[5]

Both the UK and mainland Europe have a fairly high density of airports, as well as good

[3]Airports that do not have landside access to other airports are excluded from the analysis.

[4]Airlines set their schedules for 6-months periods. Once the schedule is set, capacity may be altered slightly by applying smaller or larger plains, but most of the adjustments are made through advanced pricing mechanisms.

[5]A special feature of our study area is that the UK is not accessible by road or conventional rail. We assume that ferries are too distinct from airlines to take into account.

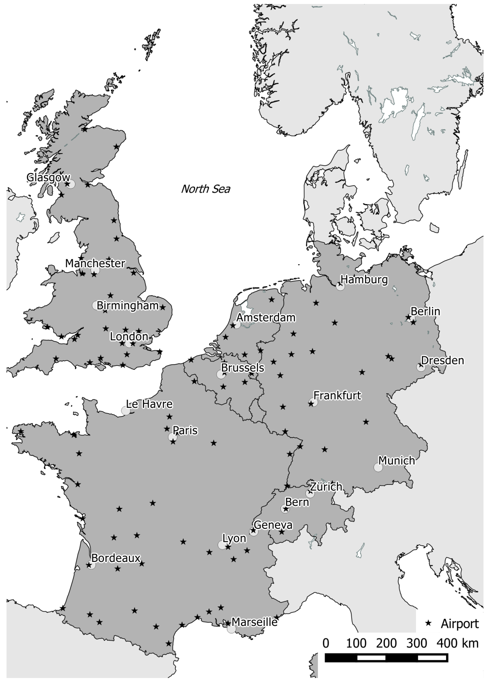

Figure 1: Study area

infrastructure to access these airports. This allows travelers to choose from several airports on both sides of the trip. Any flight between an airport pair is therefore considered to be an imperfect substitute to a flight between any other airport pair. This raises the question to what (geographical) extent substitution is present. A flight from London Luton to Paris Charles de Gaulle is likely to compete with a flight from London Heathrow to Paris Orly. But to what extent do these flights compete with a flight from Manchester to Amsterdam? Our analysis is able to answer that question empirically by looking at firms' best responses. This allows us to endogenously determine the relevant market. Moreover, we can assess the geographical scope of the impact of the High speed rail links to London on air routes. Apat from fliughts being imperfect substitutes, the 'signature' of the airline plays a role

4.2. Empirical model

The theoretical framework developed in the previous sections, provides an expression for the slope of the best response function in quasi equilibrium. We now translate this theoretical finding into an expression that we can estimate and test empirically. We assume that airlines set their schedules without knowing the new schedule of their competitors and base their decision on the current schedule. We treat previous period schedules as exogenous, just as in the theoretical framework. Under the assumption that the slope of the best response function does not depend on the level of output, we write the equilibrium output of any firm-market pair i as the sum of the products of the slopes and quantities of all other firms' outputs in the previous period, plus a constant:[6]

$$\overline{q}_{i,t} = A + \sum_{j \neq i} \frac{dq_i^*}{dq_j} q_{j,t-1}, \tag{8}$$

where A reflects a set of error terms and control variables including a constant, which we will specify later on. For now, we would like to stress that $\frac{\partial q_i^*}{\partial q_j}$ depends on the level of substitutability of products i and j. We distinguish between two sources that affect this level; the geographical distance between the routes and the 'signature' of the airline.

Geographical distance matters because the catchment areas of airports sometimes overlap. The closer the airports are, the larger this overlap is. We choose not to use predefined multiple airport regions, but use a distance decay function to account for the impact of distance on substitutability. We define:

$$\frac{dq_i^*}{dq_j} = B_{ij} \cdot e^{-\lambda \cdot d_{ij}}, \tag{9}$$

where d_{ij} is defined as the distance between both origin airports plus the distance between both destination airports of flights i and j and λ is a distance decay parameter. The distance decay parameter can not be estimated directly, but has to be chosen based on model fit.

With respect to the 'signature' of airlines, we are mainly interested in how this 'signature' affects the response to other airline's behaviour. We expect similar firms to respond in a

[6]Given the assumption that the slope of the best response function does not depend on the level of output, this is equivalent to the sum of the integrals of the best response functions.

similar manner and hence have a homogeneous B_{ij} parameter. The set M contains all airlines and $M = \bigcup_{f=1}^{F} M_f$. In other words, each airline belongs exclusively to one of the F groups, for which we use indices f. This allows us to write the summation of (9) for a homogeneous group f as:

$$\sum_i \frac{dq_i^*}{dq_j} = B_{ij} \sum_i \; e^{-\lambda \cdot d_{ij}}. \tag{10}$$

We add several controls to the model. First of all, we control for economic growth by adding the wighted average of the GDP of the origin and destination countries. Moreover, we use dummy variables (leading to an unconditional fixed effects specification) for every airline, year, airport pair and mainland airport-period combination (e.g. CDGJan2009) in the data. The combination of the lag structure and the controls used adequately deals with any possible endogeneity problem. The relationship between the equilibrium supply $\overline{q}$ in period t of firm v in group f on route k serving origin *origin* and destination *dest*, now reads as follows:

$$\begin{aligned} \overline{q}_{vr,t}^{f} =& B_{fO} \cdot \ln \overline{q}_{vr,t-1}^{f} + B_f \cdot \sum_{s \neq r} \frac{\overline{q}_{vs,t-1}}{e^{\lambda \cdot d_{sr}}} + \sum_{h=1}^{F} B_{fh} \cdot \sum_{\substack{w \neq v \\ w \in M_h}} \sum_{s} \frac{\overline{q}_{ws,t-1}}{e^{\lambda \cdot d_{sr}}} \\ &+ B_{fhsr} \cdot \sum_{s} \frac{q_{s,t-1}^{hsr}}{e^{\lambda \cdot d_{sr}}} + B_{GDP} GDP_{r,t} + \mu_v + \mu_{year} + \mu_r + \mu_{dest,t} + \varepsilon_{vr,t}, \end{aligned} \tag{11}$$

with q_s^{hsr} denoting the output of the high speed rail. The first two terms specify the group specific reactions to airline v's own output on the same route and other routes respectively. The third term captures airline v's reaction to the output of all other competitors, the reaction is specified to be group specific, including the group airline v belongs to. The fourth term captures the reaction of airline v on the output setting of the high speed rail.

4.3. Empirical strategy

The empirical estimation uses the monthly number of seats provided by carrier v on route r as the dependent variable. Although the data are monthly, we specify delayed variables by taking the value of that variable one year ago, i.e. in the same month a year ago. The number of potential route-carrier combinations is much bigger than the actual route-carrier combinations where flights are offered. This implies that the dataset holds an excessive number of observations that have value zero, for which we have to account in our analysis.

We estimate a hurdle model, with in the first step a logit model and in the second step the zero truncated negative binomial count model. This two step model relaxes the assumption that the zeros and positive outcomes come from the same data generating process (Cameron and Travedi, 2010). In other words, we see the decision to quit or enter a route as a different process than adjusting the number of seats or monthly flights to changes in the competitive environment. The binomial count model has the set of explanatory variables as defined in (11). The logit model uses the same specification, except for the exclusion of the route dummies and the inclusion of an extra variable indicating whether or not the airline already serves other destinations from the UK-airport in the route.

4.4. Data

Table 1 provides the core descriptives of our data set. We obtain monthly aviation service levels for 2004-2010, using OAG Market Analysis (OAG, 2011), for the rail schedules we use the European Rail Timetable (Thomas Cook, 2011). We obtain GDP figures from Eurostat (Eurostat, 2015). The base year for the GDP index is 2005. We weight this index over the origin and destination country using absolute GDP levels. As a measure for the proximity of routes, we add up the Eucledian distance between the airports on both sides of the route.[7]

Table 1 provides information on the groups of airlines that we distinguish between. Full service airlines in our sample serve a total of 148 route-airline combinations (the level

[7]For example the distance between routes Amsterdam-Manchester and Rotterdam Liverpool is defined as the Eucleadian distance between Amsterdam and Rotterdam (46 km) plus the distance between Manchester and Liverpool (39 km) and hence amounts to 85 km. The mean distance within our sample is 768 kilometers, with a standard deviation of 333 km. Mean and standard deviation are based on the unweighted average of all elements in the distance matrix, including high speed rail stations.

Table 1: Descriptives.

Variable	Route-airline combinations	Total observations	Total observations (Seats>0)	Mean (Seats>0)	Standard deviation (Seats>0)
Seats FSA (monthly)	148	12432	6983	12014.93	11125.06
Seats LCC, (monthly)	451	37884	13255	5174.23	4349.53
Seats RA, (monthly)	53	4452	2470	8001.06	8168.09
Seats Other, (monthly)	86	7224	514	1707.08	1354.21
GDP (index)	738	61992	23222	102.64	2.91

of observation in our analysis). With 84 time periods in our data, this leads to 12 432 observations. Many of the observations have zero values however, since not every route-airline combination was served every month. 6983 Observations have a positive capacity level for full service airline and the average number of monthly seats offered was slightly more than 12 thousand (i.e. about 70 Boeing 737-800s a month). For low cost carriers, the number of observations is much higher, but the mean number of seats per observation is lower, suggesting that -in our study area- low cost carriers fly more routes at a lower output level than full service airlines. The latter is not surprising, as the hubs of the four largest full service airlines are within our study area. The descriptives also reveal that the 'other' airlines are a small and very heterogeneous group. Despite their large number (see Appendix A), they serve a low number of routes and offer a low number of seats compared to the other airlines in our sample.

5. Estimation results and interpretation

Table 2 provides the results of the second step of the hurdle model for three different levels of distance decay parameter lambda (the first step can be found in Appendix B).

The most important parameters are statistically significant and have the expected sign and order of magnitude. Within-group responses for full service airlines, low cost carriers and regional airlines are significant and negative and their absolute values are larger than those for between group-responses. Responses regarding 'other' airlines are generally not significant, which is caused by the highly heterogeneous nature of this group. Judging by the lack of statistical significance, full service airlines do not seem to react to the actions of

Table 2: Zero truncated negative binomial model, seats

	(1) $\lambda = 0.003$	(2) $\lambda = 0.007$	(3) $\lambda = 0.01$
B_{FSA}	-0.153^{**}	-0.237^{*}	-0.436^{**}
	(0.0478)	(0.108)	(0.152)
$B_{\text{FSA,FSA}}$	-0.558^{***}	-1.111^{***}	-1.393^{***}
	(0.0534)	(0.101)	(0.132)
$B_{\text{FSA,LCC}}$	-0.0784^{*}	-0.487^{***}	-0.801^{***}
	(0.0309)	(0.0615)	(0.0868)
$B_{\text{FSA,RA}}$	0.0275	0.00860	-0.213
	(0.110)	(0.160)	(0.196)
$B_{\text{FSA,Other}}$	0.00302	-0.689	-0.927
	(0.292)	(0.444)	(0.643)
B_{LCC}	0.110	0.504^{***}	0.826^{***}
	(0.0641)	(0.150)	(0.225)
$B_{\text{LCC,FSA}}$	-0.0705	-0.218^{*}	-0.457^{***}
	(0.0460)	(0.0959)	(0.138)
$B_{\text{LCC,LCC}}$	-0.132^{***}	-0.271^{**}	-0.303^{*}
	(0.0357)	(0.0875)	(0.135)
$B_{\text{LCC,RA}}$	-0.302^{**}	-0.620^{***}	-0.756^{***}
	(0.110)	(0.170)	(0.216)
$B_{\text{LCC,Other}}$	-0.123	-0.148	-0.140
	(0.285)	(0.557)	(0.797)
B_{RA}	0.964^{***}	2.476^{***}	2.672^{***}
	(0.266)	(0.455)	(0.561)
$B_{\text{RA,FSA}}$	-0.130	-0.439^{***}	-0.732^{***}
	(0.0732)	(0.112)	(0.132)
$B_{\text{RA,LCC}}$	-0.00252	-0.0526	0.0176
	(0.0582)	(0.165)	(0.261)
$B_{\text{RA,RA}}$	-0.958^{***}	-2.230^{***}	-3.060^{***}
	(0.188)	(0.309)	(0.393)
$B_{\text{RA,Other}}$	-0.533	-0.0601	-0.930
	(0.700)	(1.414)	(2.151)
B_{Other}	64.14	124.5^{*}	194.0^{*}
	(34.71)	(60.73)	(86.46)
$B_{\text{Other,FSA}}$	-0.386	-1.449	-2.208
	(0.267)	(0.863)	(1.261)
$B_{\text{Other,LCC}}$	-0.331^{*}	-0.337	-0.267
	(0.162)	(0.536)	(1.047)
$B_{\text{Other,RA}}$	0.703	1.595	1.884
	(0.735)	(1.446)	(1.923)
$B_{\text{Other,Other}}$	1.766	1.474	-3.071
	(1.660)	(5.157)	(8.850)
$B_{\text{FSA,HSR}}$	-0.0583	-0.149^{**}	-0.245^{***}
	(0.0346)	(0.0534)	(0.0662)
$B_{\text{LCC,HSR}}$	-0.115^{**}	-0.210^{***}	-0.275^{***}
	(0.0367)	(0.0596)	(0.0797)
$B_{\text{RA,HSR}}$	-0.199^{***}	-0.248^{***}	-0.251^{**}
	(0.0472)	(0.0676)	(0.0849)
$B_{\text{Other,HSR}}$	0.216	1.824	3.863^{*}
	(0.215)	(1.002)	(1.875)
$B_{\text{FSA,Lag(Seats)}}$	0.621^{***}	0.609^{***}	0.601^{***}
	(0.0310)	(0.0328)	(0.0342)
$B_{\text{LCC,Lag(Seats)}}$	0.274^{***}	0.259^{***}	0.254^{***}
	(0.0164)	(0.0164)	(0.0164)
$B_{\text{RA,Lag(Seats)}}$	0.562^{***}	0.550^{***}	0.551^{***}
	(0.0399)	(0.0372)	(0.0366)
$B_{\text{Other,Lag(Seats)}}$	-0.116	-0.0829	-0.0496
	(0.183)	(0.153)	(0.139)
GDP	0.0424^{***}	0.0530^{***}	0.0579^{***}
	(0.00669)	(0.00646)	(0.00638)
Dispersion parameter	-2.590^{***}	-2.610^{***}	-2.612^{***}
	(0.0289)	(0.0285)	(0.0285)
Observations	16679	16679	16679
ll	-145070.7	-144900.7	-144887.4

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

regional airlines, whereas the latter do not respond to the output of low cost carriers. The parameter for the low cost response to full service airlines is significant only in model (3), i.e. where the impact of distance is assumed to be strong.

The estimated coefficients are semi-elasticities, hence in model (1) in table 3, the coefficient $B_{FSA,FSA} = -0.558$ implies that when distance between both OD pairs is arbitrarily small, adding one extra seat by a full service airline would result in a decrease in seats offered of 0.558 per cent by any other full service airline. This effect decreases as the distance between the OD pairs increases.

The difference between the three models seems not to be too large in terms of parameter values and -significance or in terms of model fit, but we do note that some parameters are statistically significant in model (2) and (3) but not in model (1).

Using the estimated results, we can calculate best responses at the route-carrier level, e.g. how does Air France on Manchester-Paris Charles de Gaulle react to a capacity increase of Easyjet on Liverpool-Paris Charles de Gaulle? These values represent the slope of the quasi equilibrium output, $\frac{dq_i^*}{dq_j}$, and are expected to vary between 0 and $-1/n$. For some route-carrier pairs, the best response was positive rather than negative however. The percentage of positive outcomes for model (1), (2) and (3) are 8.8%, 4.2% and 2.9% respectively, and all these cases relate to flights leaving from London. We note that distance is not a perfect indicator for access and egress time, especially in the case of London, where five airports are located in and around a dense metropolitan area.

The information on best responses can be used to see the responses to any output change by a particular carrier on a particular route, as is done in Figure 2 below, showing the best responses to an increase of Ryanair's output on the London Stansted to Marseille route by 1 seat.

The figure shows best responses by British Airways and Easyjet on routes from other London airports to Marseille and the fairly nearby airports of Geneva (323 km) and Nice (155 km). Note that the (absolute) size of the response depends on the distance between the airports on both sides of the routes, the type of airline and the current volume of seats that the responding carrier offers. Individual best responses already provide a first indication as to

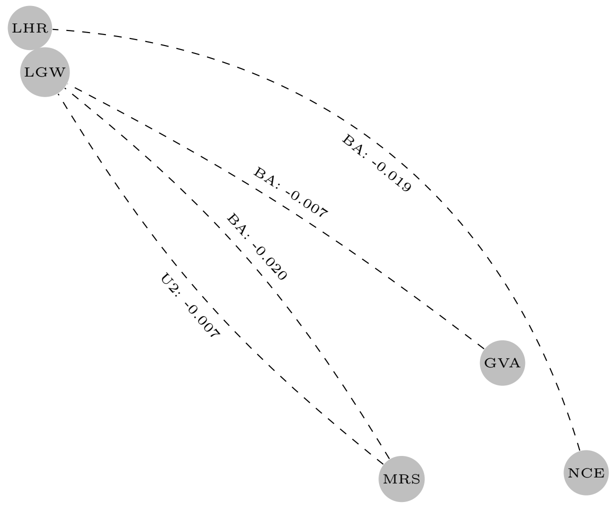

Figure 2: Best responses to Ryanair's capacity on STN-MRS (≤ -0.005)

what extent products are still substitutes and hence belong to the same relevant market. The threshold value for this level is arbitrary, but the level of the best responses is determined empirically. In Figure 2, we use -0.005 as the threshold value. Should we have used -0.01 instead, then only the BA flights from London Gattwick to Marseille and from London Heathrow to Nice would belong to the same relevant market.

We stress that the relevant market concept is more than a geographical concept; it also depends on the signature of the airlines involved, as well as on their relative size. This can be demonstrated by figures 3 and 4 below, representing a 1-seat output increase on the Manchester Frankfurt route by Lufthansa and Flybe respectively.

It is immediately clear from figures 3 and 4 that the relevant market for the full service airline (Lufthansa) is different from that of the low cost carrier (Flybe), despite the fact that they serve the exact same route.

As a policy relevant extension of the results above, we focus on the high speed rail connection between the UK and the European mainland, providing high speed links from London to Brussels and Paris. Similar to what we did for airlines above, we can determine the relevant market for one of the high speed rail links. Apart from the regulatory significance

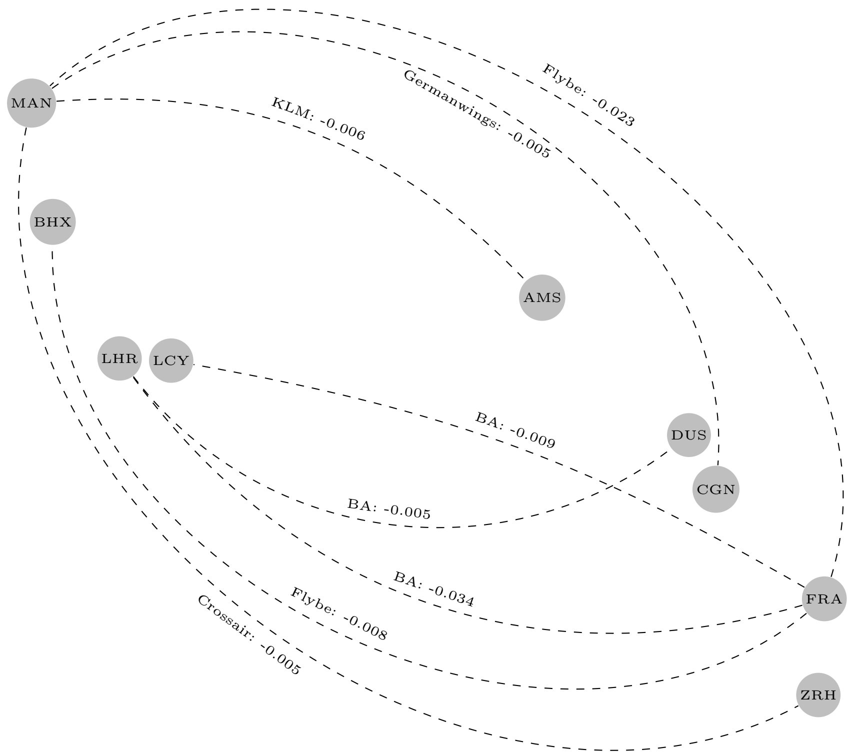

Figure 3: Best respones to Lufthansa's capacity on MAN-FRA (≤ -0.005).

of this analysis, it also provides information on how strong the substitution between air and high speed rail is. Figure 5 provides the impact of adding one seat to the output of the high speed rail between London and Brussels.

Although the effects on individual route-carrier combinations are fairly small, the impact of high speed rail on aviation is substantial, especially if one keeps in mind that the capacity of a train is considerably larger than that of an airplane. We also note that the geographical impact in the UK is limited to London, whereas it spreads out considerably on the European mainland.

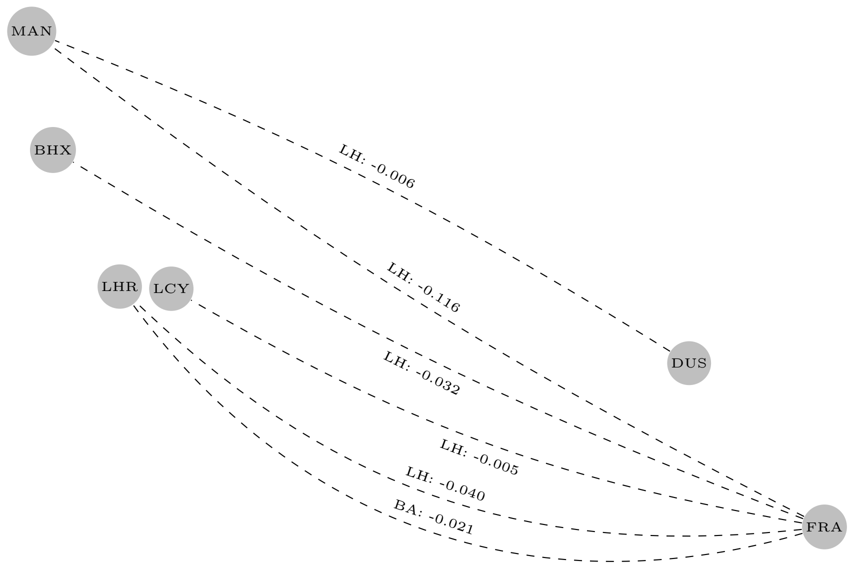

Figure 4: Best responses to Flybe's capacity on MAN-FRA (≤ -0.005).

6. The intensity of competition on short haul airline markets in western Europe

From the best responses presented in the previous section, we can derive the intensity of competition measure, BRM, as defined in (3) and (4). We choose to determine the BRM at the city pair level rather than the airport level, as we feel that this better reflects the choices made by consumers.[8] Table 3 presents the top 10 and bottom 3 most competitive city pairs in our sample for different levels of the distance decay parameter λ.

Table 3: Competitiveness ranking by city-pair level, for different distant decay values.

Rank	$\lambda = 0.003$	$\lambda = 0.007$	$\lambda = 0.01$
1	London-Antwerp [-0.569]	London-Antwerp [-0.136]	London-Amsterdam [-0.126]
2	London-Brussels [-0.212]	London-Amsterdam [-0.063]	London-Antwerp [0.112]
3	London-Frankfurt [-0.210]	London-Dusseldorf [0.002]	London-Frankfurt [0.116]
4	Manchester-Antwerp [-0.138]	London-Frankfurt [0.002]	London-Dusseldorf [0.142]
5	London-Dusseldorf [-0.113]	London-Brussels [0.105]	London-Paris [0.216]
6	London-Paris [-0.073]	London-Paris [0.179]	London-Rotterdam [0.242]
7	London-Amsterdam [0.002]	London-Cologne [0.209]	London-Brussels [0.281]
8	Birmingham-Frankfurt [0.015]	London-Rotterdam [0.220]	London-Cologne[0.382]
9	Birmingham-Brussels [0.041]	East Midlands-Brussels [0.307]	East Midlands-Brussels[0.427]
10	Norwich-Amsterdam [0.044]	London-Stuttgart [0.315]	Birmingham-Amsterdam [0.437]
...			
...			
213	Glasgow-Berlin [0.928]	Edinburgh-Nice [0.984]	Edinburgh-Toulouse [0.997]
214	Edinburgh-Nice [0.934]	Edinburgh-Lyon [0.984]	Exeter-Rennes [0.997]
215	Edinburgh-Lyon [0.935]	Edinburgh-Toulouse [0.985]	Manchester-Brest [0.999]

[8]This choice is not fundamental, it merely determines the level at which best responses are weighted.

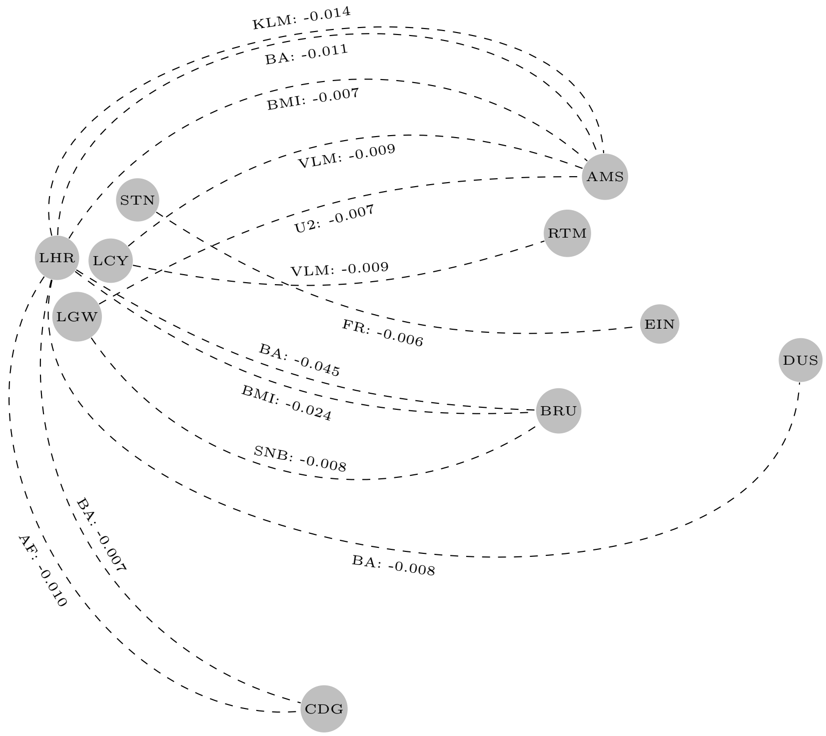

Figure 5: Best responses to HSR capacity on London-Brussels (≤ -0.005)

Several city pairs in the table have negative values for the BRM, especially for the lowest value of λ. The values for London-originating flights might be downward biased as discussed before. The ranking of city pairs does however make sense, as the high ranking city pairs indeed have larger numbers of carriers serving them and have centrally located mainland airports, implying the presence of relatively close substitutes. On the lower end of the ranking we see city pairs that are more to the periphery of our study area, where alternatives are located further apart.

Figure 6 presents the levels of the BRM, ranked by their magnitude for different levels of the distance decay parameter λ.

Recall that the BRM can be interpreted as the inverse of the number of symmetric Cournot firms that would yield an equally competitive market. This implies that, for $\lambda = 0.007$,

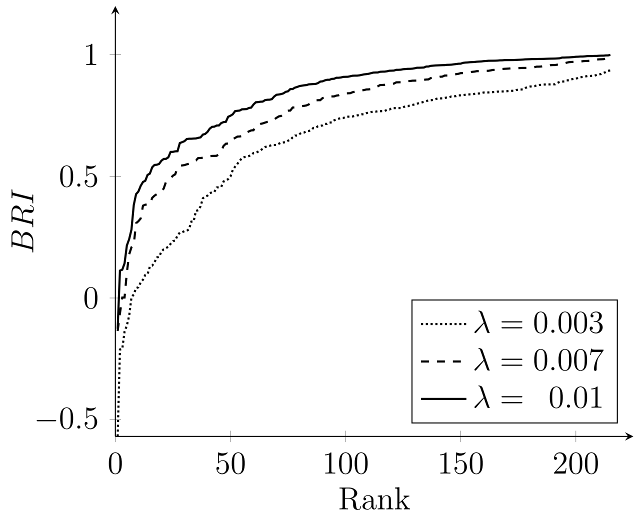

Figure 6: Intensity of competition on city-pair level, ranked by magnitude.

about 90 percent of the markets in our sample is less competitive than a symmetric Cournot duopoly would be.

7. Conclusion

We have developed an intuitive and highly flexible indicator to measure the intensity of competition, labeled BRM, and apply it to short haul airline markets in Europe. The theoretical foundation of the indicator requires just a few assumptions, all of which are widely accepted and used. This results in a highly general indicator that can be applied in many markets. Moreover, and quite uniquely, our indicator does not require any a priori market definition, as the boundaries of the relevant market can be derived from the disaggregated inputs to the indicator.

In this paper, we illustrate the working of our indicator in the case of a Cournot oligopoly market with exogenous horizontal product differentiation, showing that our indicator is capable of capturing the effect that product differentiation has on the intensity of competition. We then proceed to apply the model to real life data of airlines crossing the North Sea between the UK and the European mainland. In the application, we show how the relevant market for any specific connection can be determined, based on the estimated best responses of the competitors of the airline offering the connection. We show how both the distance between alternative airports and the signature of the airline affect those best responses. In the case of the high speed rail, airline responses to the high speed rail also provide information on the modal substitution potential of high speed rail, which is an important reason for governments investing in the associated infrastructure. Moreover, we calculate and present the BRM on the city pair level. The results suggest that the vast majority of the city pair markets is less competitive than a symmetric Cournot duopoly.

The development of our new indicator opens up a wide variety of opportunities for further research. First of all, our claim that the indicator can be used in many market types, calls for a more in-depth investigation. These investigations may be aimed at adopting the indicator in the case of e.g. contestable markets, monopolistic competition, markets with information asymmetry, markets with uncertainty and so on. Moreover, and more specific to the empirical application presented here, further research might focus on finding a more elegant way of modeling distance decay, in such a way that it can be estimated empirically.

Bibliography

Behrens, C. and Pels, E. (2012). Intermodal competition in the London-Paris passenger market: High-Speed Rail and air transport. *Journal of Urban Economics*, 71:278–288.

Boone, J. (2008). A New Way to Measure Competition. *The Economic Journal*, 118:1245–1261.

Brander, J. A. and Zhang, A. (1990). Market conduct in the airline industry: an empirical investigation. *The RAND Journal of Economics*, 21(4):567–583.

Bresnahan, T. F. (1989). Empirical Studies of Industries with Market Power. In Schmalensee, R. and Willig, R. D., editors, *Handbook of Industrial Organization*, volume II, pages 1021–1957. North-Holland, Amsterdam.

Carbó, S., Humphrey, D., Maudos, J., and Molyneux, P. (2009). Cross-country comparisons of competition and pricing power in European banking. *Journal of International Money and Finance*, 28(1):115–134.

Corts, K. S. (1999). Conduct parameters and the measurement of market power. *Journal of Econometrics*, 88(2):227–250.

Cowling, K. and Waterson, M. (1976). Price-Cost Margins and Market Structure. *Economica*, 43(171):267–274.

Dobruszkes, F., Dehon, C., and Givoni, M. (2014). Does European high-speed rail affect the current level of air services? An EU-wide analysis. *Transportation Research Part A: Policy and Practice*, 69:461–475.

Eurostat (2015). *National Accounts*. http://ec.europa.eu/eurostat/web/national-accounts/data/database.

Fageda, X. (2006). Measuring conduct and cost parameters in the Spanish airline market. *Review of Industrial Organization*, 28(4):379–399.

Fischer, T. and Kamerschen, D. R. (2003). Price-cost margins in the US airline industry using a conjectural variation approach. *Journal of Transport Economics and Policy*, 37(2):227–259.

Gonzalez-Savignat, M. (2004). Competition in air transport - The case of the high speed train. *Journal of Transport Economics and Policy*, 38:77–107.

Lieshout, R. (2012). Measuring the size of an airport's catchment area. *Journal of Transport Geography*, 25:27–34.

Marcucci, E. and Gatta, V. (2011). Regional airport choice: Consumer behaviour and policy implications. *Journal of Transport Geography*, 19(1):70–84.

OAG (2011). *OAG Historical Schedules*. OAG Aviation, Dunstable.

Oum, T. H., Zhang, A., and Zhang, Y. (1993). Inter-Firm Rivalry and Firm-Specific Elasticities in Deregulated Airline Markets. *Journal of Transport Economics and Policy*, 27(2):171–192.

Park, Y. and Ha, H. K. (2006). Analysis of the Impact of High-Speed Railroad Service on Air Transport Demand. *Transportation Research Part E: Logistics and Transportation Review*, 42(2):95–104.

Schmalensee, R. (1989). Inter-Industry Studies of Structure and Performance. In Schmalensee, R. and Willig, R. D., editors, *Handbook of Industrial Organization*, volume II, pages 952–1009. North-Holland, Amsterdam.

Thomas Cook (2011). *European Rail Timetable. Winter 2002/03 — Winter 2009/10 ed.* Thomas Cook Publishing, Peterborough.

Appendix A. Classification of carriers

Table A.1: Carriers classification

Full Service Airlines (FSA)	Low Cost Carriers (LCC)	Regional Airlines (RA)	Other
Air France	Air Berlin	Aer Lingus	Aer Annan
British Airways	BMI baby	BMI British Midland	Air Europa
KLM-Royal Dutch Airlines	Britannia Airways	Brussels Airlines	Air Exel Netherlands
Lufthansa German Airlines	EasyJet	Swiss Internation Air Lines	Air Scotland
	EasyJet Switzerland	VLM Airlines	Air Turquoise
	Fybe British European		Air Wales
	Flyglobespan		Astraeus
	Germanwings		Baboo
	Hapag-Lloyd Express		Cirrus Airlines
	Jet2.com		Condor Flugdienst
	Ryanair		Darwin Airline
	Thomsonfly		DBA Luftfahrtgesellschaft mbH
	Transavia Airlines		Duo Airways Ltd
	TUIfly		Eastern Airways
			EUjet
			European Air Express
			First Choice Airways
			Hamburg International
			Helvetic Airways
			Mytravel Airways
			OLT Ostfriesische Lufttransport
			Palmair
			ScotAirways
			SkySouth
			Thomas Cook Airlines
			Titan Airways
			V Bird
			Vladivostock Air

Appendix B. Result of logit estimation

Table B.1: Logit model, seats

	(1) $\lambda = 0.003$	(2) $\lambda = 0.007$	(3) $\lambda = 0.01$
B_{FSA}	-0.442^{**}	-0.0255	-0.453
	(0.147)	(0.209)	(0.265)
$B_{\text{FSA,FSA}}$	-1.341^{***}	-1.179^{***}	-0.978^{***}
	(0.135)	(0.168)	(0.189)
$B_{\text{FSA,LCC}}$	-0.570^{***}	-1.383^{***}	-1.767^{***}
	(0.128)	(0.227)	(0.296)
$B_{\text{FSA,RA}}$	4.019^{***}	3.381^{***}	2.855^{***}
	(0.331)	(0.305)	(0.309)
$B_{\text{FSA,Other}}$	3.096^{*}	6.177^{*}	8.384^{*}
	(1.557)	(2.911)	(3.995)
B_{LCC}	1.884^{***}	3.412^{***}	3.792^{***}
	(0.179)	(0.371)	(0.549)
$B_{\text{LCC,FSA}}$	0.189	0.474^{**}	0.866^{***}
	(0.126)	(0.178)	(0.224)
$B_{\text{LCC,LCC}}$	-0.290^{**}	-0.970^{***}	-1.915^{***}
	(0.109)	(0.205)	(0.284)
$B_{\text{LCC,RA}}$	0.243	1.091^{**}	1.656^{***}
	(0.354)	(0.408)	(0.489)
$B_{\text{LCC,Other}}$	-1.170	-5.042	-7.091
	(1.247)	(2.693)	(3.762)
B_{RA}	1.902^{**}	3.268^{***}	4.568^{***}
	(0.618)	(0.832)	(0.971)
$B_{\text{RA,FSA}}$	0.611^{***}	0.970^{***}	1.258^{***}
	(0.171)	(0.269)	(0.318)
$B_{\text{RA,LCC}}$	-0.829^{***}	-3.322^{***}	-4.971^{***}
	(0.201)	(0.434)	(0.608)
$B_{\text{RA,RA}}$	3.988^{***}	7.323^{***}	7.666^{***}
	(0.576)	(0.824)	(0.988)
$B_{\text{RA,Other}}$	-7.306^{**}	-10.16^{*}	-14.50^{**}
	(2.569)	(4.250)	(5.370)
B_{Other}	-93.40^{***}	-143.6^{**}	-159.4^{*}
	(22.53)	(50.22)	(75.15)
$B_{\text{Other,FSA}}$	-0.170	0.655	0.845
	(0.476)	(0.832)	(0.980)
$B_{\text{Other,LCC}}$	-0.974^{**}	-1.842^{*}	-2.371^{*}
	(0.333)	(0.718)	(1.013)
$B_{\text{Other,RA}}$	2.017	1.675	2.522
	(1.359)	(2.162)	(2.838)
$B_{\text{Other,Other}}$	8.762^{*}	6.212	-3.779
	(4.244)	(8.518)	(11.83)
$B_{\text{FSA,HSR}}$	0.0195	-0.0179	0.00466
	(0.0541)	(0.0521)	(0.0575)
$B_{\text{LCC,HSR}}$	-0.123^{*}	-0.287^{***}	-0.424^{***}
	(0.0603)	(0.0753)	(0.0984)
$B_{\text{RA,HSR}}$	-0.787^{***}	-0.984^{***}	-1.075^{***}
	(0.0940)	(0.110)	(0.135)
$B_{\text{Other,HSR}}$	-0.0763	0.0871	0.432
	(0.360)	(0.643)	(0.916)
GDP	-0.0153	-0.0173^{*}	-0.0208^{*}
	(0.00832)	(0.00847)	(0.00832)
Already serving UK airport	2.386^{***}	2.455^{***}	2.448^{***}
	(0.0330)	(0.0332)	(0.0325)
Observations	51194	51194	51194
AIC	47517	47519	47673
ll	-22964.5	-22965.4	-23042.3

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix C. An exploration of the properties of the heterogenous Cournot case

We start from firm i's best response in 6. Treating firm j's output as exogenous as discussed earlier and deriving similar best responses for all firms k, we find the quasi equilibrium output for firm i by solving the system of $n-1$ equations:

$$q_i^* = \frac{\alpha_i - c_i - \gamma_{ij} q_j}{2\beta_i} \frac{(n-1)2\beta_i\beta_k}{(n-1)2\beta_i\beta_k - (n-2)\gamma_{ik}^2} - \frac{\gamma_{ik}(n-2)(\alpha_k - c_k - \gamma_{kj} q_j)}{(n-1)2\beta_i\beta_k - (n-2)\gamma_{ik}^2}. \tag{C.1}$$

The slope of the quasi equilibrium output of firm i with respect to q_j is equal to:

$$\frac{dq_i^*}{dq_j} = \frac{-\gamma_{ij}}{2\beta_i} \frac{(n-1)2\beta_i\beta_k}{(n-1)2\beta_i\beta_k - (n-2)\gamma_{ik}^2} + \frac{(n-2)\gamma_{ik}\gamma_{kj}}{(n-1)2\beta_i\beta_k - (n-2)\gamma_{ik}^2}. \tag{C.2}$$

Which is equal to (7) in the main text of the paper. It is straightforward to check that this slope decreases in $gamma_{ij}$, implying that the intensity of competition between firms i and j decreases if the level of substitutability decreases. Let us now discuss a few special cases.

We first consider the case where i and j are perfect substitutes ($\gamma_{ij} = \beta_i = \beta_j$, this also implies that $\gamma_{jk} = \gamma_{ik}$), substitution yields:

$$\frac{dq_i^*}{dq_j} = \frac{\gamma_{ik}^2(n-2) - (n-1)\beta_i\beta_k}{(n-1)2\beta_i\beta_k - (n-2)\gamma_{ik}^2}, \tag{C.3}$$

which increases in γ_{ik}. If $\gamma_{ik} = 0$ (meaning that i and k are not substitutes), this reduces to $-1/2$, representing a symmetric duopoly, since products k become irrelevant. If on the other hand $\gamma_{ik}^2 = \beta_i\beta_k$, all goods are perfect substitutes, and the outcome reduces to the symmetric Cournot outcome $-1/n$.

We continue our exploration by considering i and j to be imperfect substitutes ($\gamma_{ij} < \beta_i$), while i and k are perfect substitutes (i.e. $\gamma_{ik} = \beta_i = \beta_k$) We find:

$$\frac{dq_i^*}{dq_j} = -\frac{\gamma_{ij}(n-1)}{\beta_i n} + \frac{\gamma_{jk}(n-2)}{\gamma_{ik} n}. \tag{C.4}$$

Given that i and k are perfect substitutes, $\frac{\gamma_{ij}}{\beta_i} = \frac{\gamma_{jk}}{\gamma_{ik}}$, leading to $\frac{dq_i}{dq_j} > -1/n$. In other words, the absolute value of $\frac{dq_i^*}{dq_j}$, and hence the intensity of competition between firms i and j, decreases in the level of product homogeneity, which is in line with common economic intuition. If i and j are very heterogeneous, i.e γ_{ij} (and hence also γ_{jk}) tends to zero, $\frac{dq_i^*}{dq_j}$ also tends towards zero. This also refers to common economic intuition that goods that are hardly substitutes, hardly compete. The latter notion leads us to the concept of the relevant market

We start by imposing full symmetry on the model, i.e. all goods are perfect substitutes, implying that all γs and βs are equal. This allows us to simplify (7) substantially:

$$\frac{dq_i^*}{dq_j} = -\frac{n-1}{(n-1)2-(n-2)} + \frac{n-2}{(n-1)2-(n-2)} = -1/n. \tag{C.5}$$

Substituting this result into (3) yields $1-(n-1)/n = \frac{1}{n}$, the outcome of a symmetric Cournot oligopoly with homogeneous products, ranging from 1/2 in duopoly to 0 if the number of firms is very large.