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Alexandra Belova† Philippe Gagnepain‡ Stéphane Gauthier§

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Abstract

We study competition in the U.S. airline industry relaxing the Nash equilibrium assumption that airlines are able to predict perfectly the behavior of their competitors. We assess empirically whether an equilibrium is more likely to occur if it is the unique rationalizable outcome. We find that equilibria of short distance routes with high traffic and low concentration are the most fragile, and low-cost companies appear detrimental to their occurrence. Our analysis is applied to the measurement of welfare gains from firms' entry, and to the characterization of the relevant market when some products are unobserved.

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1 Introduction

Economic analysis often refers to the Nash equilibrium concept at the moment of describing strategic interactions between agents. In this situation, every agent is assumed to be able to forecast correctly the behavior of the other agents. The recent literature in Industrial Organization shows that such an assumption is more likely to hold in a stable environment where firms operate in markets that are geographically close to the market of their competitors (Aguirregabiria and Magesan (2020)) or if agents can accumulate experience and gradually learn how the others behave. However, it also suggests that beliefs can loose accuracy in more disturbed environments where participants often change. Then the equilibrium reference is potentially less relevant (Doraszelski et al. (2018)).

While agents may not be able to forecast the behavior of their competitors, it is usually assumed that they are rational in the sense that they maximize their objective given their expectations on what the others do. An important lesson from the concept of rationalizability is that rationality, even pushed at a high degree of sophistication, is not always enough to reach a Nash equilibrium. A player is rational at level $k = 1$ if she plays a best-response given her beliefs; at level $k = 2$ she's rational and believes that the other players are rational; at level $k = 3$ she also believes that the others believe that the others are rational. Reproducing inductively at any level $k \geq 1$ this process of higher-order beliefs about rationality eventually yields the set of rationalizable outcomes which always includes but does not necessarily reduce to Nash equilibria (Bernheim (1984), Pearce (1984), Moulin (1979)).

In this paper we build an empirical index for the likelihood that an equilibrium occurs, based on the postulate that an equilibrium is more likely to occur when it is the only rationalizable outcome (Guesnerie (1992)). The index uses the characterization of rationalizable outcomes as being those surviving an iterative process of elimination of dominated strategies. The process eliminates every outcome close to an equilibrium, but not the equilibrium itself, if it is locally contracting around this equilibrium. Contraction obtains when the spectral radius of the Jacobian matrix governing locally the process is less than 1. We estimate a proxy for the spectral radius and use it as an index for the likelihood that the observed market will reach an equilibrium: the theory predicts that the market should be in equilibrium if the index is lower than 1.

The value of the index depends on sufficient statistics for supply and demand characteristics. To recover these statistics we construct a structural model applied to the case of the U.S. air transportation industry. Our model generalizes Desgranges and Gauthier (2016) to the case of heterogeneous production facilities, which is known to be a crucial ingredient in the airline industry. We merge several Department of Transportation databases for the period 2003:2016 to estimate supply and demand functions for a large number of air routes. This information provides us with the sufficient statistics that enter the value of the index on every route. It also allows us to calculate the hypothetical volume of transported passengers by each airline at the equilibrium, and so the difference between the actual observed production levels and those that would prevail in the equilibrium.

Our main result is that our index is a reliable indicator of this difference: we find that a 10% increase of the index is associated with a 7% increase in the difference between observed and Nash quantities. Descriptive statistics show that the Nash equilibrium is less likely to occur on short distance and intense traffic routes linking populated cities. Low cost companies also complicate the convergence toward the equilibrium whereas greater concentration tends to yield a lower value of the index. At this stage of the analysis, we conclude that an equilibrium would be reached on approximately 90% of the markets in our dataset.

We then extend our main analysis into three directions. First, we note that adaptive learning in a dynamic horizon can also explain convergence toward the equilibrium. We propose a simple test that allows us to shed light on whether convergence toward the equilibrium is also facilitated when airlines use past observations to form their anticipations on the decisions that their competitors will take. We find that, on top of rationalizability-based deductive arguments, adaptive learning is also potentially relevant as the current observed/Nash spread is significantly reduced by those two and three quarters before.

Our second extension of the baseline analysis illustrates how nonequilibrium outcomes in a particular market may affect consumer surplus. The empirical studies on firms' entry and exit usually assume that the market is in equilibrium both before and after entry/exit and so refer to the corresponding prices and quantities in each period. Here, we view entry/exit as potential perturbations that may lead to a multiplicity of rationalizable outcomes. In an illustration based on the New York-Tampa route, we show how firms may over-estimate other airlines' fares and schedule too many seats following entry: consumer surplus is in this case higher than what one would get in equilibrium.

Our third extension relates to the debate on what competition authorities call the relevant market (Davis and Garcés (2009)). In practice, there are in our data markets where the observed quantity produced differs from Nash even though the index is below 1. We argue that the relevant threshold should in fact be lower than 1 when the econometrician does not observe the full set of services supplied by the competing airlines due to missing data issues. The higher the share of missing observations, the smaller the value of the relevant threshold. We propose a method based on machine learning to identify the relevant threshold for each market. We obtain an average threshold of 0.80, which implies that almost one-third of the markets in our database could fail to reach an equilibrium. We confront our methodology whith a natural experiment, namely the Wright amendment, which restricted flights from the Dallas Love airport in order to promote the development of the Dallas/Fort Worth airport (Ciliberto et Tamer (2009)). We suggest that the estimated relevant threshold in routes from Dallas/Fort Worth is sharply reduced after the repeal of the amendment, as the relevant market that includes the airline services of this airport expands over the period.

The rest of the paper is organized as follows. We build the theoretical model applied to the airline industry in Section 2 and Section 3 discusses the details of the estimation strategy, including data cleaning and descriptive statistics. Section 4 reports the estimation results of the cost and demand functions and uses this information to compute the index that governs the plausibility of the equilibrium. This section shows how the index correlates with observed departures from Nash behavior. In section 5 we introduce adaptive learning and we also compute both the actual and equilibrium welfare difference following a change in the set of competing airlines in a given route. Section 6 extends our analysis to the identification of the relevant market. Finally section 7 concludes.

2 Theoretical benchmark

2.1 General framework

In the airline industry a market is defined as the set of air services offered by different carriers in a route linking a pair of origin and destination airports or cities. The airlines compete in the route for carrying freight and passengers. They all face the same demand function for transportation services but they typically differ according to their technological and organizational characteristics summarized by their cost structure. Some airlines may use a few large capacity aircraft to spread the cost of booking airport slots, boarding passengers and operating flights on few departures, whereas others rely on lower capacity aircraft but schedule more departures. Such choices result from medium-run intermittent contractual negotiations between airlines and airports and long-run airlines capacity investment policies. Over a shorter horizon, the fact that Delta Airlines in the route linking Chicago and Atlanta allocates a A320 Airbus to a booked slot at O'Hara airport from 8h00 to 8h30am every Monday is essentially given.

Over this shorter horizon, airlines instead rely on yield management to control prices and quantities of transported passengers given the available aircraft allocated to the route (Borenstein and Rose, 1994). Following Ciliberto and Tamer (2009), we allow for a firm f specific cost function $c_{af}(q)$ for transporting q passengers using a type a aircraft that varies with aircraft type as well as additional firm characteristics, e.g., negotiated input (fuel and employees) prices. We assume that the cost function is twice differentiable, increasing and convex with the number of transported passengers. A polar case obtains if the marginal cost for transporting one additional passenger is low except when the total number of passengers approaches the aircraft capacity.

Let $\mathcal{A}_f$ be the given set of aircraft used by airlines f in the route and n_{af} be the given number of flights operated by the airlines using type a aircraft. The total cost of firm f for transporting q_f passengers is

$$C_f(q_f) = \min_{(q_{af})} \left\{ \sum_{a \in \mathcal{A}_f} n_{af} c_{af}(q_{af}) \mid \sum_{a \in \mathcal{A}_f} n_{af} q_{af} \geq q_f \right\}, \tag{1}$$

which is also an increasing and convex $\mathcal{C}^2$-function with the number q_f of passengers. Assuming Cournot-Nash behavior, as in e.g., Brander and Zhang (1990), Brueckner (2002) or Basso (2008), firm f takes as given the number Q_{-f} of passengers transported by the other airlines and produces

$$q_f \in \arg\max_q P(Q_{-f} + q)q - C_f(q),$$

where $P(Q)$ is the inverse demand function, and $Q = Q_{-f} + q_f$ is the total number of passengers transported in the route. Assuming that the marginal revenue $P(Q_{-f} + q)q$

is decreasing in q, the best choice for firm f is $q_f = R_f(Q_{-f})$, where the best-response function $R_f(\cdot)$ is decreasing.

A Cournot-Nash equilibrium is a F component vector $\mathbf{q}^* = (q_f^*)$ such that $q_f^* = R_f(Q_{-f}^*)$ for all f, with Q_{-f}^* being the aggregate production of others in the equilibrium. Thus, in an equilibrium, every airline f is assumed to predict correctly the number Q_{-f}^* of passengers transported by its competitors.

Our paper provides an empirical assessment of this assumption appealing to rationalizability. Rationalizable outcomes can be characterized by referring to an iterative process of elimination of dominated strategies (see, e.g., Osborne and Rubinstein, 1994). The process starts from the assumption of common knowledge among airlines that at some initial step $\tau = 0$ production satisfies

$$q_f \in [q_f^{\inf}(0), q_f^{\sup}(0)] \tag{2}$$

for every f, with $q_f^{\inf}(0) \leq q_f^* \leq q_f^{\sup}(0)$. Assuming the equilibrium amounts to require $q_f^{\inf}(0) = q_f^* = q_f^{\sup}(0)$ for all f. In the sequel we assume that firms restrict attention to a neighborhood of the equilibrium, with $(q_f^{\inf}(0), q_f^{\sup}(0))$ is close to, but different from (q_f^*, q_f^*).

By individual rationality airlines only select volumes of transported passengers that are best-response to decisions consistent with (2). Airlines f thus chooses some production in a new interval $[q_f^{\inf}(1), q_f^{\sup}(1)]$ at step $\tau = 1$ of the process, with[1]

$$q_f^{\inf}(1) = R_f\left(\sum_{k \neq f} q_k^{\sup}(0)\right), \quad q_f^{\sup}(1) = R_f\left(\sum_{k \neq f} q_k^{\inf}(0)\right).$$

This reasoning applies to every airlines. Thus, in the immediate vicinity of an equilibrium, we have

$$q_f^{\inf}(1) - q_f^* = R_f'(Q_{-f}^*) \sum_{k \neq f} [q_k^{\sup}(0) - q_k^*] \tag{3}$$

and

$$q_f^{\sup}(1) - q_f^* = R_f'(Q_{-f}^*) \sum_{k \neq f} \left[q_k^{\inf}(0) - q_k^*\right] \tag{4}$$

[1]If $q_f^{\inf}(1) \leq q_f^{\inf}(0)$ then we set $q_f^{\inf}(1) = q_f^{\inf}(0)$. Similarly, if $q_f^{\sup}(1) \geq q_f^{\sup}(0)$ then we set $q_f^{\sup}(1) = q_f^{\sup}(0)$. The process therefore remains at (2) if both $q_f^{\inf}(1) \leq q_f^{\inf}(0)$ and $q_f^{\sup}(1) \geq q_f^{\sup}(0)$. No strategy is eliminated. The same procedure applies to every step $\tau \geq 1$ of elimination.

for all f. Under common knowledge of rationality and the slopes $R'_f(Q^*_{-f})$ of the firms' best-response functions, one can iterate the above argument. The iterative process of elimination of dominated strategies defined by (3) and (4) is governed by the $F \times F$ matrix $\mathbf{B}$ whose every entry in the f-th row equals $R'_f(Q^*_{-f})$ except the diagonal entry (in the f-th column) which is 0. It has the Cournot-Nash equilibrium $\mathbf{q}^*$ is a fixed point.

Level-k thinking popularized by Crawford and Iriberri (2007) would iterate the process k times, for some finite number k. If iterated ad infinitum, the process eventually pins down the equilibrium if and only if the spectral radius of $\mathbf{B}$ is less than 1. If the Nash equilibrium is locally the only rationalizable outcome, one can argue that firms should eventually convince themselves that their competitors will behave according to Nash. In this case we say that the equilibrium is locally 'stable'. Otherwise, if the spectral radius is greater than 1, there are multiple rationalizable outcomes and the iterative process can no longer justify that firms eventually pin down their Nash productions. We say that the equilibrium then is 'unstable'. The following proposition gives a condition for local stability.

Proposition 1. *The Nash equilibrium is locally stable if and only if*

$$S(\mathbf{q}^*) = \sum_f \frac{R'_f(Q^*_{-f})}{R'_f(Q^*_{-f}) - 1} < 1 \tag{5}$$

where

$$R'_f(Q_{-f}) = -\frac{P''(Q)\,q_f + P'(Q)}{P''(Q)\,q_f + 2P'(Q) - C''_f(q_f)}, \tag{6}$$

and

$$C''_f(q_f) \sum_{a \in \mathcal{A}_f} \frac{n_{af}}{c''_{af}(q_{af})} = 1.$$

Proof. See Appendix A ■

Proposition 1 forms the basis of our empirical illustration by providing us with a simple criterion for the plausibility of the occurrence of the Nash equilibrium. It predicts that the spread between the theoretical Nash equilibrium productions $\mathbf{q}^*$ and the actual observed productions should be magnified if the 'stability index' $S(\mathbf{q}^*)$ defined in (5) is greater than a threshold of 1.

Condition (5) shows that local stability of the Nash equilibrium obtains if firms are not too sensitive to the production of others, i.e., $R'_f(Q^*_{-f})$ is close to 0, which accords with the early insights developed by Guesnerie (1992) for the competitive case. The intuition is that firms find it difficult to understand the behavior of others when others are sensitive to their beliefs.

2.2 Linear-quadratic specification

One can derive simple comparative static properties for the stability index $S(\mathbf{q}^*)$ in the particular case where demand is linear and cost is quadratic. Then the slope of the best-reaction function, and so the value of the stability index, no longer depends on the number $\mathbf{q}^*$ of transported passengers in the equilibrium. With a linear demand function,

$$P(Q) = \delta_0 - \delta Q, \quad \delta_0 > 0, \, \delta > 0, \tag{7}$$

and a quadratic cost,

$$c_{af}(q) = \frac{q^2}{2\sigma_{af}},$$

where $\sigma_{af} > 0$ is a technological parameter that is specific to aircraft $\times$ airlines, the cost function solution to the program (1) is

$$C_f(q) = \frac{q^2}{2\sigma_f}, \qquad \sigma_f = \sum_{a \in \mathcal{A}_f} n_{af}\sigma_{af}. \tag{8}$$

The parameter σ_f plays a central role in our model. It can be interpreted by noticing that both the marginal cost $C'_f(q)$ associated with (8) and its derivative $C''_f(q)$ are decreasing with σ_f for any given production q. Since $C_f(0) = 0$ a higher value of σ_f implies a production efficiency gain (a lower production cost), which is made possible thanks to an increase in the individual σ_{af} or because the capacity n_{af} goes up. This efficiency gain however comes with greater flexibility captured by dampened marginal costs. This makes firms more sensitive to expected changes in the production of others: the slope of the best-response function of firm f

$$R'_f(Q^*_{-f}) = -\frac{\delta\sigma_f}{2\delta\sigma_f + 1} \tag{9}$$

is decreasing with σ_f. This bundle of efficiency gains and greater flexibility drives a trade-off between surplus maximization in the Nash equilibrium and stability of this equilibrium illustrated by Proposition 2.

Proposition 2. *The transfer of an additional aircraft to some airlines in the linear-quadratic setup increases the aggregate equilibrium production Q^* but it locally destabilizes the equilibrium, i.e., it leads to an increase in the index $S(\mathbf{q}^*)$.*

Proof. See Appendix B. ■

An additional aircraft allocated to the route corresponds to a higher transportation seat capacity, and so corresponds to an increase in the σ_f parameter. By Proposition 2 one should consequently observe in the data that routes with high traffic display a higher spread between the theoretical Nash equilibrium and the actual production.

The next result controls for route size by considering a transfer of aircraft between two airlines in the same route. This allows us to highlight the impact of the distribution of transportation capacities across airlines.

Proposition 3. *An aircraft reallocation from airlines f to airlines f' in the linear-quadratic setup increases the aggregate equilibrium production Q^* if and only if $\sigma_f > \sigma_{f'}$. This reallocation locally destabilizes the equilibrium, i.e., it leads to an increase in the index $S(\mathbf{q}^*)$, if and only if $\sigma_f > \sigma_{f'}$.*

Proof. See Appendix C. ■

The trade-off between efficiency and stability illustrated in Proposition 2 is still valid. However, Proposition 2 would not allow us to discuss the impact of the transfer considered in Proposition 3 since the contributing airlines f entails an efficiency loss and a stability gain whereas airlines f', which enjoys the additional aircraft, is associated with an efficiency gain and a stability loss. Proposition 3 actually obtains by comparing the magnitudes of these two changes. It leads to the new testable prediction that some asymmetry in the airlines capacity in a given route, with large seat capacity firms competing against smaller ones, should be associated with a theoretical Nash equilibrium production closer to the actual one.

3 Empirical illustration to the airline industry

Our theoretical analysis predicts that the Nash equilibrium production should stand far from the observed production when the stability index $S(\mathbf{q}^*)$ is high (Proposition 1), the total production capacity is high (Proposition 2), and the total production capacity is distributed evenly across firms (Proposition 3). We assess these predictions in the U.S. domestic airline industry over the period 2003:2016 using data from the Bureau of Transportation Statistics to estimate the demand for airlines tickets and aircraft cost functions fitting the linear-quadratic setup developed in Section 2.2. These data allow us to compute the stability index $S(\mathbf{q}^*)$ and the volumes of transported passengers in the Nash equilibrium $\mathbf{q}^*$ by each airline, which can then be compared to the actual observed number of transported passengers.

3.1 Data

A market consists of all the flights between two endpoint cities, identified by their City Market ID number assigned by the U.S. Department of Transportation (DOT). To estimate market supply and demand functions, we combine demographic and climate information with three publicly available databases released by the Bureau of Transportation Statistics of the U.S. DOT: the Air Carrier Financial Reports, the Air Carrier Statistics and the Airline Origin and Destination Survey (DB1B).

Our analysis of the supply side of transportation services exploits information contained in schedule P-5.1 of the Air Carrier Financial Reports and the Air Carrier Statistics T-100 Domestic Segment. Schedule P-5.1 includes cost information, namely, data on input prices, maintenance expenses, equipment depreciation, rental costs, and total operating expenses disaggregated by airlines $\times$ aircraft type. Costs are available for each aircraft type, but the data does not include cost broken out by airline route. This data limitation obliges us to refer in the cost function to an output defined at the aircraft level as well. Since airlines produce passenger transportation services on non-stop flights using a single aircraft, the aircraft level coincides with the segment level, i.e., direct non-stop flights. A flight from city A to city C that entails a stop at city B consists of the two segments AB and BC, and we will estimate in section 3.2 separate costs for each of the two segments. At the segment level we can ultimately recover the costs at airlines $\times$ segment $\times$ aircraft type level that appear in the theoretical model.

The financial information in Schedule P-5.1 is merged with Air Carrier Statistics T-100 Domestic Segment (U.S. Carriers) which contains domestic non-stop segment monthly data reported by U.S. air carriers, including origin and destination points, number of passengers carried, flight frequency, aircraft type and route length. The T-100 consists of more than three million observations over the sample window 2003:2016. We select the segments with distance above 100 miles, with more than 10 passengers per flight, with at least eight departures and 600 passengers during every quarter[2]. This yields a database with $3,575$ observations at the carrier $\times$ segment level that contains 22 carriers operating on $1,298$ segments and carrying 80 percent of the passengers transported in the U.S. domestic market. Some descriptive statistics for the average carrier are provided in Table 1.

Table 1: Carrier cost descriptive statistics

	Mean	Standard deviation	Min	Max
Aircraft costs (thousands of USD)	148,887	187,083	329	1,895,361
Passengers per carrier (in thousands)	1,931.1	2,657.2	16.242	26,000
Number of operated segments	196.41	112.96	17	604
Salary[1] (in thousands of USD)	22.59	6.51	8.19	46.34
Average fuel price[1] per 1000 gallons (in USD)	2,199.3	649.6	834.4	6,867.9
Number of observations: 3,575				

1. Prices and costs are adjusted using the transportation sector price index of the Bureau of Labor Statistics, `http://www.bls.gov/cpi/`

Demand is estimated from the Airline Origin and Destination Survey (DB1B) database over the 2003:2016 period. The DB1B sample contains more than 4 million observations at the ticket level for every quarter. In order to match the segment perspective used on the supply side, we restrict our attention to markets with a high enough proportion of direct flights. We have chosen a threshold that eliminates routes with less than 60 percent of direct non-stop flight tickets. As shown in Table 2 there remains $3,337$ routes in the DB1B database. We disregard routes with one airlines in a monopoly situation, to which the theoretical part does not apply, and we only keep routes matching a segment existing in our final T-100 dataset. Then we use a cleaning process that mirrors the one applied to the T-100 dataset: we remove routes with distance below 100 miles and get rid of the routes with few passengers. We also discard tickets with extreme reported prices in the bottom and top 5% quantiles of the price per mile distribution, and we remove routes observed

[2]The T-100 dataset has been frequently used in the economic literature interested in airline competition. For further discussion on data selection, see for instance Ciliberto and Tamer (2009).

during less than 12 years in our 14-year sample window. We are eventually left with 379 routes. Compared to the original sample, our dataset tends to be biased toward routes with greater passenger traffic.

Table 2: ROUTE SUB-SAMPLE SELECTION FROM DB1B DATASET

	Number of routes	Mean	Standard deviation	Min	Max
Original base	11141				
Passengers per route (in thousands)		18.146	65.839	0.010	2986.0
Share of direct tickets per route		0.46	0.39	0	1
Direct routes (share of direct flights > 0.6)	3337				
Passengers per route (in thousands)		38.118	95.359	0.050	2986.0
Share of direct tickets per route		0.87	0.12	0.60	1
Routes in the final sample	379				
Passengers per route (in thousands)		265.9	263.8	9.9	2986.0
Share of direct tickets per route		0.90	0.09	0.60	1

To estimate demand we compute the average quarterly number of passengers booking a flight on the selected segments and the corresponding average fare for each of these 379 routes. Fares are adjusted using the transportation sector price index of the Bureau of Labor Statistics. The database is enlarged with temperature and population of origin and destination cities.[3] Descriptive statistics are presented in Table 3.

Table 3: ROUTE DESCRIPTIVE STATISTICS

	Mean	Standard deviation	Min	Max
Population in larger city (million)	6.419	4.552	0.928	18.663
Population in smaller city (million)	1.785	1.518	0.011	12.368
Average ticket price on the route* (USD)	182.8	74.6	23.9	586.8
Medium ticket price on the route* (USD)	161.7	54.2	8.2	467.1
Average price per mile (in USD)	0.286	0.108	0.079	0.654
Distance between two cities (thousand km)	0.783	0.557	0.013	2.918
Passengers per route (thousand)	265.9	263.8	9.9	2986.0
Number of airlines	3.084		2	7
Number of observations: 20,808				

* Corrected by the consumer price index for transportation sector

[3]This information is obtained from `ggweather.com` and `citypopulation.de`.

3.2 Costs

The estimation of an aircraft cost function is based on the quadratic specification

$$c_{afst} = \frac{q_{afst}^2}{2\sigma_{afst}}, \tag{10}$$

which applies to a given flight operated by airline f with a type a aircraft during period t on segment s. The T-100 dataset provides information on the number of passengers q_{afst} transported on segment s by airlines f using aircraft type a during quarter t. However we only observe in the schedule P-5.1 the aggregate cost over all the segments served by airlines, namely

$$C_{aft} = \sum_s n_{afst}\, c_{afst} \tag{11}$$

where n_{afst} denotes a number of departures. In order to estimate the parameter σ_{afst} that enters the stability index at the segment level using the aggregate cost in (11), we express this parameter as

$$\frac{1}{2\sigma_{afst}} = \beta_0\, \xi_{ft}\, \mu_s\, \nu_a \tag{12}$$

where β_0 is a constant term, ξ_{ft} varies across firms and time periods, while μ_s and ν_a are segment and aircraft fixed effects, respectively. The variable ξ_{ft} accounts for unobserved characteristics of airlines productive efficiency, e.g., managerial effort or marketing strategies, each of which plausibly varies over time. In (12), segment and aircraft fixed effects are restricted to be time invariant, but our final cost specification includes time fixed effects common to segments and aircraft. Using (10) and (12) the aggregate cost C_{aft} given in (11) becomes

$$C_{aft} = \beta_0\, \xi_{ft}\, \nu_a \sum_s \mu_s\, n_{afst}\, q_{afst}^2. \tag{13}$$

We argue that unobserved managerial efforts and/or marketing strategies in ξ_{ft} are correlated with the input prices that airlines bargain with input providers. The contribution ξ_{ft} is modeled as a linear function of wages and fuel prices faced by each airline f during period t; in other words,

$$\log \xi_{ft} = b\, \log \texttt{Wage}_{ft} + (1-b)\, \log \texttt{PFuel}_{ft} + \xi_f + \texttt{Quarter}_t + \texttt{Year}_t, \tag{14}$$

where ξ_f is a carrier fixed effect, and $\texttt{Quarter}_t$ and $\texttt{Year}_t$ are quarter and year time dummies. The property of linear homogeneity of degree one in input prices guarantees that the corresponding coefficients sum to 1.

The 3,575 observation data used to estimate cost only entails 1,298 different segments (see Table 1), which prevents us from estimating reliable individual segment fixed effects μ_s for every segment. To circumvent this difficulty we assume that

$$\mu_s = d_0 + d_1\,\texttt{Distance}_s + d_2\,\texttt{Temperature}_s, \tag{15}$$

where $\texttt{Distance}_s$ is the segment length measured as the geographical distance between two cities, and $\texttt{Temperature}_s$ is the average temperature at the departure and arrival cities over the whole sample window.

The cost function to be estimated obtains by reintroducing (14) and (15) into (13). The final expression of this function is

$$\begin{aligned}\log C_{aft} = {} & \log b_0 + b\,\log \texttt{Wage}_{ft} + (1-b)\,\log \texttt{PFuel}_{ft} \\ & + \log\left[\sum_s \left(1 + d_1^*\,\texttt{Distance}_s + d_2^*\,\texttt{Temperature}_s\right) n_{afst}\, q_{afst}^2\right] \\ & + \xi_f + \nu_g + \texttt{Quarter}_t + \texttt{Year}_t + \varepsilon_{aft},\end{aligned} \tag{16}$$

where ε_{aft} is an error term. To get this expression, we have made three main simplifications. First the constant log b_0 replaces the sum of the two constants log β_0 and log d_0 that cannot be estimated separately. Second, we normalize the coefficients $d_1^* = d_1/d_0$ and $d_2^* = d_2/d_0$. Third, in the data airlines have preferences for specific aircraft types that gives rise to a high correlation between the airlines and aircraft fixed effects ξ_f and ν_a. This prevents us to keep track of both airlines and aircraft unobserved heterogeneity at the detailed level of the aircraft type. We therefore work with a more aggregated aircraft group by clustering the 29 different aircraft types into 12 groups referring to model characteristics and carrier[4]. This provides us with an aircraft group g fixed effect ν_g that replaces the original aircraft fixed effect ν_a.

[4] Aircraft in the same cluster belong to the same generation of models and have similar size. For example, Boeing 737-300, Boeing 737-400 and Boeing 737-500 are allocated to the same cluster while next generation larger Boeing 737-800 and Boeing 737-900 are in another cluster. There remain small clusters with rare aircraft types like Aerospatiale/Aeritalia ATR-72 or Saab-Fairchild 340/B.

Table 4: ESTIMATED COST FUNCTION C_{aft}

	$\log C_{aft}$		
	(1)	(2)	(3)
Constant ($\log b_0$)	2.513***	1.127***	2.182***
	(0.34)	(0.31)	(0.45)
$\log$ `Wage` (b)	0.558***	0.597***	0.602***
	(0.08)	(0.07)	(0.07)
`Distance` (d_1^*)	0.025	0.709***	0.205*
	(0.02)	(0.37)	(0.11)
`Temperature` (d_2^*)	-0.006***		-0.006***
	(0.00)		(0.00)
Quarter 2	-0.170***	-0.157***	-0.164***
	(0.01)	(0.01)	(0.01)
Quarter 3	-0.199***	-0.180***	-0.193***
	(0.01)	(0.01)	(0.01)
Quarter 4	-0.096***	-0.086***	-0.089***
	(0.01)	(0.01)	(0.01)
Aircraft group f.e. (ν_g)	No	Yes	Yes
Airlines f.e. (ξ_f)	Yes	Yes	Yes
Year f.e. ($\texttt{Year}_t$)	Yes	Yes	Yes
Number of observations	3,575	3,575	3,575
Log-Likelihood	-1010	-453	-407

Note: *** (resp., ** and *) Significant at the 1 (resp., 5 and 10) percent level.

Table 4 reports the maximum likelihood estimates of the parameters of the cost function (16) for three variants. The results are very similar in each case, except from the impact of distance between the two cities located at the endpoints of the segment. Costs increase with input prices; they are also higher on cold weather segments and during the colder first and fourth quarters. There is a positive significant correlation between route distance and temperature in our data that makes the impact of distance on cost in variant (2) magnified when temperature is omitted. The likelihood of the variant (1), which only differs from the one in (3) by excluding aircraft group fixed effects on the segment, shows the importance of taking into account the aircraft type in airline costs. In the absence of control for the aircraft type, we find that a greater distance does not involve higher costs for the operating airlines. The expected positive impact is recovered once the control is introduced, which reflects the fact that airlines allocate specific aircraft types conditionally on the length of each segment.

3.3 Demand

We start from the linear demand specification (7),

$$Q_{st} = \gamma^0_{st} + \gamma_{st} P_{st} + \zeta_s + \texttt{Quarter}_t + \texttt{Year}_t + \nu_{st}, \tag{17}$$

where P_{st} and Q_{st} are respectively the average price level and the aggregate quantity of passengers transported in segment s during period t. Both are computed from the DB1B dataset. We have added segment fixed effects ζ_s and quarter and year fixed effects, $\texttt{Quarter}_t$ and $\texttt{Year}_t$. The intercept γ^0_{st} and the slope γ_{st} are two parameters to be estimated. We assume that they depend on route distance and population size of endpoint cities, $\texttt{Pop}^1_{st}$ and $\texttt{Pop}^2_{st}$ (with $\texttt{Pop}^1_{st} \leq \texttt{Pop}^2_{st}$). We also assume that the slope γ_{st} may directly depend on time. The expressions of the intercept and the slope rewrite as

$$\gamma^0_{st} = \alpha_0 + \alpha_1 \text{Pop}^1_{st} + \alpha_2 \text{Pop}^2_{st}, \tag{18}$$

and

$$\gamma_{st} = \alpha_3 + \alpha_4 \texttt{Distance}_s + \alpha_5 \texttt{Pop}^1_{st} + \alpha_6 \texttt{Pop}^2_{st} + \texttt{Quarter}_t + \texttt{Year}_t. \tag{19}$$

The demand equation that we estimate is (17) with intercept and slope given by (18) and (19), respectively.

The (one quarter) lagged price or input prices are two potential candidates that can be used to deal with the joint determination of the price P_{st} and the quantity Q_{st}. As the input prices also enter the cost expression (16), we prefer to use lagged prices in what follows. Table 5 presents the demand function estimated from the 379 selected routes. The price variable is the route average ticket price in columns 1 and 2 and the median price in columns 3 and 4. The specification in columns 2 and 4 fits the specification described in (7), (18) and (19). For comparison purposes, we report in columns 1 and 3 the results in the case where the slope of the demand function is assumed to be independent from route characteristics.

We observe a higher demand for routes linking densely populated cities. In such markets demand displays lower price sensitivity. The greater distance between origin and destination points makes substitution with alternative transport facilities more difficult as α_4 is positive. Moreover, α_5 and α_6 are both positive, which suggests that consumers departing from or

Table 5: Estimated demand function

	Number of passengers			
	(1)	(2)	(3)	(4)
Intercept γ^0_{st} – eq. (18)				
Constant α_0	133.646***	207.210***	126.531***	196.328***
	(16.24)	(16.58)	(16.26)	(16.62)
Pop[1] (α_1)	18.116***	19.037***	18.829***	18.518***
	(2.45)	(2.45)	(2.46)	(2.46)
Pop[2] (α_2)	47.003***	22.234***	46.288***	17.078***
	(3.02)	(3.70)	(3.03)	(3.82)
Slope γ_{st} – eq. (19)				
Constant (α_3)	-0.505***	-0.986***	-0.583***	-1.060***
	(0.02)	(0.04)	(0.02)	(0.04)
Distance (α_4)		0.168***		0.148***
		(0.02)		(0.053)
Pop[1] (α_5)		0.004**		0.013***
		(0.00)		(0.00)
Pop[2] (α_6)		0.051***		0.078***
		(0.01)		(0.01)
Year f.e.	Yes	Yes	Yes	Yes
Quarter f.e.	Yes	Yes	Yes	Yes
R^2	0.176	0.204	0.170	0.198
Obs.	20808	20808	20808	20808
F test (route f.e.)	1003.8	982.9	1008.7	978.1

Note: fixed-effects (within) IV regression

*** (resp., ** and *) Significant at the 1 (resp., 5 and 10) percent level.

(1), (2) - mean price is employed, (3), (4) - median price is employed arriving to cities with a larger population (i.e., hubs) are less sensitive to price fluctuations.

The contribution of demand to market stability captured by the index $S(\mathbf{q}^*)$ for route s at time t only relies on the slope $\delta = \delta_{st} = -1/\gamma_{st}$ in Table 5. The results are very similar when we use average and median lagged prices as instruments. In the sequel we shall use the specification in column 2 referring to the average price. To provide the reader with an order of magnitude for this slope from this specification, we obtain $\gamma_{st} = -0.986 + 0.168 \times 0.783 + 0.004 \times 1.785 + 0.051 \times 6.419 \simeq -0.519$ plus quarter and year fixed effects in the average segment in Table 3. Including the time fixed effects one gets $\gamma_{st} = -0.621$: a 10 USD increase in the fare yields $6,210$ passengers less in the route (see Oum et al., 1992, for an overview of transport demand elasticity estimates).

4 Empirical results

The cost estimation procedure is based on $1,298$ segments of the T-100 dataset while we estimate demand from 379 routes of the DB1B dataset. In order to match supply and demand information, all the subsequent results are based on the 301 common segments that appear in the two samples.

4.1 Stability index

The cost efficiency parameter $\hat{\sigma}_{afst}$ obtains by replacing the parameters that appear in (12) with their estimated values reported in Table 4. The constant term β_0 is set to the estimate $\hat{b}_0 = \beta_0 + d_0$ and the statistics $\hat{\sigma}_{afst}$ can only be recovered at the coarse level of aggregation of the aircraft group g rather than the fine level of the aircraft type a. We use (8) to aggregate $\hat{\sigma}_{afst}$ over aircraft groups to get the sufficient statistics $\hat{\sigma}_{fst}$ for the contribution of market supply to the stability of the Nash equilibrium. On the demand side, the results in Table 5 give the estimated slopes of the demand function $\hat{\gamma}_{st} = -1/\delta_{st}$ that provide us with the relevant summary statistics for the contribution of market demand to stability. We therefore have all the information that is needed to compute the slope of the best-response function (9) in the linear-quadratic specification of the theoretical model, and so the stability index $S(\mathbf{q}^*)$ in (22). Figure 2 in Appendix D depicts the distribution of $\hat{\sigma}_{fst}$, $\hat{\delta}_{st}$, and the best-response slope.

We use formula (5) to recover the stability index $S(\mathbf{q}^*)$ at each segment $\times$ period level

Table 6: Sufficient statistics for stability

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Cost efficiency σ_{fst}	0.002	0.28	0.515	0.762	0.965	5.935
Inverse demand slope δ_{st}	0.915	1.28	1.495	1.609	1.816	5.113
Best-response slope $R'(\mathbf{q}^*)$	-0.482	-0.375	-0.309	-0.299	-0.231	-0.002
Stability index $S(\mathbf{q}^*)$	0.167	0.458	0.568	0.629	0.774	1.794

from the estimated slopes $R'_{fst}(\mathbf{q}^*)$. Table 6 shows that $S(\mathbf{q}^*)$ is lower than 1 for most segments: it exceeds 1 for only 9 percent of the segment $\times$ quarter observations. Our theoretical model thus predicts successful coordination in most markets, conditional on the fact that the set of the observed services $\times$ airlines coincides with the complete set of the services $\times$ airlines that constitute the relevant market.

The variability in the stability index comes from within and between segment heterogeneity. Although our sample window includes the 2007 crisis and the Great Recession we find that time only explains 5 percent of the variance of the stability index whereas segments contribute to 81 percent of this variance. Table 7 provides us with a more detailed picture of the stability index by reporting the results of the regression $\log(S_{st}) = X'\beta + \text{period}_t + \varepsilon_{st}$ where the right-hand side variables in X consist of exogenous route characteristics as well as potentially endogenous competition indicators.

Higher values of the stability index apply to segments linking two distant and densely populated cities. Population matters even after controlling for the number of passengers. In accordance with Proposition 2, routes with high traffic display a higher stability index. Such segments are likely to involve high competition intensity. We have looked at two measures of competition. A higher number of competitors does not influence the value of the stability index. However we find that a lower Herfindahl index, which reflects greater similarity of passenger transportation market shares among the competing airlines, is associated with higher values of the stability index. This fits Proposition 3, using market shares as proxies for airlines seat capacity.

The bottom of Table 7 delineates the types of interactions among airlines that give rise to higher indexes by clustering routes based on the operating airlines. Unlike the clustering relying on exogenous route characteristics that was used to estimate the cost function, the decision to enter is probably correlated with components of the stability index. We apply

Table 7: A picture of the stability index

	$\log(S_{st})$
Constant	-2.958^{***}
	(0.069)
Market structure	
$\log(\texttt{Distance}_s)$	-0.031^{***}
	(0.004)
$\log(\texttt{Lowest population}^1_{st})$	0.022^{***}
	(0.003)
$\log(\texttt{Highest population}^2_{st})$	0.019^{**}
	(0.008)
$\log(\texttt{Nb of airlines}_{st})$	0.060
	(0.044)
$\log(\texttt{Herfindahl index}_{st})$	-0.685^{***}
	(0.017)
$\log(\texttt{Share of direct flights}_{st})$	0.097^{***}
	(0.032)
$\log(\texttt{Nb of passengers}_{st})$	0.251^{***}
	(0.017)
Airlines cluster	
Cluster 3 (AA)	-0.044^{***}
	(0.006)
Cluster 6 (UA-AA)	-0.036^{***}
	(0.008)
Cluster 4 (UA)	-0.034^{***}
	(0.003)
Cluster 2 (No high market share airlines)	-0.033^{***}
	(0.006)
Cluster 8 (WN-AA)	-0.031^{***}
	(0.003)
Cluster 7 (WN-UA-AA)	-0.012
	(0.010)
Cluster 9 (WN-UA)	-0.002
	(0.009)
Cluster 1 (WN)	reference
Cluster 5 (DL)	0.007
	(0.005)
Cluster 10 (WN-DL)	0.015^{**}
	(0.006)
Number of observations	7,422
R^2	0.897
Adjusted R^2	0.896
Residual Std. Error	0.123 (df = 7350)
F Statistic	899.472^{***} (df = 71; 7350)

Note: robust standard errors clustered by route.

*** (resp., ** and *) Significant at the 1 (resp., 5 and 10) percent level.

the Fanny clustering by Kaufman and Rousseeuw (1990) to the four airlines with the greatest market share in our whole sample: American Airlines (AA), Delta Airlines (DL), United Airlines (UA) and Southwest Airlines (WN). The clusters and an associated measure of within cluster similarity are reported in Table 8 (the highest within cluster similarity, which is normalized to 1, obtains when all the observations in the cluster are identical).

Table 8: Airlines network from the main airlines

cluster	WN	UA	AA	DL	Within homogeneity	Nb of segments	Nb of observations
1	100	0	0	0	1	83	1,448
2	0	0	0	0	1	71	631
5	0	0	0	100	1	62	1,071
8	100	0	100	0	1	57	738
10	100	17	8	100	0.580	57	719
9	100	100	0	0	1	56	957
4	0	100	0	15	0.740	50	486
7	100	100	100	5	0.920	43	614
3	0	0	100	32	0.570	30	490
6	0	100	100	36	0.590	21	268

Columns 2 to 5 of Table 8 give the percentage of observations classified in the clusters where the four main airlines is active. In cluster 1 the low-cost airlines WN is present in every segment and quarter, occupying a quasi-monopoly position by competing against airlines with low market shares in the whole sample. Cluster 2 only consists of segments $\times$ quarter operated by low market share airlines. In cluster 10, UA appears in 17% of observations, and it always compete against WN and DL. The lower within cluster similarity found for cluster 10 shows that the competition structure changes over segments and time: some observations correspond to a duopoly with WN and DL possibly competing against smallest airlines, while other observations in cluster 10 involve WN and DL competing against UA and/or AA as well as smaller airlines.

Table 7 delineates three groups of airlines clusters. A first group with low stability indexes is formed by routes where UA and AA hold a dominant position and routes where they compete against each other. This group also includes routes where no major airlines is active. There is a second set of routes with intermediate values of the index, where WN compete against AA and UA. The presence of the low-cost company WN thus tends to be associated with higher values of the stability index. In the last group, with the highest values of the index, we find routes where WN and the major airlines DL interact.

4.2 Assessing the Nash equilibrium

We are now in a position to assess whether the spread between the actual and the theoretical Nash numbers of transported passengers is positively correlated with the indexes S_{st} over segments s and quarters t. We start from the squared spread between actual and Nash productions as

$$\|\mathbf{q}_{st} - \mathbf{q}^*_{st}\|^2 = \sum_{f \in \mathcal{F}_{st}} \left(q_{fst} - q^*_{fst}\right)^2,$$

where $\mathcal{F}_{st}$ represents the set of airlines active in segment s during quarter t. However, in order to avoid a mechanical bias with a higher spread in segments with intense traffic, the above spread is normalized by the squared number of passengers

$$\|\mathbf{q}^*_{st}\|^2 = \sum_{f \in \mathcal{F}_{st}} q^{*2}_{fst}.$$

Our normalized measure for the spread between Nash and actual production (at the segment $\times$ period level) is therefore

$$\Delta_{st} = \frac{\|\mathbf{q}_{st} - \mathbf{q}^*_{st}\|}{\|\mathbf{q}^*_{st}\|}.$$

We refer to the linear-quadratic specification to get the equilibrium production q^*_f of airlines f,

$$q^*_f = \sigma_f \frac{\delta_0 - \delta Q^*}{1 + \sigma\delta},$$

where the aggregate equilibrium production Q^* obtains by summation over airlines. The estimate of q^*_f in segment s during quarter t obtains by replacing δ with the estimate of $-1/\gamma_{st}$ and σ_f with the estimate of σ_{fst} used in Section 4.1, and by using the results in Table 5 to replace δ_0 with the estimate of $-\gamma^0_{st}/\gamma_{st}$ satisfying (18). Some details about the resulting spread density distribution are given in Appendix E.

Figure 1 shows the high positive correlation between the stability index S_{st} and the spread Δ_{st}. The figure displays a smooth rise in the spread from 0 (where actual and Nash number of transported passengers coincide) when the index increases. The spread reaches its highest level around 0.8: the departure from Nash then represents 80% of the Nash production. The density of $S_{st} \times \Delta_{st}$ observations depicted in dotted red shows that this pattern applies to most observations, with a stability index between $\exp(-1.5) \simeq 0.2$ and $\exp(-0.25) \simeq 0.8$. Unlike the theoretical prediction of Proposition 1, the spread is not

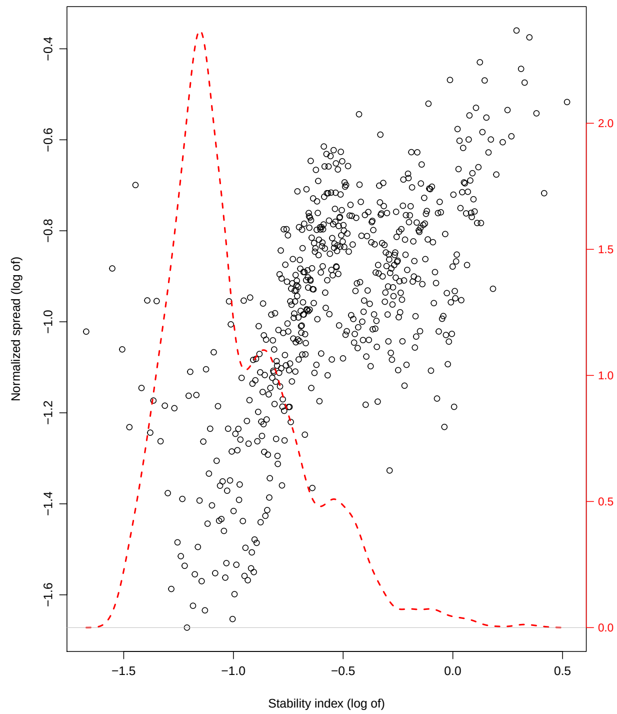

Figure 1: Density and average spread per range 2e-02 stability indexes

close to 0 when the index is below 1. In section 6 we will argue that the consideration of unobserved competition within the relevant market may contribute to account for a positive spread for stability indexes below 1. Here we abstract from such features and focus on the econometric relationship

$$\log \Delta_{st} = b_0 + b_1 \log S_{st} + \texttt{Segment}_s + \texttt{Quarter}_t + \varepsilon_{st}.$$

The results of this regression are reported in Table 9.

All the three variants reported in Table 9 display a positive high significant relation between the theoretical stability index and departures from Nash outcomes. We conclude that the stability index can be considered as a reliable predictor of the occurrence of the Nash equilibrium.

The variants differ according to fixed effects that are controlled for. The inclusion of time fixed effects does not yield substantial changes in the results. Instead, unobserved heterogeneity across segments explains an important large part of Nash departures. Our preferred specification in the third column includes both segments and quarter fixed effects:

Table 9: NASH DEPARTURE AND STABILITY INDEX

	Nash spread $\log \Delta_{st}$		
	(1)	(2)	(3)
Stability index $\log S_{st}$ (b_1)	0.539***	0.574***	0.713***
	(0.131)	(0.145)	(0.089)
Constant (b_0)	−0.829***	−0.731***	−0.560***
	(0.077)	(0.117)	(0.085)
Quarter fixed effect	No	Yes	Yes
Segment fixed effect	No	No	Yes
Number of observations	7,422	7,422	7,422
R^2	0.096	0.117	0.596
Adjusted R^2	0.096	0.110	0.575
Residual Standard Error	0.632 (df = 7420)	0.627 (df = 7365)	0.433 (df = 7065)
F-statistic	788.090*** (df = 1; 7420)	17.459*** (df = 56; 7365)	29.230*** (df = 356; 7065)

Notes: *** (resp., ** and *), significant at the 1 (resp., 5 and 10) percent level
We report robust standard errors at the segment level.

a 1 percent increase in the stability index is associated with a 0.713 percent rise in the spread between actual and Nash numbers of transported passengers.

The recent literature provides mixed evidence about whether firm size asymmetry helps stability by facilitating equilibrium coordination. In Kumar et al. (2015), competitive pressure improves firms' attention to global macroeconomic indicators and so makes forecasts about current market outcomes more accurate. In Byrne and de Roos (2019), the dominant firm BP in the retail gasoline industry is able to orient price strategies of the smaller retailers toward some focal point. The results reported in Tables 8 and 9 show that coordination failures on Nash outcomes are more likely in competitive markets with high traffic where competitors have similar market shares. The presence of Delta Airlines (DL), which completed its merger with Northwest (NW) from 2010, favors non-Nash behavior whereas Southwest (WN) complicates convergence toward a Nash equilibrium. This echoes the empirical literature that documents the ability of Southwest to trigger fierce reactions by its competitors (see Morrison (2001) and Goolsbee and Syverson (2008)).

5 Time and welfare

In this section we first depart from the strictly static perspective we took so far and test whether firms accumulate any experience over time. In a second step, we shed light on potential welfare biases in the analysis of the effect of changes in competition, in situations where the entry and exit of firms creates instability and impedes firms from reaching a Nash equilibrium.

5.1 Adaptive learning

The stability index governs a process where airlines iteratively eliminate dominated choices of volumes of passenger-carrying services that can be viewed as taking place within every period t. Empirical evidence from surveys about expectations documents an extrapolative nature of expectations based on past observations and forecasts (see Ma, Sraer and Thesmar (2018) for recent examples). In our context, it seems plausible that airlines also process past information, e.g., past capacity choices of their competitors, to form/revise their beliefs about period t choices of their competitors. The existing literature has actually shown close links between the two approaches (Nachbar (1990)): a unique rationalizable outcome often implies convergence of adaptive learning toward the Nash equilibrium. One can therefore interpret the results reported in Table 9 as a signal that airlines process past information using some ad hoc myopic learning rule which eventually yields the equilibrium if the stability index is below 1.

Here we test whether the role of the stability index only transits through adaptive learning. We restrict our attention to the special case where airlines hold identical beliefs over the individual productions of their competitors. Then, a reduced form for the actual realization of the spread Δ_{st} that fits the local stability properties of our theoretical setup is $\Delta_{st} = S_{st}\Delta^e_{st}$ where Δ^e_{st} stands for the common forecast about the (normalized) spread between the actual and Nash volume of passengers in segment s during quarter t. We introduce adaptive learning by assuming that the belief Δ^e_{st} is determined by a log-linear function of past forecast errors,

$$\Delta^e_{st} = \prod_{i>0} \Delta^{\gamma_i}_{s(t-i)},$$

where γ_i is a parameter that weights the realized error i quarters before the formation of the forecast Δ^e_{st}. With this rule, the actual dynamics of the spread writes

$$\Delta_{st} = S_{st} \prod_{i>0} \Delta^{\gamma_i}_{s(t-i)},$$

or equivalently

$$\log \Delta_{st} = \log S_{st} + \sum_{i>0} \gamma_i \log \Delta_{s(t-i)}.$$

This specification highlights that $\log \Delta_{st}$ should be in the same proportion as $\log S_{st}$ if the role played by the stability index S_{st} only transits through adaptive learning. Hence we consider the following econometric specification:

$$\log \Delta_{st} = b_1 \log S_{st} + \sum_{i>0} \gamma_i \log \Delta_{s(t-i)} + \texttt{Segment}_s + \texttt{Quarter}_t + \varepsilon_{st}.$$

If the estimated parameter $\hat{b}_1$ differs from 1, we can reject the null hypothesis that only adaptive learning matters in the determination of the current departure from Nash.

The model is estimated using the extended linear GMM estimator based upon lagged differences of Δ_{st} in addition to lagged levels of Δ_{st} as instruments (Blundell and Bond, 1998). The results are provided in Table 10 together with several specification tests. The Sargan test is not completely convincing as the statistic shown presents significant evidence against the null hypothesis that the overidentifying restrictions are valid. The latter implies that we need in principle to reconsider our model or our instruments, unless we attribute the rejection to heteroskedasticity in the data-generating process. The presence of heteroskedasticity is a realistic assumption, as suggested by Arellano and Bond (1991). Another important assumption is that, when the errors ε are independently and identically distributed, the first difference errors are first-order serially correlated, which is confirmed here: first, the test statistic presents strong evidence against the null hypothesis of zero autocorrelation in the first-differenced errors at order 1; second, it presents no significant evidence of serial correlation in the first-differenced errors at order 2, which strengthens the validity of our results.

The results reported in Table 10 show that past forecasting errors do indeed matter. The estimate $\hat{b}_1$ is usually significantly different from 1. One can thus reject the null hypothesis that the role played by the stability index is only adaptive learning based. The specification used in Column 1 shows that errors made by airlines two and three quarters

Table 10: Adaptive versus rationalizability-based justifications of the Nash equilibrium

	$\log \Delta_{st}$			
	(1)	(2)	(3)	(4)
$\log \Delta_{s(t-1)}$	0.258			
	(0.577)			
$\log \Delta_{s(t-2)}$	-0.382^{***}	-0.320^{***}	-0.348^{***}	-0.301^{***}
	(0.142)	(0.057)	(0.074)	(0.080)
$\log \Delta_{s(t-3)}$	-0.175	-0.227^{***}	-0.247^{***}	-0.221^{***}
	(0.137)	(0.033)	(0.050)	(0.038)
$\log S_{st}$	0.705^{***}	0.774^{***}	0.705^{***}	0.799^{***}
	(0.200)	(0.089)	(0.123)	(0.125)
Nb of segments	301	301	178	123
Quarters used (over 56)	1-51	1-51	1-47	2-51
Nb of observations	7422	7422	3510	3912
Sargan test (p-value)	0.01	0.05	0.151	0.331
Autocorrelation test (1) (p-value)	0.287	1.77e-07	1.71e-04	5.92e-05
Autocorrelation test (2) (p-value)	0.519	0.676	0.241	0.320
Wald test for coefficients (p-value)	≤ 2.22e-16	≤ 2.22e-16	5.01e-12	≤ 2.22e-16
Wald test for time dummies (p-value)	4.55e-11	5.54e-09	1.44e-05	≤ 2.22e-16

Notes: *** (resp., ** and *), significant at the 1 (resp., 5 and 10) percent level
We use the robust covariance matrix proposed by Windmeijer (2005).

earlier have a significant impact on the current Nash spread, but not the errors made in the last quarter; the short-run stickiness of seat capacity adjustments makes the last quarter seat capacity the best proxy for the current one, but this information may not be publicly available when airlines form their forecasts. In every specification airlines put less weight on far distance past errors, $|\hat{\gamma}_2| > |\hat{\gamma}_3|$.

The full sample of observations is used in the first two columns of Table 10. The impact $\hat{b}_1$ of the stability index on the current departure from Nash remains very similar to the one found when neglecting the effect of past departures from Nash (in Column 3 of Table 9). The results in the last two columns apply to sub-samples that only consist of segments where there is no major airlines among the four companies selected in the clustering made in Table 8 (Column 3), or segments where only these airlines are active (Column 4). The specifications in these last two columns suggest that large airlines display a greater confidence in past strategic choices of their competitors than small airlines to form their current forecasts as the difference between $\hat{b}_1$ and 1 seems to loose significance in column 4.

5.2 Welfare impact of entry

A frequent exercise proposed by competition authorities consists in assessing the impact of a new firm entry (or exit) on the consumer surplus. The empirical framework usually assumes that a Nash equilibrium is obtained before and after entry (Scenario 1). Hence, the change in consumers' surplus is

$$\Delta^*_{Surplus} = -\frac{1}{2}\left(p_1^* Q_1^* - p_0^* Q_0^*\right),$$

where Q_0^* and Q_1^* are the equilibrium productions before and after entry, respectively.

Here, we relax this hypothesis and assume instead that higher competition following entry possibly entails instability so that firms may not be able to play Nash quantities. We are thus interested in a scenario where airlines play a Nash equilibrium before entry while the equilibrium becomes unstable after entry and entails a production level Q_1 which is different from the Nash quantity and is directly observed in our sample (Scenario 2). The change in consumers' surplus after entry can then be computed as

$$\Delta_{Surplus} = -\frac{1}{2}\left(p_1 Q_1 - p_0^* Q_0^*\right).$$

To evaluate the difference between $\Delta^*_{Surplus}$ and $\Delta_{Surplus}$, we pick up a specific market, namely New-York/Tampa, where a change in the number of the competitors makes the value of the stability index jump above 1. In this market, Continental (CO), Southwest (WN), Delta (DL), and Jetblue (B6) compete against each other in 2011:4, while the next quarter witnesses the exit of Continental, and the simultaneous entry of American Airlines and United Airlines. We compute the equilibrium productions Q_0^* and Q_1^* as suggested in Section 4.2. As shown in Table 11, the corresponding prices p_0^* and p_1^* obtain using the estimated demand slope and intercept on segment s at time t from $\hat{\delta}^0_{st}$ and $\hat{\delta}_{st}$ in Table 5. We find that the Nash quantity Q_1^* is greater than Q_0^* while the Nash price decreases from 336.2 USD to 321.2 USD. Thus, the increase in total surplus $\Delta^*_{Surplus}$ per passenger in Scenario 1 is equal to 19.5 USD. In Scenario 2, where carriers make prediction mistakes in 2012:1, the increase in total surplus $\Delta_{Surplus}$ per passenger is equal to 34.2 USD. Hence assuming Nash behavior after entry in this particular market leads to an under-evaluation of the surplus gain.

The change in total production from one period to another can be decomposed at the

Table 11: Welfare in the New-York/Tampa segment

Period	2011:4	2012:1
Competing careers	CO, WN, DL, B6	UA, WN, DL, B6, AA
Stability index S_{st}	0.974	1.055
Nash Quantity (thousands)	405.5	417.1
Observed Quantity (thousands)	405.5	426,5
Nash price (in USD)	336.2	321.2
Observed price (in USD)	336.2	305.9
Nash Surplus (in USD)	133,498.6	141,640.4
$\Delta^*_{Surplus}$ (in USD)		+8,141.8
$\Delta^*_{Surplus}$ per passenger (in USD)		+19.5
Real Surplus (in USD)	133,498.6	148,088.9
$\Delta_{Surplus}$ (in USD)		+14,590.3
$\Delta_{Surplus}$ per passenger (in USD)		+34.2

airline level, as illustrated in Table 12. We find that Delta (DL) behaves very much in line with Nash while JetBlue (B6) and American Airlines (AA) produce much more than what the Nash equilibrium would predict.

Table 12: Actual and Nash passengers in the New-York/Tampa segment

Airlines	Nash Quantity 2011:4	Nash Quantity 2012:1	Observed Quantity 2012:1
CO	105,9	-	-
NW	58.6	51.6	36.9
DL	101.8	94.9	89.7
B6	118.8	104.6	141.7
AA	-	28.5	19.7
UA	-	109.4	138.2

6 Nash departures and the relevant market

The theoretical prediction derived from Proposition 1 is that large departures from Nash equilibria should occur in routes with a stability index above 1. This prediction does not always fit the actual pattern reproduced in Figure 1 where the spread is sometimes positive for values of the stability index falling below 1. We now explore a potential explanation for this particular feature. We show that a greater scope for unobserved competition translates into a lower value of the stability index threshold S_s^* above which large departures from

Nash equilibria can occur. That is, $S_s^* = 1$ if the full set of products which constitute the relevant market is accounted for by the econometrician. Otherwise, the stability index threshold S_s^* should fall below 1. In this section, we assess the relevant threshold in every route of our dataset and comment upon the size of the relevant market.

6.1 Stability from sub-market observations

There are many circumstances in which the relevant market, i.e., the market that includes all the services that are relevant substitutes, cannot be considered in isolation. One may think of multimarket contacts through common endpoints or transportation services as a composite good that consists of differentiated items, e.g., economy versus business class services, or non-stop direct versus indirect flights. Also, on short distance routes, alternative products could entail other modes of transportation such as car or railway. Neglecting part of the potential goods or services in the relevant market leads to underestimate the overall transportation capacity that the airlines observed in our sample have actually to predict.

In order to highlight the possible biases associated with missing competition, we first examine a simple variant of our theoretical setup where the relevant market consists of two substitutable items. The demand for item m ($m = 1, 2$) is $P^m(Q^m, Q^{-m})$, where Q^m and Q^{-m} stand for the aggregate demands for the two items. On the supply side we assume that the set of firms producing the two items are disjoint. This is a strong assumption if the missing information about the relevant market mostly consists of indirect flights since traditional carriers often offer both direct and indirect flights. The assumption could be better suited on short distance routes which involve few alternatives to direct flights, with airline services competing against rail transportation or other inland transport modes for instance. In addition, we simplify the exposition by working under two symmetry assumptions:

Assumption A1. Symmetry of demand: $P^{-m}(Q^{-m}, Q^m) = P^m(Q^{-m}, Q^m)$ for all (Q^{-m}, Q^m) and all m.

Assumption A2. Symmetry of supply: every firm f producing item 1 has a mirror firm $F + f$ producing item 2, i.e., $\sigma_f = \sigma_{F+f}$ for every $f = 1, \ldots, F$, with F being the total number of airlines producing any given item.

Firm f in market m produces q_f that maximizes its profit given the aggregate production Q^m_{-f} of the other firms in market m and the aggregate production Q^{-m} in the other market. Its best-response can be written $q_f = R^m_f(Q^m_{-f}, Q^{-m})$, which is decreasing with its two arguments if the two items are substitutes. In view of Assumptions A1 and A2, we focus attention on a symmetric Nash equilibrium where $q^*_f = q^*_{F+f}$ for every $f \leq F$. In equilibrium the aggregate output is Q^* in each sub-market. The iterated process of elimination of dominated strategies in the neighborhood of such an equilibrium is now driven by the partial derivatives

$$R'_{f1}(\mathbf{q}^*) = \frac{\partial R^m_f}{\partial Q^m_{-f}} \left(Q^*_{-f}, Q^*\right), \quad \text{and } R'_{f2}(\mathbf{q}^*) = \frac{\partial R^m_f}{\partial Q^{-m}} \left(Q^*_{-f}, Q^*\right)$$

of the best-response function of firms f and $F + f$ with respect to its first and second argument, respectively. In this setup the stability condition given in Proposition 1 becomes:

Proposition 4. *A symmetric Nash equilibrium is locally the unique rationalizable outcome if and only if*

$$\sum_{f \leq F} \frac{R'_{f1}(\mathbf{q}^*) + R'_{f2}(\mathbf{q}^*)}{R'_{f1}(\mathbf{q}^*) - 1} < \frac{1}{2}. \tag{20}$$

Proof. See Appendix F. ■

Proposition 4 departs from Proposition 1 in two respects. First, the new stability index that appears in the left-hand side of (20), computed using information from sub-market m only, now accounts for the cross derivative $R'_{f2}(\mathbf{q}^*)$ since firms active in sub-market m need to predict the behavior of firms in the other sub-market. With two substitutable items, $R'_{f2}(\mathbf{q}^*) \leq 0$ and so the new index tends to be higher than the one derived in Proposition 1. The need of predicting the behavior of competitors in the other sub-market makes stability more difficult to achieve.

Second, in the right-hand side, there is a reduction from 1 to 1/2 in the route threshold S^*_s above which stability is lost. In a route s where $S^*_s < S_s < 1$, the equilibrium is unstable even though the stability index S_s computed in Proposition 1 is below 1. A threshold S^*_s below 1 can be used as a signal that the relevant market of route s is larger than the observed one.

In practice, in the situation where the econometrician has no a priori knowledge about how far the relevant market goes beyond the observed one, the derivative $R'_{f2}(\mathbf{q}^*)$ cannot be computed. In the empirical illustration below we will neglect this derivative by setting $R'_{f2}(\mathbf{q}^*)$ equal to 0, and continue to refer to the stability index given in Proposition 1. Rewriting (20) as

$$\sum_{f\leq F}\frac{R'_{f1}(\mathbf{q}^*)}{R'_{f1}(\mathbf{q}^*)-1}<\frac{1}{2}-\sum_{f\leq F}\frac{R'_{f2}(\mathbf{q}^*)}{R'_{f1}(\mathbf{q}^*)-1} \tag{21}$$

shows that we underestimate the true right-hand side of (20) when we set $R'_{f2}(\mathbf{q}^*)$ to 0.

6.2 Stability index threshold

To identify the S^*_s threshold, we exploit the fact that a route s with a high spread Δ_{st} is more likely to originate from a high spread regime, i.e., a regime where $S_{st} \geq S^*_s$. Instead a low spread is more likely to be associated with a low spread regime where $S_{st} < S^*_s$. Our estimation strategy works as follows. In a first step, we compute the empirical probability π_{st} that route s falls in the low spread regime during quarter t using the machine learning EM algorithm developed by Dempster, Laird and Rubin (1977). The details of the estimation procedure are provided in Appendix G. In a second step, we obtain individual estimates of the threshold $\hat{S}^*_{st}$ by matching π_{st} to the probability $\Pr(S_{st} \leq \hat{S}^*_{st})$ referring to the empirical distribution of the estimated stability index, where the stability index S_{st} for all s and t is estimated from (5).

To switch from $\hat{S}^*_{st}$ to one single statistic $\hat{S}^*_s$ for each segment s, we set $\hat{S}^*_s = \max_t \hat{S}^*_{st}$. This should be seen as a conservative choice that classifies segment s as in equilibrium if it is in equilibrium during at least one period t. In most routes this choice is without loss of great generality since the time dispersion of $\hat{S}^*_{st}$ within routes is low (see Figure 5 in Appendix).[5]

Table 13: Estimated stability index threshold distribution

$\hat{S}^*_s$

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.1862	0.8360	0.8698	0.8097	0.8714	0.8715

Number of routes: 301

[5]Our illustration on the Wright amendment in Section 6.3 weakens this criterion by considering several sub-periods in a given route.

Table 13 provides summary statistics about the estimated $\hat{S}_s^*$ at the route level. All values fall below 1, ranging from 0.18 to 0.87, which suggests that all routes in our dataset suffer to a certain extend from unobserved competition. The scope of unobserved competition is however limited since most routes involve a threshold above 0.8. With these new estimates we find that one-third of the routes can be regarded as falling in the high spread regime, while our initial threshold equal to 1 led to significantly more optimistic conclusions (less than 10% of the markets were supposed to be out of an equilibrium).

Table 14 illustrates how the estimated statistics $\hat{S}_s^*$ interacts with several explanatory variables. In column 1 we regress $\hat{S}_s^*$ on variables that can be considered as exogenous. A high value of the threshold (a narrower scope for unobserved competition) is associated with routes linking less populated cities, which probably indicates that the share of indirect services supplied by competing airlines is lower in this case. The second column, which introduces additional regressors, sheds light on the fact that more concentrated markets are associated with lower $\hat{S}_s^*$, which is not completely surprising given that these markets are generally operated by big traditional airlines supplying large menus of indirect services in addition to direct flights.

The effect of the observed market size when one accounts for unobserved competition can be put in perspective with our previous results in Table 7. We report in Table 15 information about the 10 routes with respectively the largest and smallest average number of passengers per quarter. The 10 largest routes display a larger average spread Δ_s and these departures from Nash behavior appear to reflect the combination of both higher stability index S_s and lower route threshold $\hat{S}_s^*$. No largest route in our sample eventually reaches equilibrium ($S_s > \hat{S}_s^*$) and instability here comes with high share of unobserved products ($\hat{S}_s^*$ is further away from 1); the two routes Atlanta–Miami and Boston–Washington are detected to be especially subject to high unobserved competition.

6.3 The Wright amendment repeal

The Wright amendment (WA) investigated in Ciliberto and Tamer (2009) serves as an interesting natural experiment which can be exploited in order to provide additional feedback about the validity of our methodology. The aim of the WA was to restrict airline services out of the Dallas Love airport (DAL) in order to stimulate the activity of the Dallas/Fort Worth airport (DFW).

Table 14: Stability index thresholds

	$\hat{S}_s^*$	
	(1)	(2)
Route distance	7.515e-05***	6.186e-05***
	(1.618e-05)	(1.842e-01)
Least population endpoint	-2.789e-08***	-1.080e-08
	(5.947e-09)	(7.549e-09)
Highest population endpoint	-4.314e-09**	-1.984e-09
	(2.063e-09)	(2.288e-09)
Least temperature endpoint	-1.845e-03	-5.621e-04
	(1.373e-03)	(1.358e-03)
Least temperature endpoint	-1.410e-04	-1.384e-04
	(1.188e-03)	(1.152e-03)
Passenger per quarter		-2.743e-04***
		(5.819e-05)
Share of direct flights		2.089e-02
		(1.313e-01)
Nb of airlines		-1.224e-02
		(2.038e-02)
Herfindahl index		-3.222e-01**
		(1.312e-01)
Constant	0.933***	1.055***
	(6.872e-02)	(1.842e-01)
Nb of (route) observations	301	301
R^2	0.135	0.219
Adjusted R^2	0.120	0.195
Residual Std. Error	0.126 (df = 295)	0.121 (df = 291)
F Statistic	9.197*** (df = 5; 295)	9.052*** (df = 9; 291)

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

Table 15: Relevant market for 20 airlines routes

Origin (US DOT city market)	Destination (US DOT city market)	Passengers (per quarter – thousand)	Distance (km)	Spread (within route average)	Stability index (within route average)	Threshold S_s^* (upper bound)
10 routes with the greatest average traffic per quarter						
Boston, MA	Washington, DC	1117	358	0.70	1.52	0.45
Orlando, FL	New York City, NY	1029	937	0.58	1.29	0.54
San Francisco, CA	Los Angeles, CA	948	332	0.46	1.40	0.60
Atlanta, GA	New York City, NY	924	748	0.81	1.02	0.54
Atlanta, GA	Miami, FL	905	584	0.90	0.95	0.31
Washington, DC	Chicago, IL	854	596	0.65	1.03	0.79
Atlanta, GA	Washington, DC	839	551	0.65	0.62	0.58
Las Vegas, NV	San Francisco, CA	761	399	0.59	1.06	0.84
Denver, CO	Los Angeles, CA	740	846	0.56	1.01	0.73
Phoenix, AZ	Los Angeles, CA	739	350	0.50	0.76	0.65
10 routes with the least average traffic per quarter						
Burlington, VT	Philadelphia, PA	44	335	0.27	0.29	0.87
Chicago, IL	Fort Wayne, IN	41	157	0.49	0.35	0.79
Denver, CO	Sioux Falls, SD	40	483	0.20	0.27	0.87
Jackson, WY	Salt Lake City, UT	39	205	0.79	0.25	0.85
Philadelphia, PA	Syracuse, NY	36	228	0.54	0.26	0.35
Philadelphia, PA	Richmond, VA	36	198	0.64	0.26	0.30
Chicago, IL	Sioux Falls, SD	34	462	0.35	0.25	0.82
Philadelphia, PA	Rochester, NY	33	257	0.35	0.24	0.84
Greensboro/High Point, NC	Philadelphia, PA	32	365	0.44	0.26	0.64
Denver, CO	Jackson, WY	32	406	0.16	0.21	0.87
Denver, CO	Rapid City, SD	32	300	0.23	0.19	0.85

In 1980, the WA gets effective and states that airline services in DAL using large aircraft could be provided only to airports within Texas and its four neighboring U.S. states, namely Arkansas, Louisiana, New Mexico and Oklahoma (Allen (1989)). Flights to other states are allowed only on small aircraft. Airlines could not offer connecting flights, through service on another airline, or through ticketing beyond the five-state region. In October 2006 a partial repeal is decided and the full repeal gets effective in 2014.

The abrogation of airline service restrictions from DAL in a Southwest stronghold area implies greater competitive pressure on DFW, where American Airlines operates direct non-stop long-haul flights. The abrogation of service restrictions affects the expansion of the size of the relevant market of services including the Dallas/Fort Worth area as an origin or destination point, depending on whether the point of destination of origin belongs to the so-called five-state region or not. Consider the case of the Dallas-Washington market for instance: under the WA, all flights had to go through DFW since no services were allowed from/to DAL; all of the airline services of the relevant market Dallas-Washington would therefore be products operated from/to DFW. After the abrogation of the WA, the same relevant market would typically include all airline services from both DAL and DFW. If the econometrician has only data on airline services from/to DFW, she does not suffer from any missing information as long as the WA is effective (in which case the stability index threshold should be close to 1); after the abrogation of the WA however, a significant share of information would be missing, and this should be reflected in a fall in the stability index threshold. The results reported in Table 17 are largely consistent with these predictions.

We propose to test empirically this prediction with our data, using only information on services from/to DFW. We consider three sub-periods, namely 2003:1-2006:2 (before the announcement of the repeal of the WA), 2006:3-2014:2 (from the announcement to the repeal of the WA) and 2014:2-2016:4 (after the repeal of the WA). Our subsample contains 18 routes that include DFW at some endpoints. Table 17 in the Appendix shows that the stability index threshold is stable across the three periods in every market that makes a connection between the Dallas/Fort Worth area and a city market in the WA zone (i.e., a city market located in Texas, Arkansas, Louisiana, New Mexico or Oklahoma). We do not detect any systematic change in the stability index or the spread between actual and Nash volumes of transported passengers in these routes.

The situation is however quite different for markets connecting the Dallas/Fort Worth area to cities outside the Wright zone. Indeed we find that the threshold is sharply reduced after the repeal of the amendment (i.e., from 2006:3-2014:2 to 2014:2-2016:4), while the announcement effect seems to be not significant (there is no significant difference between 2003:1-2006:2 and 2006:3-2014:2). We also find a larger spread after the repeal as we observe higher stability indexes. This probably suggests that the repeal of the WA introduced some instability in each market from/to the Dallas/Fort Worth area.

7 Conclusion

Greater competition is often viewed as driving welfare gains from lower equilibrium prices; our paper shows that it may also compromise the occurrence of an equilibrium. Thus, in markets where the usual indicators of high competitive pressure are present, i.e., those where several airlines with similar market shares or competitive low cost companies are present, the traditional equilibrium welfare analysis has to be worked out carefully. Eventually the equilibrium would be a reliable reference in only $70 - 90\%$ of the routes.

Our analysis is subject to a number of potential limitations that could be analyzed in future work.

1. Data from the U.S. Department of Transportation provide us with information about

airlines costs at the non-stop flight segment level. We therefore estimate demand at the same level, i.e., we restrict ourselves to routes where the share of direct flights is high enough. Our identification procedure for the scope of the relevant market however suggests that indirect flights matter, especially in routes with large flows of passengers, and so should be explicitly taken into account. Any initiative that could ease the combination of the two types of information is obviously welcome.

2. Our analysis abstracts from dynamic aspects that are certainly important in shaping the regular interactions between the airline companies that compete in a route. The insights from our robustness check suggest that firms certainly retrieve valuable information from bad prediction in the past. Brandenburger, Danieli and Friedenberg (2019) makes progress toward identification of the level of rationality in this context. An empirical application on the airline industry may be more challenging to implement as medium and long-run strategies also encompass both slot portfolios, which requires introducing airports into the analysis, as well as capacity choices.

3. A relevant choice for the measure of the discrepancy between the actual and equilibrium strategies regarding volumes of transported passengers needs a suitable equilibrium reference. Our paper refers to a version of a non-cooperative Cournot game with linear passengers demand and quadratic airline costs, but a positive spread could also come from an inadequate reference. There are two main sources of model misspecification in our context. The first one relates to the restrictive linear-quadratic modeling of market fundamentals that precludes multiplicity of Nash equilibria. In the presence of multiple Nash equilibria, local rationalizability can still be employed as a selection device to eliminate unstable equilibria from the set of empirically relevant outcomes. Still multiplicity of locally stable equilibria is possible, in which case there is no longer any obvious equilibrium reference. The second source of misspecification relates to the short-run strategies assigned to airlines. Volumes of passengers is only part of yield management strategies: individual price setting certainly also enters the airlines choice set; and explicit alliances or collusive behaviors weaken the status of the non-cooperative equilibrium reference.

We hope to investigate some of those issues in future research.

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A Proof Proposition 1

By Lemma 3 in Desgranges and Gauthier (2016) the matrix $\mathbf{B}$ has a spectral radius less than 1 if and only if (5) is satisfied. The slope in (6) obtains by differentiating the first-order condition for firm f profit maximization. The expression of $C''_f(q^*_f)$ obtains by applying the generalized envelope theorem to the cost minimization program (1). This yields $C'_f(q_f) = \lambda$, where λ is the non-negative Lagrange multiplier associated with the production constraint in (1). Therefore,

$$C''_f(q_f) = \frac{d\lambda}{dq_f}.$$

The first-order conditions for the cost minimization problem (1) are

$$\lambda = c'_{af}(q_{af}) \text{ for all } a \in \mathcal{A}_f \quad \text{ and } \sum_{a\in\mathcal{A}_f} n_{af} q_{af} = q_f$$

for every f. Differentiating these first-order conditions yields

$$d\lambda = c''_{af}(q_{af}) dq_{af} \text{ for all } a \in \mathcal{A}_f \quad \text{ and } \sum_{a\in\mathcal{A}_f} n_{af} dq_{af} = dq_f$$

for every f. Reintroducing the expression of dq_{af} into the last equality we finally obtain

$$d\lambda \sum_{a\in\mathcal{A}_f} \frac{n_{af}}{c''_{af}(q_{af})} = dq_f.$$

This completes the proof.

B Proof Proposition 2

In the linear-quadratic specification, the stability index

$$S(\mathbf{q}^*) = \sum_f \frac{\delta\sigma_f}{1 + 3\delta\sigma_f}. \tag{22}$$

does not depend on production. The equilibrium production of firm f satisfies

$$q_f^* = \frac{\sigma_f}{1+\sigma_f \delta}(\delta_0 - \delta Q^*), \tag{23}$$

Summing gives the aggregate equilibrium production

$$Q^* = \frac{\displaystyle\sum_f \frac{\delta_0\, \sigma_f}{1+\delta\sigma_f}}{1+\displaystyle\sum_f \frac{\delta\, \sigma_f}{1+\delta\sigma_f}}. \tag{24}$$

Both the index $S(\mathbf{q}^*)$ and the production Q^* are increasing with σ_f (which itself increases with σ_{af}). An additional marginal aircraft transfer corresponds to $d\sigma_f > 0$. The result follows.

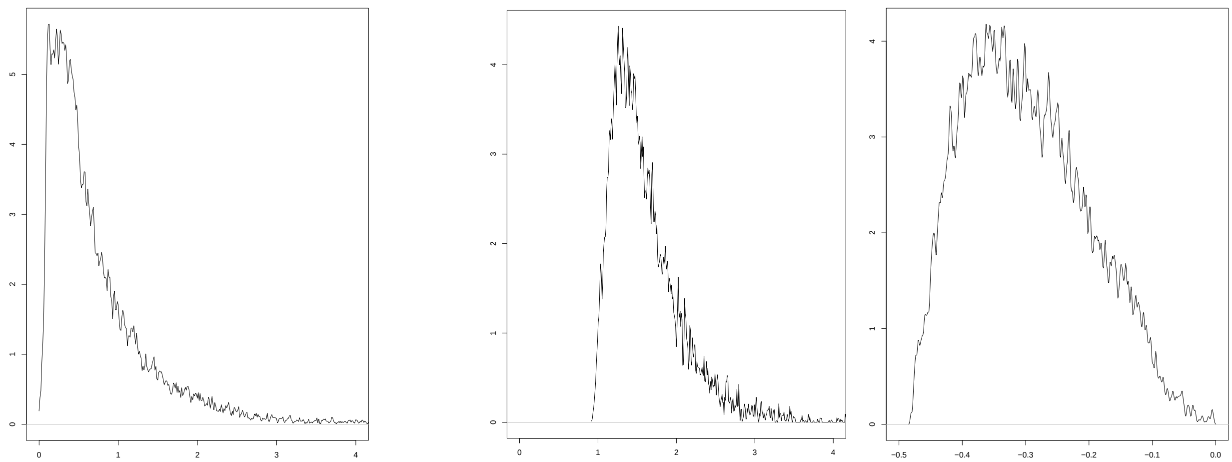
C Proof Proposition 3

It is similar to the proof of proposition 2 but now exploits second-order derivatives of $S(\mathbf{q}^*)$ and Q^*. In the linear-quadratic specification, $S(\mathbf{q}^*)$ and Q^* are increasing concave functions of σ_f (which is itself increasing linear in σ_{af}). A marginal aircraft transfer $dn_{af} = -dn_{af'} = -1$ yields $d\sigma_f = -\sigma_{af} < 0$ and $d\sigma_{f'} = -d\sigma_f > 0$. The result follows.

D Stability index estimate

The left-panel of Figure 2 depicts the density of $\hat{\sigma}_{fst}$ at the airlines $\times$ segment $\times$ quarter level. Its distribution is positively skewed with a long right tail (Table 6 shows that the median estimated value of this parameter is 0.515 while its average of 0.762). The statistics $\hat{\sigma}_{fst}$ is inversely related to the marginal cost. Hence Figure 2 shows that the marginal cost for transporting one additional passenger quickly increases with the total number of transported passengers. The small subset succeeding to contain marginal costs consists of the largest airlines: we find that the average number of transported passengers is 3.6 times higher for observations in the last quartile of the $\hat{\sigma}_{fst}$ distribution ($\sigma_{fst} \geq 0.965$).

The shape of the density of $\hat{\delta}_{st}$ shown in the middle panel in Figure 2 is quite different.



Cost (σ_{fst}) Demand ($-\delta_{st}$) Best-response slope

Figure 2: Probability density functions

Price sensitivity of demand indeed appears symmetrically distributed and displays a high concentration around an average sensitivity of $1/0.621 = 1.609$.

The homogeneity of demand behavior (the low variability of $\hat{\delta}_{st}$) across segments makes the distribution of the slope of the best-response $R'_{fst}(\mathbf{q}^*)$ in (9) at the airlines $\times$ segment $\times$ quarter level to be mostly driven by cost heterogeneity (the high variability of $\hat{\sigma}_{fst}$). It is reported in the right panel in Figure 2. Airlines are found to display significant inertia in how they react to the production of others. The average slope equals -0.299, i.e., an average airlines would only transport 30 passengers less when its competitors are expected to transport 100 additional passengers. Short-run inertia is plausible in the airline industry since the number of passengers can be adjusted within the limit of the route transportation seat capacity, which is mostly fixed over a quarter. The theory predicts that this inertia favors stability of the Nash equilibrium, but we know from (5) that stability relies on the sum of all the slopes of the best-response functions of the airlines active on the segment. Despite individual inertia, stability would be lost with more than 4 identical competing airlines characterized by a -0.299 average best-response slope.

E Spread density distribution

Figure 3 depicts in solid black the density of the spread between actual and Nash production at the more disaggregated segment × airlines × period level. This distribution combines situations where airlines produce below the equilibrium number of passengers and situations where they instead produce above it. The first (resp. last) type of situations reflects an underestimated (resp., overestimated) expected price. Figure 3 highlights some symmetry between under and overestimated prices when forecast errors are small (the spread stands below 0.25). For larger values of the spread, the density corresponding to an overestimated production of others / an underestimated price is depicted in dashed blue. Figure 3 clearly shows limited errors in this case, compared to the case where airlines underestimate the production of others / overestimate prices (depicted in dashed red). If one considers a predicted low price as a symptom of firms' pessimism, Figure 3 suggests limited forecasting errors from pessimistic airlines. This would accord with the recent findings based on surveys about financial analysts, CEO or Chief Financial Officers expectations or proxies for managerial expectations that errors relate to overconfidence and optimism (see, e.g., Ma, Sraer and Thesmar (2018)).

F Proof Proposition 4

The new $\mathbf{B}$ matrix that governs the iterated process of elimination of dominated strategies is a $2F \times 2F$ matrix whose f-th row, $f \leq F$, is 0 at f-th column, is $R'_{f2}(\mathbf{q}^*)$ in every column $j > F$ and $R'_{f1}(\mathbf{q}^*)$ otherwise. Similarly, its $(F+f)$-th row is 0 at $F+f$-th column, is $R'_{f2}(\mathbf{q}^*)$ in every column $j \leq F$ and $R'_{f1}(\mathbf{q}^*)$ otherwise. Matrix $\mathbf{B}$ is contracting if and only if the spectral radius of the positive matrix $-\mathbf{B}$ is lower than 1. Let e some eigenvalue e of $-\mathbf{B}$ and $\mathbf{v}$ be the associated $2F$-eigenvector $(v_1, \ldots, v_{2F})$. From $e\mathbf{v} = -\mathbf{B}\mathbf{v}$, we have: for all $f \leq F$,

$$ev_f - R'_{f1}v_f = -\sum_{k \leq F} R'_{f1}v_k - \sum_{F<k\leq 2F} R'_{f2}v_k$$

$$\Leftrightarrow v_f = -\frac{R'_{f1}}{e - R'_{f1}} \sum_{k \leq F} v_k - \frac{R'_{f2}}{e - R'_{f1}} \sum_{F<k\leq 2F} v_k$$

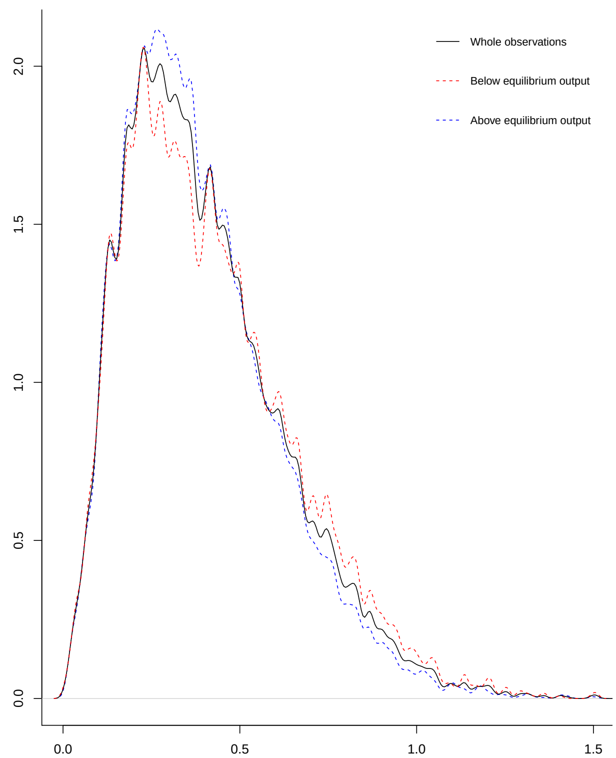


Figure 3: Spread density distribution

and

$$v_{F+f} = -\frac{R'_{f2}}{e - R'_{f1}} \sum_{k \leq F} v_k - \frac{R'_{f1}}{e - R'_{f1}} \sum_{F<k\leq 2F} v_k.$$

All the derivatives of the best-response functions are evaluated at $\mathbf{q}^*$. Summing over firms yields

$$\sum_{f\leq F} v_f = -\sum_{f\leq F} \frac{R'_{f1}}{e - R'_{f1}} \sum_{k\leq F} v_k - \sum_{f\leq F} \frac{R'_{f2}}{e - R'_{f1}} \sum_{F<k\leq 2F} v_k$$

and

$$\sum_{F<f\leq 2F} v_{F+f} = -\sum_{F<f\leq 2F} \frac{R'_{f2}}{e - R'_{f1}} \sum_{k\leq F} v_k - \sum_{F<f\leq 2F} \frac{R'_{f1}}{e - R'_{f1}} \sum_{F<k\leq 2F} v_k.$$

The symmetry properties of $\mathbf{B}$ imply that the eigenvectors are such that $v_f = v_{F+f}$ for all $f \leq F$. Hence the two previous equations reduce to

$$\sum_{f\leq 2F} v_f = -\sum_{f\leq 2F} \frac{R'_{f1} + R'_{f2}}{e - R'_{f1}} \sum_{k\leq 2F} v_k.$$

Eigenvalues e of $-\mathbf{B}$ thus are solutions to

$$G(e) \equiv -\sum_{f\leq 2F} \frac{R'_{f1} + R'_{f2}}{e - R'_{f1}} - 1 = 0$$

The function G is continuous decreasing for all $e \geq 0$, with $G(0) > 0 > -1 = G(+\infty)$. There is consequently a unique $e \geq 0$ solution to $G(e) = 0$. This is the spectral radius. Since G is decreasing, this eigenvalue is lower than 1 if and only if $G(1) < 0$, or equivalently,

$$-\sum_{f\leq 2F} \frac{R'_{f1} + R'_{f2}}{1 - R'_{f1}} - 1 < 0.$$

The result follows from $R'_{fm} = R'_{(F+f)m}$ for every $f \leq F$ and $m = 1, 2$.

G Spread regimes from the EM algorithm

The EM algorithm is unsupervised as it is designed to cluster points (the various spreads in our setup) that do not come with any specific label (a low or high spread regime). We assume that the distribution of the spread Δ_{st} reproduced in plain black in Figure 4 arises from a mixture of two Gaussian distributions: the first distribution is associated with a low spread, in which case the Nash equilibrium is a plausible outcome of competition; the second distribution is associated with a high spread, which corresponds to a more unstable regime. The EM algorithm aims at generating the probability that a spread point originates from any of the two regimes. This probability is then used to derive the individual market threshold we are interested in.

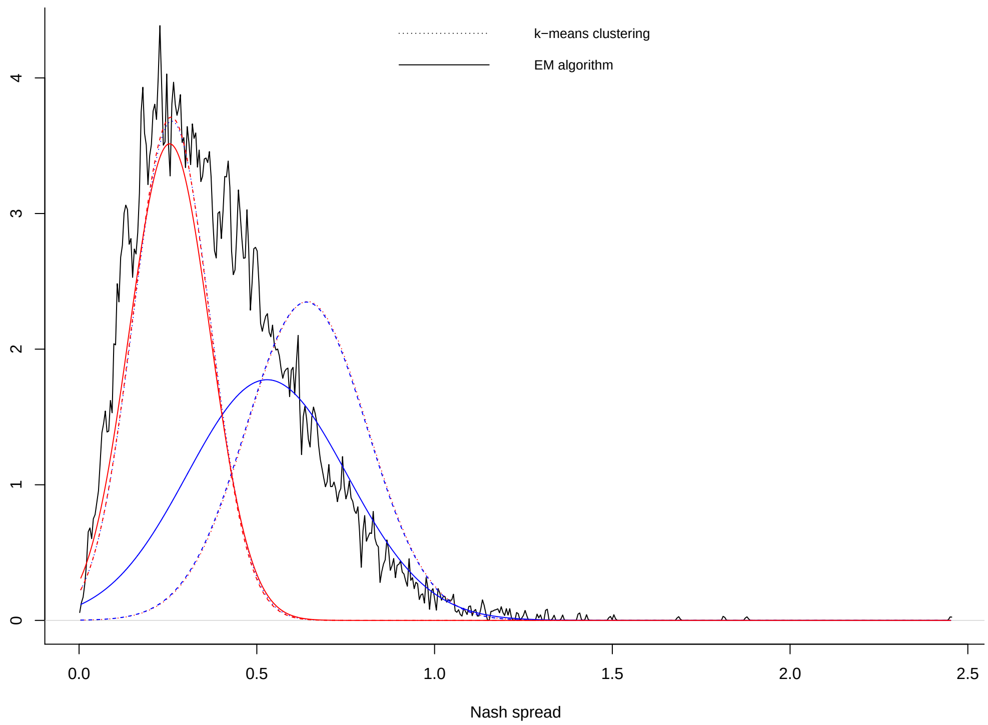


Figure 4: Spread Gaussian mixture from the EM algorithm

In order to initialize the EM algorithm, we compute a preliminary allocation of all the spread points to two different sets with the help of a standard k-means clustering technique. The average spread in the preliminary low spread group G_1 is 0.26 (standard deviation is 0.108). The density of the corresponding Gaussian distribution is depicted in dotted red in Figure 4. Similarly, the average spread in the high spread regime G_2 is 0.64 (standard deviation is 0.169), and the density of the corresponding Gaussian distribution is depicted in dotted blue in Figure 4. Hence, in the low (resp., high) spread regime the mean to standard deviation ratio of the spread equals 2.4 (resp., 3.79), which highlights a much greater concentration of the departures from the Nash equilibrium in the low spread regime.

The k-means clustering yields an average probability of $\pi_{st}(0) = 0.65$ that a specific spread drawn randomly in the sample originates from the low spread regime. Given this probability and the mean and standard error in each regime, we can compute from Bayes's rule the probability $\pi_{st}(1)$ that Δ_{st} is actually drawn from the low spread regime for all s and t. Then, given these a posteriori probabilities, we can compute the maximum likelihood estimators for the means and standard errors of the two regimes. The new Gaussian distributions are used to revise $\pi_{st}(1)$ into $\pi_{st}(2)$ for every s and t according to Bayes's rule, which allows us to initiate another step of estimation for the two moments of the two Gaussian distributions. The EM algorithm repeats these steps until convergence.[6]

In Table 16 we report the moments of the two Gaussian distributions for two variants.[7] In both cases, the spread distribution for the subsample of routes with a stability index above 1, that we know are part of the high spread regime, is the same as the spread distribution in the high spread regime. The mean spread in the low spread regime is 0.25; it is twice as high in the high spread regime. The dispersion of the spread is also twice as high in the high spread regime (0.11 versus 0.22). The low spread regime thus will be characterized by dampened fare and volume of transported passengers fluctuations. The two Gaussian distributions are depicted in red (for the low spread regime) and blue (for the high spread regime) in Figure 4. It is clear from this figure that observations with a very low (resp. high) spread are almost surely allocated to the low (resp. high) spread regime. However the algorithm fails to identify clearly the regime of observations with an intermediate spread located around 0.4.

The final probability π_{st} that Δ_{st} is drawn from the low spread regime distribution ranges from 0 to 0.83. In Figure 5 we plot the within route average probability and its standard error for each of our 301 route sample. In the horizontal axis routes are ranked in the order of increasing within route average probabilities. The routes with low or high

[6]The EM algorithm stabilizes in a local maximum for the likelihood. In our setup it always converges to the same outcome.

[7]In the first variant, we a priori require that the spread mean and standard error in the high spread regime are respectively equal to the empirical mean and standard error of the spread among the subset of points Δ_{st} with a stability index S_{st} above 1. That is, we only apply the EM algorithm to estimate the first two moments of the Gaussian distribution of the spread in the low spread regime. This variant thus a priori imposes the theoretical consistency requirement that observations with a stability index above 1 are drawn from the same probability distribution as those falling in the high spread regime, even though the associated stability index is below 1. In the second variant, we impose no constraint on the moments of the Gaussian distribution of the spread in the high spread regime.

Table 16: NASH SPREAD GAUSSIAN MIXTURE

	Low spread regime		High spread regime	
Variant of the EM algorithm	Mean	Standard error	Mean	Standard error
Constrained	0.2615397	0.1162918	0.5156821	0.2419057
Unconstrained	0.2546883	0.1135389	0.5286944	0.2248107

Number of observations: 7422

probabilities display the greatest spread concentration over time. The uncertainty about the relevant regime of airline routes with an average probability around 0.4 translates into quarters where the probability of a ruling low spread regime varies a lot over time.

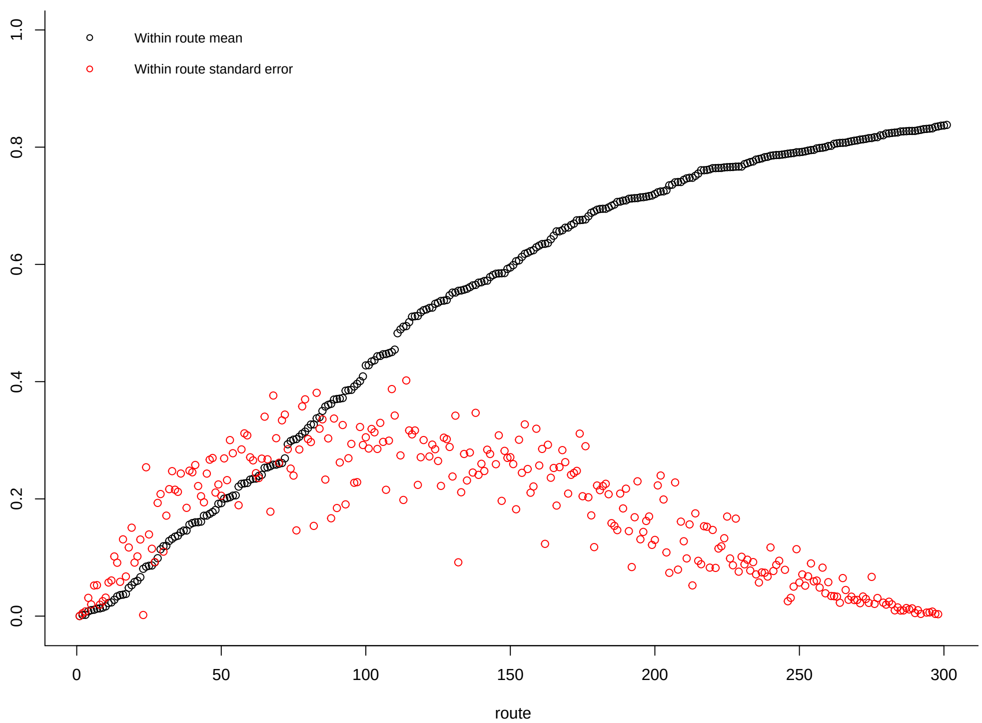


Figure 5: Probability of the low spread regime

H The Wright amendment repeal

Table 17: THE RELEVANT MARKET OF DALLAS/FORT WORTH

Origin (US DOT city market)	Destination (US DOT city market)	Sub-period	Passengers (per quarter – thousand)	Distance (km)	Spread (within route average)	Stability index (within route average)	Threshold S_s^* (upper bound)
AREA UNRESTRICTED BY WRIGHT AMENDMENT[1]							
Dallas/Fort Worth, TX	Lubbock, TX	2003:1-2006:2	161	282	0.29	0.45	0.86
Dallas/Fort Worth, TX	Lubbock, TX	2006:3-2014:2	164	282	0.35	0.47	0.87
Dallas/Fort Worth, TX	Lubbock, TX	2014:3-2016:4	138	282	0.12	0.50	0.86
Dallas/Fort Worth, TX	San Antonio, TX	2003:1-2006:2	480	247	0.45	0.58	0.61
Dallas/Fort Worth, TX	San Antonio, TX	2006:3-2014:2	502	247	0.51	0.59	0.79
Dallas/Fort Worth, TX	San Antonio, TX	2014:3-2016:4	472	247	0.36	0.60	0.80
Dallas/Fort Worth, TX	New Orleans, LA	2003:1-2006:2	196	437	0.30	0.45	0.83
Dallas/Fort Worth, TX	New Orleans, LA	2006:3-2014:2	243	437	0.34	0.54	0.87
Dallas/Fort Worth, TX	New Orleans, LA	2014:3-2016:4	299	436	0.47	0.71	0.79
Dallas/Fort Worth, TX	Tulsa, OK	2003:1-2006:2	209	237	0.19	0.66	0.87
Dallas/Fort Worth, TX	Tulsa, OK	2006:3-2014:2	222	237	0.45	0.58	0.86
Dallas/Fort Worth, TX	Tulsa, OK	2014:3-2016:4	199	237	0.37	0.53	0.82
Albuquerque, NM	Dallas/Fort Worth, TX	2003:1-2006:2	221	569	0.35	0.63	0.73
Albuquerque, NM	Dallas/Fort Worth, TX	2006:3-2014:2	276	569	0.38	0.54	0.87
Albuquerque, NM	Dallas/Fort Worth, TX	2014:3-2016:4	231	569	0.18	0.52	0.87
Dallas/Fort Worth, TX	Kansas City, MO	2003:1-2006:2	221	460	0.48	0.49	0.64
Dallas/Fort Worth, TX	Kansas City, MO	2006:3-2014:2	285	460	0.40	0.56	0.84
Dallas/Fort Worth, TX	Kansas City, MO	2014:3-2016:4	285	460	0.27	0.61	0.87
Dallas/Fort Worth, TX	Austin, TX	2003:1-2006:2	454	189	0.50	0.58	0.51
Dallas/Fort Worth, TX	Austin, TX	2006:3-2014:2	480	189	0.57	0.59	0.60
Dallas/Fort Worth, TX	Austin, TX	2014:3-2016:4	487	189	0.48	0.60	0.59
AREA RESTRICTED BY WRIGHT AMENDMENT							
Dallas/Fort Worth, TX	Philadelphia, PA	2003:1-2006:2	155	1302	0.30	0.45	0.85
Dallas/Fort Worth, TX	Philadelphia, PA	2006:3-2014:2	207	1302	0.41	0.51	0.86
Dallas/Fort Worth, TX	Philadelphia, PA	2014:3-2016:4	274	1300	0.66	0.68	0.65
Dallas/Fort Worth, TX	Denver, CO	2003:1-2006:2	373	641	0.42	0.76	0.79
Dallas/Fort Worth, TX	Denver, CO	2006:3-2014:2	406	641	0.51	0.86	0.78
Dallas/Fort Worth, TX	Denver, CO	2014:3-2016:4	512	641	0.61	1.08	0.27
Dallas/Fort Worth, TX	Atlanta, GA	2003:1-2006:2	513	732	0.35	0.83	0.84
Dallas/Fort Worth, TX	Atlanta, GA	2006:3-2014:2	516	730	0.36	0.88	0.87
Dallas/Fort Worth, TX	Atlanta, GA	2014:3-2016:4	584	725	0.55	0.95	0.42
Dallas/Fort Worth, TX	Phoenix, AZ	2003:1-2006:2	335	868	0.43	0.60	0.83
Dallas/Fort Worth, TX	Phoenix, AZ	2006:3-2014:2	319	866	0.41	0.59	0.87
Dallas/Fort Worth, TX	Phoenix, AZ	2014:3-2016:4	422	868	0.71	0.78	0.67
Dallas/Fort Worth, TX	Seattle, WA	2003:1-2006:2	236	1660	0.50	0.46	0.77
Dallas/Fort Worth, TX	Seattle, WA	2006:3-2014:2	250	1660	0.53	0.49	0.69
Dallas/Fort Worth, TX	Seattle, WA	2014:3-2016:4	294	1660	0.54	0.54	0.49
Dallas/Fort Worth, TX	Salt Lake City, UT	2003:1-2006:2	178	988	0.27	0.48	0.82
Dallas/Fort Worth, TX	Salt Lake City, UT	2006:3-2014:2	162	988	0.30	0.51	0.87
Dallas/Fort Worth, TX	Salt Lake City, UT	2014:3-2016:4	204	988	0.30	0.62	0.86
Dallas/Fort Worth, TX	Chicago, IL	2003:1-2006:2	426	802	0.49	0.54	0.41
Dallas/Fort Worth, TX	Chicago, IL	2006:3-2014:2	443	800	0.67	0.76	0.41
Dallas/Fort Worth, TX	Chicago, IL	2014:3-2016:4	588	795	0.80	1.03	0.22
Dallas/Fort Worth, TX	Charlotte, NC	2003:1-2006:2	147	936	0.28	0.47	0.86
Dallas/Fort Worth, TX	Charlotte, NC	2006:3-2014:2	248	935	0.30	0.49	0.87
Dallas/Fort Worth, TX	Charlotte, NC	2014:3-2016:4	320	931	0.57	0.50	0.69
Dallas/Fort Worth, TX	Orlando, FL	2003:1-2006:2	305	984	0.63	0.49	0.81
Dallas/Fort Worth, TX	Orlando, FL	2006:3-2014:2	277	983	0.60	0.45	0.74
Dallas/Fort Worth, TX	Orlando, FL	2014:3-2016:4	344	977	0.71	0.68	0.24
Dallas/Fort Worth, TX	Las Vegas, NV	2003:1-2006:2	382	1055	0.65	0.66	0.42
Dallas/Fort Worth, TX	Las Vegas, NV	2006:3-2014:2	352	1055	0.62	0.58	0.52
Dallas/Fort Worth, TX	Las Vegas, NV	2014:3-2016:4	445	1055	0.72	0.80	0.26
Dallas/Fort Worth, TX	San Francisco, CA	2003:1-2006:2	436	1456	0.71	0.56	0.30
Dallas/Fort Worth, TX	San Francisco, CA	2006:3-2014:2	427	1458	0.75	0.53	0.45
Dallas/Fort Worth, TX	San Francisco, CA	2014:3-2016:4	498	1455	0.91	0.80	0.17

The amendment initially restricted service from Dallas Love outside Texas, Arkansas, Louisiana, New Mexico and Oklahoma; and Missouri from 2005.