Journal of Air Transport Management 36 (2014) 59–68

Contents lists available at ScienceDirect

Journal of Air Transport Management

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

# Modeling the effects of wage premiums on airline competition under asymmetric economies of density: A case study from Brazil☆

Cícero R. Melo Filho [a], Lucia Helena Salgado [b], Renato Cesar Sato [c], Alessandro V. M. Oliveira [a,*,1]

[a] Latin American Center for Transportation Economics, Aeronautics Institute of Technology, Brazil
[b] Institute for Applied Economic Research, Brazil
[c] Federal University of São Paulo, Brazil

*JEL classification:*
L93
L13
J3

*Keywords:*
Airlines
Markups
Cost-price pass-through
Economies of density

A B S T R A C T

This paper investigates the effects of wage premiums on the competition between Full Service Carriers (FSC) and Low Fare Carriers (LFC) in the airline industry. We study the impact of changes in the labor market and the resulting effects on performance in the product market and examine the role of economies of density. We develop an oligopoly model of airline competition with endogenous wages and simulate increases in labor costs. We apply the model to the case of the most important domestic route of Brazil using airline/route-specific demand and costs data. Our chief contribution relies on the empirical model of asymmetric economies of density for the competing business models. We estimate that LFCs have higher economies of density than FSCs. With the empirical models of demand, costs and wages, we compute the wage-elasticities of price-cost markups. We find that, on account of the higher sensitivity of marginal costs to labor costs of the FSCs, their markups are more affected by wage premium increases than the markups of the LFCs. The results are attenuated by higher economies of density, but amplified by higher price-elasticities of demand and lower economic growth.



## 1. Introduction

This paper analyzes the impact of wage premiums on the product market competition of major Full Service Carriers (FSC) and Low Fare Carriers (LFC) in the airline industry. We impose exogenous flight crew unit cost increases on the cost structures of airlines engaged in Bertrand–Nash competition with product differentiation. The cost increases are caused by pilot and cabin crew wage hikes with airlines facing stronger union power, short-term labor scarcity and resulting higher labor market rents. We apply our model to a booming airline market with rapid growth in the demand for cabin crew – the Brazilian airline industry of the late 1990s and early 2000s. More precisely, we apply the model to the case of the densest domestic route of Brazil using airline/route-specific demand and costs data.

Labor relations issues such as collective bargaining and strike threat power have gained increasing attention in the Brazilian air transportation market over the years. As the market has faced a clear shortage of qualified labor with the continuing departure of many experienced pilots for job opportunities abroad, stronger pilot and air traffic controller unions began demanding better working conditions and wages. Strike threats and non-strike work actions – such as work-to-rule procedures – have been implemented in many situations since then, particularly after the last major strike episode of 1988. The situation has been exacerbated since the 1990s with the notable expansion of the industry permitted by the country's macroeconomic stabilization, opening of the economy and, more specifically, deregulation of the air transportation sector. Actually, demand for air travel has more than trebled since the early 1990s.[2] In addition to the emergence of airport capacity bottlenecks, demand pressure has factored into the rapid growth in industry labor costs that has outpaced any other cost category in recent years.[3]

☆ We thank Carlos Müller, Eliseu Lucena Neto and Paulo Ivo Queiroz for useful comments. We also thank the anonymous reviewers and the editor for the careful reading of our manuscript and the valuable comments.

* Corresponding author.
*E-mail addresses:* ciceromelofilho@gmail.com (C.R. Melo Filho), lucia.salgado@ipea.gov.br (L.H. Salgado), rcsato@unifesp.br (R.C. Sato), alessandro.oliveira@pq.cnpq.br, avmoliveira@gmail.com (A.V.M. Oliveira).

1 The author thanks Fapesp, CAPES and CNPq for financial support.

2 According to the Institute for Applied Economic Research (www.ipeadata.gov.br), airlines produced 29.0 billion revenue-passenger kilometers (RPK) in 1990, against 95.9 billion RPK in 2010.

3 Although labor unit costs declined during the 2000s (to a low of 12.72% of total operating cost in 2004), they have had been on an increasing path since, reaching 19.39% in 2010. By contrast, labor costs were typically greater than 20% of operational costs during the 1990s (source: regulator's Statistical Yearbooks, 1997–2010). See Turolla et al. (2011) for a discussion.

0969-6997/$ – see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.jairtraman.2013.12.010

We model the impact of increases in wage premiums on the competitive interaction of FSCs and LFCs.[4] So far the impact of crew costs on downstream airline competition has received little attention in air transportation studies. The chief contribution of the present paper relies on modeling asymmetric economies of density between the different business models of carriers. Since Brueckner et al. (1992) the literature has incorporated the fact that increases in traffic volume on spokes of a network of an FSC typically decrease fares on account of economies of spoke density. In parallel, it has been reported that not only FSCs may benefit from economies of density. For example, Boguslaski et al. (2004) note that in the 1990s the most prominent LCC, Southwest Airlines, focused almost exclusively on short haul, dense markets aiming at rapidly expanding and keeping low unit costs to exploit economies of density. However, virtually no previous study has explicitly assumed asymmetric economies of density among FSCs and LFCs when modeling airline competition. Assuming asymmetries mean that the production processes of the different business models are also asymmetric, and that differences that are not only due to relative sizes of carriers must be taken into account in the airline competition model. We therefore make use of this assumption when inspecting the effects of wage premiums on competition, and assess the impacts of a wide range of possible returns to density values on the relative competitive advantage of carriers.

In this paper, we also assume that wages are endogenously determined and therefore explicitly model wages as a function of endogenous and exogenous carrier-specific shifters. Neven and Röller (1996) and Neven et al. (2006) also considered endogenous airline labor costs, by assuming that carriers bargain over wages. We also utilize instrumental variables aiming at consistent econometric estimation of wage determinants. The contribution of our identification strategy is that, as opposed to the previous literature, we test for the relevance and validity of the proposed set of instrumental variables.

Thus, our model of differentiated oligopoly aims to pinpoint the product-market effects of wage hikes in the airline industry. More specifically, we propose to apply this model to the case of the most important Brazilian route – the São Paulo-Rio de Janeiro air shuttle. We estimate panel data models of demand, costs and wages. Estimated structural parameters are then used to simulate the effects of labor cost shifts – increases in wage premiums that result from stronger union bargaining power – on airline competition. We compute the wage-elasticities of quantities, prices, marginal costs and price-cost markups, and consider alternative scenarios of economies of density, price elasticities and economic growth in performing a sensitivity analysis with respect to the effects of wage hikes. We find that markups for FSCs are considerably more affected by shocks in wage premiums than the markups for LFCs in all scenarios, even considering that the cost-price pass through of FSCs is slightly higher than that of LFCs. This result is driven by the fact that FSCs' marginal costs and demand are more vulnerable to wage premium shocks. The results are amplified by weaker (more exhausted) economies of density, higher price-elasticity of demand and lower economic growth.

This paper is organized as follows. In Section 2, we present the Brazilian airline industry and the evolution of airline labor costs in the country. Section 3 presents the theoretical model, the available data and the estimation results of the empirical models of demand, costs and wages. In Section 4, we present the results of comparative-static simulations that attempt to assess the impact of a wage premium increase by computing the wage-elasticities of each group of carriers. In Section 5, we present the concluding section.

## 2. Labor relations in the Brazilian air transportation of the late 1990s

Brazilian flight crew regulations are provided for in Federal Law Number 7,183, enacted on April 5, 1984. This law provides safety, operational and flight rules for crewmembers, including work assignments and work limits with respect to the number of consecutive hours of rest between assignments. The Brazilian regulatory framework of airline labor relations is considered by many analysts to be strict and outdated, particularly in comparison to other jurisdictions in South America, such as Chile and Uruguay. These countries allow greater flexibility in terms of working hours. Moreover, the Brazilian law explicitly forbids recruitment of foreign pilots. By contrast, in India, for example, carriers are allowed to hire expatriate pilots, who have recently become a majority of the workforce at certain airlines. China is another emerging market that began allowing foreign crew recruitment. In Brazil, conversely, qualified pilots have been leaving the country in recent years for better salaries in expanding airline markets abroad, which complicates a labor market for airlines already saddled with a prohibition on hiring foreign pilots.[5]

Historically, the major labor union representing pilots, flight attendants, mechanics, and other classes in Brazil has been the Aeronauts National Union (SNA), founded in 1946. In 1960, another important labor association was founded, Varig Pilots Association (APVAR), to represent pilots at the Brazilian flagship carrier, Varig Airlines. Although employees of other carriers had their own associations, APVAR was the most significant until the early 2000s. In Brazil, the outcomes of negotiations between labor unions, associations and airlines now typically cover the employees of all major carriers, with the signature of a Collective Work Convention.

During the late 1990s, labor costs were typically more than 20% of carriers' total operating costs.[6] From this period forward, air transportation in Brazil began a considerable expansion. After several episodes of crisis and intense economic problems in the 1970s and 1980s, the scenario in Brazil changed dramatically in the mid-1990s. First, a macroeconomic stabilization policy led to the end of hyperinflation and a relative increase in consumer income. In parallel, a set of measures of economic liberalization in the airline industry provided greater price competition between carriers. The expansion of income combined with increasingly competitive pricing resulted in a considerable expansion of air transportation during this period. In fact, the demand for air travel in the country increased from 29 billion RPK in 1990, to more than 95 billion RPK in 2010 – representing growth of 228% over twenty years. As a comparison, the country's entire economy grew approximately 82% during the same period.[7]

Fig. 1 shows the evolution of certain important metrics of the Brazilian air transportation industry during the period. Medium-term growth rates of revenue passenger kilometers ("RPK") and pilot workforce ("Pilots") may be observed. Medium-term growth rates were calculated using the average growth rate over a period of three years – denoted by "yo3y". Fig. 1 also depicts the evolution of average captain compensation ("Wages") during the period. There

[4] See Hofer et al. (2008) for a study of the determinants of price premiums in the airline industry. For an application of an oligopoly model to the Brazilian airline industry, see Silveira and Oliveira (2008).

[5] According to flightglobal.com, in 2008, more than 200 Brazilian pilots were flying for carriers based in the Middle East and India, among other regions outside the Americas.

[6] Source: regulator's Statistical Yearbooks (1990–2000). After Gol's entry in the market, because of cost restructuring and the bankruptcy of incumbents, the proportion of labor-related costs dropped to figures close to 14%.

[7] Source: www.ipeadata.gov.br (series of annual Revenue Passenger-Kilometers and real Gross Domestic Product, deflated by using the country's Consumer Price Index – IPCA).

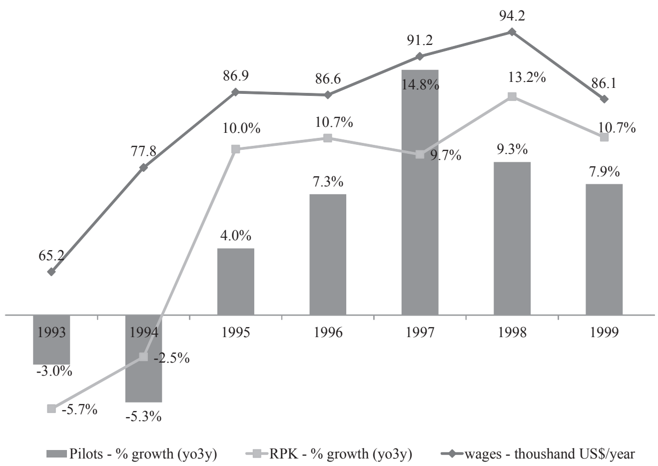


**Fig. 1.** Evolution of average captain compensations.
Source: Annual Social Information Report (RAIS), Ministry of Labor and Employment, Brazil, 1993–1999, data on commanders wages of the commercial aviation and merchant marine, deflated by using the country's Consumer Price Index – IPCA (source: www.ipeadata.gov).

is a notable positive correlation pattern between the three series. The correlation between RPK and pilot workforce growth rates is 0.85, whereas the correlation between RPK growth and average captain compensation is 0.93. Consistent with the correlation statistics, it is possible to note in Fig. 1 that, following the significant increase in demand for air travel from 1995 – with RPK growth rates almost always above 10% – there was an ever-increasing demand for pilots, with the workforce expanding to a peak of 14.8% in 1997. Notably, captain compensation levels accompanied the growth of the sector. In fact, captain compensation grew from an average of USD 65,000 a year in 1993 to above USD 85,000 at the end of the decade. In fact, average captain compensation peaked at USD 94,200 in 1998. Between 1993 and 1999, there was a real increase in captain compensation of almost one-third.

Fig. 1 suggests that increased growth in the demand for air transportation in the late 1990s accelerated new pilot hirings. However, given the scarcity of highly skilled labor and the consequent inelasticity of supply in the labor market, rapid growth in air transportation demand and employment ultimately produced wage hikes. We suggest as an explanation that the increase in the bargaining power of unions during this period exerted an upward pressure on wages. This suggestion is in line with Hirsch and Macpherson (2000), who indicate that labor rents in the airline industry are largely attributable to union bargaining power. Strikes as instruments for strengthening labor union bargaining power for pay increase and work condition negotiations have not occurred in the Brazilian airline industry for decades. Since the last strike in 1988, however, non-strike work actions have been common during periods of wage negotiations. During the 1990s, APVAR and SNA played a role in effecting pilot slow down practices known as work-to-rule. A work-to-rule practice is when pilots slow down operations by meticulous adherence to a narrow interpretation of work rules. By contrast to a strike, they do not withdraw their labor.

The sample period of the empirical model of this paper is 1997–2001, which covers both the years of the intensification in pilot hiring during the mid-1990s and also the boom in the demand for domestic air travel of the late 1990s.[8]

## 3. Modeling airline competition with endogenous wages

### 3.1. The structural model

Consider an oligopolistic airline market with carriers grouped into business models. Assume two groups: the Full-Service Carriers (FSC) and the Low-Fare Carriers (LFC). Assuming product differentiation, the market-level demand of airline $j$ is therefore equal to

$$q_j = q(\mathbf{p}, \mathbf{Y}_j), \tag{1}$$

where $\mathbf{p}$ and $\mathbf{Y}_j$ are a vector of prices of all airlines in the market and a vector of demand shifters of $j$. With respect to costs, assume the following variable cost function:

$$\mathrm{VC}_j = \mathrm{VC}\left(\mathbf{W}_j, \mathbf{X}_j, K_j, E_j, q_j\right), \tag{2}$$

where $\mathrm{VC}_j$ is the variable cost of carrier $j$ and VC is the respective cost function. $\mathbf{W}_j$ is a vector of prices of the variable inputs, one of which is the unit price of labor, $\mathrm{wl}_j$. $\mathbf{X}_j$ is a vector of cost controls. $K_j$ is the capital stock, which is assumed to be fixed in the short run. $E_j$ is the efficiency level of firm $j$. Finally, $q_j$ is the output of $j$. Consistently with Good et al. (1991) and Neven et al. (2006), we assume that $\mathrm{wl}_j$ is endogenous because of union power and wage bargaining. We have

$$\mathrm{wl}_j = \mathrm{wl}\left(\mathbf{Z}_j, q_j\right), \tag{3}$$

where $\mathrm{wl}_j$ is jointly determined with output $q_j$, and $\mathbf{Z}_j$ is a vector of exogenous wage shifters. We then have $\mathrm{VC}_j = \mathrm{VC}(\mathrm{wl}(\mathbf{Z}_j, q_j), \mathbf{W}_j^-, \mathbf{X}_j, K_j, E_j, q_j)$, where $\mathbf{W}_j^-$ is the vector of airline input prices excluding the unit price of labor variable, $\mathrm{wl}_j$.[9]

Assume a price-setting game with the outcome of a Bertrand–Nash equilibrium. With this setting, it is possible to reach the following first-order condition for the profit maximization of carrier $j$:

$$p_j^* = \frac{\partial \mathrm{VC}\left\{\mathrm{wl}\left[\mathbf{Z}_j, q_j(\mathbf{p}, \mathbf{Y}_j)\right], \mathbf{W}_j^-, \mathbf{X}_j, K_j, E_j, q_j(\mathbf{p}, \mathbf{Y}_j)\right\}}{\partial q_j} + \frac{q_j(\mathbf{p}, \mathbf{Y}_j)}{-\partial q_j(\mathbf{p}, \mathbf{Y}_j)/\partial p_j}. \tag{4}$$

Our structural model of airline competition employs the solution of the simultaneous equations model formed by expressions (1), (2), (3) and (4). Of these expressions, the first three must be precisely specified and estimated, whereas (4) is directly derived from the entire system. We then turn to the issue of econometric specification of (1), (2) and (3) and to the discussion of the empirical implementation of the structural model.

### 3.2. The empirical implementation

We perform the empirical implementation of the structural model discussed above using a specific database for the Ponte Aérea (air shuttle) – the densest air route in Brazil. In the period under analysis, this domestic market was serviced by five carriers. The Ponte Aérea market consists of the downtown airports of Rio de Janeiro (Santos Dumont, IATA code SDU) and São Paulo (Congonhas, IATA code CGH); the trip between the airports is a nonstop

8 During the 2000s major cost restructuring was undertaken in the industry because of the entry of ultralow cost carrier Gol Airlines. Because of these major changes and to examine the effects of wage increases in a period of higher labor costs, we restrict our analysis to the 1997–2001 period.

9 That is $\mathbf{W}_j = W(\mathrm{wl}_j, \mathrm{W}_j^-)$ For a description of the other input prices used in the empirical specification $\mathrm{W}_j^-$ of see Sub Section 3.2.

flight of 225 miles that takes approximately 45 min flight time. The route connects the two largest financial and service center in the country. In the sample period considered in this study, the SDU-CGH airport-pair was the only relevant market for travel between Rio de Janeiro and São Paulo.[10]

During the sample period (1997–2001), the following five airlines were active in the Ponte Aérea market: Varig (RG), Rio Sul (SL), Tam (TA), Vasp (VP) and Transbrasil (TB). During this period, RG was Brazil's flagship carrier and for decades had been the dominant airline on most domestic and international markets. It had the largest market share at the airport and city endpoints, in addition to having the largest market share on the route. With outstanding in-flight service, a dedicated departure lounge with amenities at CGH and a broader portfolio of destinations, RG was known for its appeal to the mainstream shuttle passenger, i.e., those frequent-fliers willing to accumulate mileage points. SL was a subsidiary of RG and, since 1998, was operating under a codeshare agreement with RG. TA was a former regional carrier and a rising star that ultimately conquered the domestic leader in the mid-2000s. VP and TB were low-fare (but not low-cost) alternatives with a reputation for low quality. They were financially fragile during the sample period; these airlines went bankrupt and exited the market in 2001 and 2004, respectively.

### 3.2.1. *Econometric specification*

Consider a panel data of carriers in a market over time. With respect to the airline-specific market-level demand function (1), we assume a linear specification, with quantity demanded decreasing in a carrier's own price and increasing in the price of rival carriers. We then have demand for carrier $j$ at time $t$ equal to

$$q_{jt} = \alpha_{jt} - \beta_j p_{jt} + \sum_{k \neq j}^{N} \gamma_{jk} p_{kt} + \delta_j Y_t + \varepsilon^d_{jt}, \quad (5)$$

where $q_{jt}$ and $p_{jt}$ are the quantities and price of firm $j$ at time $t$, $p_{kt}$ ($k \neq j$) is the price of $j$'s rival firm $k$ at $t$, and $Y_t$ is the income at $t$. $\alpha_{jt}$, $\beta_j$, $\delta_j$ and the $\gamma_{jk}$ terms are demand parameters, with $\beta_j > 0$ and $\gamma_{jk} > 0$, $\forall k \neq j$. $\alpha_{jt}$ is a firm-specific, time-varying term that will be controlled with fixed effects and trend terms, as other intercepts in our model. $\varepsilon^d_{jt}$ is an error term associated with the unobserved demand factors at $t$.

One important issue regarding (5) is the modeling of the cross-price sensitivities of demand ($\gamma_{jk}$) because we have a potential problem with the large number of parameters to estimate. This dimensionality problem is common in the context of firm-specific (or product-specific) demand functions, particularly with many firms/products in the market or with high multicollinearity in prices. To address this problem, we follow Slade (1986) and impose a certain structure on the demand specification that enables us to arrive at an average rival price as a regressor in (5), instead of estimating $N-1$ cross-price sensitivities terms – the $\gamma_{jk}$ terms. Our method of addressing the dimensionality problem thus becomes clearer. First, we consider a more general version of (5) by allowing for a time-varying term $\gamma_{jkt} = \gamma_j \times \psi_{kt}$, where $\psi_{kt} = q_{kt}/q_{-jt}$, $q_{-jt} = \sum_{h \neq j} q_{ht}$. $\psi_{kt}$ are time-varying weights, as $\sum_{h \neq j} \psi_{ht} = 1$. By using $\gamma_{jkt}$ instead of $\gamma_{jk}$ we reach the expression $q_{jt} = \alpha_{jt} - \beta_j p_{jt} + \gamma_j p_{-jt} + \delta_j Y_t + \varepsilon^d_{jt}$, where $p_{-jt} = \sum_{h \neq j} \psi_{ht} p_{ht}$ is the average price of carrier $j$'s rivals at $t$. Finally, consider index $g$ that accounts for the two different business models – groups LFC and FSC. We assume that firms have group-specific price and income sensitivities of demand and therefore impose $\beta_j = \beta_g$, $\gamma_j = \gamma_g$ and $\delta_j = \delta_g$, with $g = \{\text{FSC}, \text{LFC}\}$. We then finally have[11]

$$q_{jt} = \alpha_{jt} - \beta_g p_{jt} + \gamma_g p_{-jt} + \delta_g Y_t + \varepsilon^d_{jt}. \quad (6)$$

Regarding the income shifters (variable $Y_t$), we use the aggregate gross domestic product of Brazil ($\text{gdp}_t$) for the FSC specification and the average economically active population of endpoint cities ($\text{eap}_t$) for the LFC specification.[12] The motivation for these alternative specifications is that the demand of the FSCs is typically more business travelers-related than the demand of the LFCs, which are more associated with leisure travelers.

With respect to the costs side, we assume that capital stock is a quasi-fixed factor and therefore use the approach of Caves et al. (1981). We then employ a variable cost function with controls for airline capital stock on the right-hand side as Caves et al. (1984) and Oum and Yu (1998). We have $\text{VC}_j$ now defined with time $t$ index, i.e., $\text{VC}_{jt} = \text{VC}(\mathbf{W}_{jt}, \mathbf{X}_{jt}, K_{jt}, E_{jt}, q_{jt}, \varepsilon^c_{jt})$, where $\text{VC}_{jt}$ is the variable cost of carrier $j$ at time $t$.[13] Assume, as in Caves et al. (1984), that $\mathbf{W}_{jt} = W(\text{wl}_{jt}, \text{wf}_{jt}, \text{wm}_{jt})$, where $\text{wl}_{jt}$, $\text{wf}_{jt}$ and $\text{wm}_{jt}$ are the unit cost of labor, fuel and materials *per* trip of $j$ at $t$, respectively. The catchall category is $\text{wm}_{jt}$, that includes costs on maintenance and overhaul, station and in-flight service, and airport and air traffic control fees. The vector of other cost shifters is set equal to $\mathbf{X}_{jt} = X(\text{avstl}_{jt}, \text{nd}_{jt}, \text{lf}_{jt})$, where $\text{avstl}_{jt}\text{avstl}_{jt}$ is the average stage length, $\text{nd}_{jt}$ is the number of total destinations – the number of points served – and $\text{lf}_{jt}$ is the average load factor of carrier $j$ at time $t$. Both $\text{avstl}_{jt}$ and $\text{nd}_{jt}$ are network measures, i.e., not route specific but related to the overall system of carrier $j$. $K_{jt}$ and $E_{jt}$ are the capital stock and efficiency levels of $j$ at $t$, which we discuss in detail in the next section. We then follow Swan and Adler (2006) and use a Cobb–Douglas specification:

$$\begin{aligned} \ln\text{VC}_{jt} = {} & \rho_{0jt} + \rho_{1g} \ln\text{wl}_{jt} + \rho_{2g} \ln\text{wf}_{jt} + \rho_{3g} \ln\text{wm}_{jt} \\ & + \tau_{1g} \ln\text{avstl}_{jt} + \tau_{2g} \ln\text{nd}_{jt} + \tau_{3g} \ln\text{lf}_{jt} + \phi_g \ln q_{jt} \\ & + \nu_{1g} \ln K_{jt} + \nu_{2g} \ln E_{jt} + \varepsilon^c_{jt}, \end{aligned} \quad (7)$$

where $\rho_{0jt}$ is a carrier-specific cost parameter and $\rho_{1g}$, $\rho_{2g}$, $\rho_{3g}$, $\tau_{1g}$, $\tau_{2g}$, $\tau_{3g}$, $\nu_{1g}$, $\nu_{2g}$ and $\phi_g$ are group-specific cost parameters, with $\phi_g$ being the output elasticity of variable costs, which is used to measure the degree of economies of density of group $g$. $\varepsilon^c_{jt}$ is the error term. Because a cost function must be homogeneous of degree one in input prices, we impose linear homogeneity by setting $\sum_i \rho_{ig} = 1$. Contrary to Caves et al. (1984) and Oum and Yu (1998), we did not employ a translog specification. We experimented with the translog – see the discussion of estimation issues below – but multicollinearity was a major estimation problem in our sample. Smith (2012) also had the translog specification as the preferred model but, based on a likelihood ratio, the Cobb–Douglas

[10] Source: Brazilian Institute of Geography and Statistics (IBGE), 2000. See Salgado et al. (2010) and Oliveira (2003) for further details of the Brazilian airline industry and the air shuttle market.

[11] With this framework, we arrive at the own-price elasticities of the demand for $j$ implied by (6) is $-(\partial q_{jt}/\partial p_{jt})(p_{jt}/q_{jt}) = \beta g p_{jt}/q_{jt}$. The cross-price elasticity of demand for carrier $j$ with respect to the carrier $k$ is $(\partial q_{jt}/\partial p_{kt})(p_{kt}/q_{jt}) = \gamma_g(q_{kt}/q_{jt})(p_{kt}/q_{-jt})$.

[12] Source: ipeadata.gov.br and sidra.ibge.gov.br. Both variables are transformed into indices with the sample average set equal to 100. We use the consumer price index to deflate $\text{gdp}_t$. The average economically active population of endpoint cities at month $t$ is $\text{eap}_t$.

[13] Because it is a short-run analysis of costs, we consider capital as a fixed input and thus include capital stock $K_{jt}$ in the specification of $\text{VC}_{jt}$. We exclude expenses associated with fixed input, such as capital costs, depreciation, insurance and leasing costs. We also do not take into account sales and administration expenses.

restriction could not be rejected. In our case, the translog specification could not be properly estimated – and the Cobb–Douglas restriction could not be tested – because we did not have enough instrumental variables to cope with endogeneity of the first-order and second-order interactions with $q_j$ and $\text{wl}_j$. Even when considering these variables as exogenous, many individual hypothesis tests of interacted and non-interacted variables were affected by multicollinearity. Independently of these estimation problems, we believe that constant elasticity of substitution might be a reasonable local approximation to costs, particularly in the short term (our case).

Finally, we have the endoneous wages model $\text{wl}_{jt} = \text{wl}(\mathbf{Z}_{jt}, q_{jt})$. We set the vector of exogenous wage shifters equal to $\mathbf{Z}_j = Z(\text{asize}_{jt}, \text{trend}_j, \text{season}_{gt})$, where $\text{asize}_{jt}$ is the route-specific average aircraft size of carrier $j$ at time $t$.[14] We also include carrier-specific trends ($\text{trend}_j$) and market seasonality controls – the monthly dummy variables $\text{season}_{gt}$- to account for the evolution of compensations over time and across the year, respectively. We then arrive at:

$$\ln \text{wl}_{jt} = \tau_{0jt} + \tau_{1g} \ln \text{asize}_{jt} + \tau_{2g} \ln q_{jt} + \text{trend}_j + \text{season}_{gt} + \varepsilon^{w}_{jt}, \quad (8)$$

where $\tau_{0j}$, $\tau_1$ and $\tau_1$ are parameters and $\varepsilon^{w}_{jt}$ is the error term.

The solution of the system of simultaneous equations formed by Equations (6)–(8) results in final vectors of equilibrium $p^*_{jt}$, $q^*_{jt}$, $VC^*_{jt}$ and $wl^*_{jt}$. Reaching the solution analytically is straightforward (but rather tedious) and results in a non-linear expression with several interactions between the basic parameters of the model that is also difficult to interpret. In our application, we employ a quasi-Newtonian method for reaching the solution.[15]

### 3.2.2. Data

We apply the above econometric framework to the SDU-CGH route. The data used to estimate the parameters were provided by the National Agency for Civil Aviation (ANAC). Because of its importance, regulators have historically collected specific statistics for this route as a part of the regulatory framework. The available passenger and price data are airline/airport-pair specific for all passenger carried in the respective month, whereas the cost data are airline/aircraft-specific.[16] The database structure consists of panel data of the existing five carriers with monthly observations during the period January 1997–December 2001. As discussed above, the airlines are Varig (RG), Rio Sul (SL), TAM (TA), Vasp (VP) and Transbrasil (TB). The market is defined as one-way directional, so that the data set includes information about both SDU-CGH and CGH-SDU. The total sample size was 572 observations.[17] Table 1 presents descriptive statistics of the most important variables used in the econometric study. Data are disaggregated by airline business model; the FSC group is formed by RG, SL and TA, and the LFC group is formed by VP and TB.

[14] Source: regulator's HOTRAN reports, a database that is similar to the commonly used OAG database.We also experimented with $f_{jt}$, the number of flight frequencies of carrier $j$ at time $t$. This variable was not statistically significant.

[15] This iterative method is a widely used algorithm for solving nonlinear systems of equations. We experimented with different starting values for a sensitivity analysis and the results were robust to these changes.

[16] Most aircraft assigned to the CGH-SDU shuttle were fully dedicated to this airport-pair. These aircraft typically consisted of Boeing B737-300s, but other aircraft models were also utilized in the sample period, such as the B737-500, Airbus A319, Fokker F50 and F100 and Embraer E145.

[17] RG, SL, TA and VP had 120 observations each (5 years × 12 month × 2 directions). TB ceased operations from June 2000 to January 2001 and again after June 2001; therefore, TB had only 92 observations.

**Table 1**
Descriptive statistics.

| Variable | Description | FSC | | LFC | |
|---|---|---|---|---|---|
| | | Mean | S.E. | Mean | S.E. |
| $p_{jt}$ | Average one-way fare (USD) | 82.2 | 15.9 | 63.7 | 15.6 |
| $\text{AVC}_{jt}$ | Variable cost per passenger (USD) | 24.1 | 9.6 | 34.7 | 22.2 |
| $q_{jt}$ | Daily quantity (passengers) | 938.2 | 285.9 | 608.6 | 185.4 |
| $\text{wl}_{jt}$ | Labor cost per trip (USD) | 349.2 | 46.4 | 341.5 | 105.1 |
| $\text{wf}_{jt}$ | Fuel cost per trip (USD) | 556.6 | 271.8 | 538.2 | 229.0 |
| $\text{wm}_{jt}$ | Material cost per trip (USD) | 1023.4 | 275.3 | 1079.3 | 232.4 |
| $\text{avstl}_{jt}$ | Systemwide average stage length (in km) | 978.0 | 295.0 | 900.6 | 386.4 |
| $\text{nd}_{jt}$ | Systemwide number of destinations | 60.7 | 7.2 | 41.2 | 4.1 |
| $\text{lf}_{jt}$ | Load factor | 0.52 | 0.08 | 0.47 | 0.17 |
| $\text{asize}_{jt}$ | Average aircraft size (seats) | 120.6 | 4.8 | 132.6 | 0.2 |

Source: National Agency for Civil Aviation. BRL is the local currency. Monetary figures were deflated by the Consumer Price Index (CPI). Here we display figures in US dollars (USD), but the data set has all monetary figures in local Brazilian currency (BRL). The exchange rate used is 2 BRL = 1 USD. Note that $\text{AVC}_{jt} = \text{VC}_{jt}/q_{jt}$ is the average cost *per* passenger.

### 3.2.3. Estimation issues

Given the panel data structure of our sample (airlines-months), we employ a fixed effects estimator for the demand, costs and wages equations. We therefore assume a composite-error structure for $\varepsilon^{d}_{jt}$, $\varepsilon^{c}_{jt}$ and $\varepsilon^{w}_{jt}$ of Equations (6)–(8), respectively. We control for the effects of airline-codesharing periods, monthly seasonality and airline-specific trends. For estimation purposes, and to allow for asymmetry, we separate the data sample into two subsets according to the business model (FSC and LFC).

One important feature of our proposed framework is that prices ($p_j$), quantities ($q_j$), variable costs ($\text{VC}_j$) and wages ($\text{wl}_j$) are jointly determined and therefore must be treated as endogenous in our econometric modeling. Therefore, we must employ a proper simultaneous equations framework and instrument these variables aiming at consistent estimation. The estimation method employed is the equation-by-equation two-step feasible efficient generalized method of moments (GMM) estimator. The bandwidth used in the estimation with a Newey–West kernel was set equal to seven – a six-months autocorrelation structure. Additionally, as wages are typically negotiated yearly, the order of autocorrelation was set to twelve for the wages equations.

Other papers have also employed instrumental variables to avoid the endogeneity bias in the estimation of cost equations. A classic example is Good et al. (1991). The contribution of the identification strategy described above is that, differently from previous literature, we test for the relevance and validity of the proposed instrumental variables. As instrumental variables we employ demand and cost shifters from the data set: gross domestic product (levels, squared and lagged), activity level (endpoint cities, levels, squared and in logs), unit cost of fuel (airline, group and industry, in levels and logs), number of destinations (levels and logs), lagged quantities and flight frequencies during peak hours. We perform an under identification test to check for the relevance and orthogonality of excluded instruments. All tests suggested that our proposed instruments were relevant and valid for the econometric identification of our estimated equations using the available data sample.[18]

With respect to the variable cost Equation (7), we follow Caves et al. (1981) by modeling a partial static equilibrium in costs. In this setup, we specify a variable cost function conditional on the level of capital stock, as described above. We assume, however, that

[18] We used the Kleibergen-Paap and the Hansen $J$ tests. See results of the tests below each results table in Sub Section 3.3.

**Table 2**
Estimation results – demand[a].

| Dependent variable: $q_j$ | FSC | | LFC | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $p_j$ (endogenous) | −7.2751*** [1.863] | −7.3882*** [1.947] | −12.1681*** [1.477] | −11.3157*** [1.547] |
| $p_{-j}$ (endogenous) | 5.5574*** [1.980] | 5.5672*** [2.041] | 8.6649*** [1.299] | 8.4797*** [1.309] |
| gdp | 5.9862** [2.824] | 7.2544** [2.879] | −4.4115 [5.150] | |
| eap | 8.7620 [8.042] | | 43.3229*** [13.938] | 39.9462*** [13.034] |
| Number of observations | 360 | 360 | 212 | 212 |
| RMSE | 141.6 | 135.6 | 123.7 | 121.6 |
| Kleibergen-Paap statistic | 18.274* | 19.713** | 23.209** | 22.968** |
| Hansen *J* statistic | 11.466 | 10.616 | 13.140 | 10.530 |

[a] Heteroskedasticity and autocorrelation-robust standard errors in brackets. Superscripts *, **, and *** denote, respectively, significance at the 10%, 5%, and 1% levels. Estimated effects of airline-codesharing periods, seasonality and airline-specific trends not reported.

the capital stock of carrier $j$ ($K_{jt}$) is unobserved by the econometrician. Following Oum and Yu (1998), we allow for asymmetric efficiency among carriers because certain firms are more efficient than others. The authors suggest that not including an efficiency indicator causes inconsistent estimation of the cost function. Contrary to Oum and Yu (1998), however, we assume that efficiency ($E_{jt}$) is unobserved. As described above, we partially correct for potential biased estimation using instrumental variables to control for the endogeneity of wages. Additionally, we use a fixed effects structure to address the problem further. We employ the following composite-error structure for (7):

$$\xi_{jt}^{c} = \nu_{1g} \ln K_{jt} + \nu_{2g} \ln E_{jt} + \varepsilon_{jt}^{c} = \upsilon_{js}^{c} + \varepsilon_{jt}^{c},$$

where $\xi_{jt}^{c}$ is a composite-error that accounts for unobserved variation in $K_{jt}$ and $E_{jt}$. The variable cost error term remains $\varepsilon_{jt}^{c}$. The novelty here is the introduction of $\upsilon_{js}^{c}$ for firm $j$ in quarter $s$, a term that substitutes $\nu_{1g} \ln K_{jt} + \nu_{2g} \ln E_{jt}$ in (7). We propose controlling for this unobserved component of $\xi_{jt}^{c}$ with interacted carrier $j$ – quarter $s$ fixed effects. With this procedure, we introduce the innovation suggested by Bai (2009) and use interactive effects aiming at controlling for heterogeneous responses over cross sections within our panel data framework. In other words, because we are notable to observe fluctuations in either the stock of capital $K_{jt}$ – both the size of the fleet in operation and its market value – or in the efficiency levels $E_{jt}$, we could not explicitly control for such changes on the right-hand side of the (short-run) variable costs equation as the previous literature did.[19] We therefore control for airline-specific quarterly variations using carrier-quarter fixed effects ($\upsilon_{js}^{c}$) to avoid the potential omitted variables bias. Intuitively, we exploit the fact that airlines do not typically revise their fleet planning assessments monthly to avoid excessive (or insufficient) capacity growth. On the contrary, fleet planning assessment revisions commonly take longer periods to be implemented, because aircraft manufacturers commonly have order backlogs and the delivery of new aircraft may therefore take a reasonably long time.[20] In addition, leased aircraft acquisitions or returns may also take time to implement, depending on general economic conditions and contractual terms. We therefore reasonably believe that $K_{jt}$ does not typically have monthly variations.[21] Identical arguments are valid for production and cost decisions that may impact efficiency. Note that we impose a more strict fixed effects control by using interactive fixed effects than simply by adding carrier and time controls as in a conventional two-way fixed effects model.

### 3.3. Estimation results

In the following section, we present the estimation results of the empirical counterparts of Equations (6)–(8). Table 2 presents the results of demand for the FSCs (Columns 1 and 2) and the LFCs (Columns 3 and 4). The alternative specifications differ with respect to income shifters by either including both $\text{gdp}_t$ and $\text{eap}_t$ or just one of these shifters. Whereas $\text{gdp}_t$ is clearly statistically significant only for the FSCs, $\text{eap}_t$ is statistically significant only for the LFCs. This is consistent with prior expectations, because FSCs carry a great number of business travelers whose demand for air travel is strongly influenced by the growth of the economy as a whole. Conversely, the demand of the LFCs is more influenced by employment levels because they carry a significant number of leisure travelers, whose demand is influenced by personal income. Our preferred estimates are therefore those of Columns (2) and (4).

Inspecting the coefficients of own price ($p_j$) and average price of rivals ($p_{-j}$) of the two groups of carriers in Table 2, we observe that their signs and magnitudes are consistent with economic theory. Additionally, our estimation results are consistent with the market positioning of the different business models. The FSCs have estimated price coefficients that are 35% lower than the LFCs in absolute value when comparing Columns (2) and (4) – 7.3882 against 11.3157 for $p_j$, and 5.5672 against 8.4797 for $p_{-j}$. The implied mean own-price and rival-price elasticities were $\{-2.3474, 1.7036\}$ for the FSCs and $\{-3.7817, 3.2063\}$ for the LFCs. As a comparison, and consistent with our results, Armantier and Richard (2008) find that FSCs have estimated own price elasticities that were from 25% to 41% lower than low cost carriers in the US airline industry. The higher perceived quality of FSCs indicated by the relative magnitude of our estimated elasticities is also consistent with the study of Fu et al. (2011), who find that the low cost carrier Southwest Airlines in the US market is perceived to provide services differentiated from its FSC rivals.

Table 3 presents the estimation results for the variable costs. The coefficients are all interpretable as cost elasticities. The elasticities of cost with respect to the factor prices ($\text{wl}_j$, $\text{wf}_j$ and $\text{wm}_j$) may be regarded as shares in variable cost. They have the expected signs and most of them are statistically significant. For both groups of carriers, fuel input accounts for approximately one-third of variable costs – with estimated $\text{wf}_j$ coefficients of 0.3485 for FSCs and 0.3085 for LFCs. This is notably higher than the estimates of the classic literature, which were between 15% and 20% – such as Caves et al. (1984) and Oum and Yu (1998), but is more in accordance with the recent estimates for the US airline industry of Johnston and

[19] For example, Oum and Yu (1998) use an index of residual total factor productivity as a regressor.

[20] Typically, airlines adjust their fleet plannings with respect to new fleet acquisitions and aircraft lease renewals one year in advance. See "Brazil's TAM cuts fleet plan as demand slows" (Reuters, August 30, 2011 available at www.reuters.com).

[21] Our econometric procedure allows for up to four capital stock adjustments *per* year for each carrier, i.e., quarterly tactical fleet planning revisions.

**Table 3**
Estimation results: variable costs[a].

| Dependent variable: ln $VC_j$ | FSC | LFC |
|---|---|---|
| $\text{lnwl}_j$ (endogenous) | 0.4615** [0.218] | 0.1580** [0.788] |
| $\text{lnwf}_j$ | 0.3485*** [0.086] | 0.3085*** [0.040] |
| $\text{lnwm}_j$ | 0.1900 [0.167] | 0.5335*** [0.058] |
| $\text{lnlf}_j$ (endogenous) | −0.0564 [0.199] | −0.1364* [0.076] |
| $\text{lnavstl}_j$ | 0.0779 [0.147] | −0.1051* [0.057] |
| ln $nd_j$ | 0.1125 [0.076] | 0.7327*** [0.1578] |
| ln $q_j$ (endogenous) | 0.7071*** [0.193] | 0.6652*** [0.089] |
| Number of observations | 360 | 212 |
| RMSE | 0.1657 | 0.0799 |
| Kleibergen-Paap statistic | 18.658** | 22.757*** |
| Hansen $J$ statistic | 8.790 | 15.480 |

[a] Heteroskedasticity and autocorrelation-robust standard errors in brackets. Superscripts *, **, and *** denote, respectively, significance at the 10%, 5%, and 1% levels. Estimated effects of airline-codesharing periods, seasonality and airline-specific trends not reported.

Ozment (2013), but using a total cost function. Table 3 also shows the difference of wage share estimates between FSCs and LFCs, which are 46.2% and 15.9%, respectively. These estimates are a consequence of the higher wage concessions from the flight operations staff of the LFCs. Because these carriers were financially fragile during the period, they were capable of exerting more pressure to obtain wage concessions from employees. Additionally, they lost qualified workforce to rivals and to foreign airlines.

Consistent with previous econometric studies of airline cost estimation, we also have a positive relation between costs and output. In fact, a 1% increase in output leads to a 0.71% and 0.67% increase in costs of the FSCs and LFCs, respectively. The estimated returns to density implied by the above results are 1.1978 for FSCs and 1.2742 for LFCs.[22] With respect to the cost controllers $\text{lf}_j$, $\text{avst}_j$ and $\text{nd}_j$; these were statistically significant only for the LFCs. Nonetheless, we prefer to keep these variables in the FSC specification to avoid omitted-variable bias in the estimation of other elasticities. Estimated returns to scale are 1.0334 for the FSCs and 0.6064 for the LFCs.[23] We cannot reject the hypothesis of constant return to scale for the FSCs, but we have enough evidence of decreasing returns to scale for the LFCs. The results suggest, therefore, that the existing LFCs tended to be confined to operating in niche markets, most likely restricted to only the densest routes of the country.

Table 4 presents the results of the wage equation regressions. Only LFCs have estimated coefficients of $q_j$ that are statistically significant. For each 1% increase in output of LFCs, wage costs increase by 0.38%. This may represent the fact that LFCs are more capacity constrained and must hire more personnel to quickly expand operations. Facing rapid growth, FSCs are likely to be more capable of performing crew reassignments between different routes of their networks without incurring significant additional costs. Additionally, LFC pilots typically have fewer benefits and

**Table 4**
Estimation results: wages[a].

| Dependent variable: $\text{lnwl}_j$ | FSC | LFC |
|---|---|---|
| ln $q_j$ (endogenous) | 0.0171 [0.054] | 0.3808*** [0.067] |
| $\text{lnasize}_j$ | 2.1835*** [0.768] | 0.7735*** [0.091] |
| Number of observations | 354 | 206 |
| RMSE | 0.1952 | 0.2559 |
| Kleibergen-Paap statistic | 20.961*** | 16.543** |
| Hansen $J$ statistic | 0.129 | 0.193 |

[a] Heteroskedasticity and autocorrelation-robust standard errors in brackets. Superscripts *, **, and *** denote, respectively, significance at the 10%, 5%, and 1% levels. Estimated effects of airline-codesharing periods, seasonality and airline-specific trends not reported.

therefore must provide incentives to hire new pilots. The estimated coefficient of aircraft size ($\text{asize}_j$) is statistically significant for both groups of carriers, which is consistent with the fact that pilots of larger aircraft earn relatively more. The effect is notably higher for FSCs than for LFCs – with estimated elasticities of 2.1835 and 0.7735, respectively.

## 4. Simulations of wage premium increases

In this section, we simulate the impact of wage premium increases in the competition between FSCs and LFCs. For the simulations, we assume that an increase in union bargaining power generates wage shifts that cause variations in fundamental market variables. In particular, we investigate the impact on marginal costs ($c_j$), prices ($p_j$), output ($q_j$) and price-cost markup ($\text{mpc}_j$). [24] To extract the elasticities of the variables under analysis, we first compute the Bertrand–Nash equilibrium, impose a small shift in wages and then compute the results from a new Bertrand–Nash equilibrium.[25] By analyzing the sign and magnitude of the elasticities, we ultimately study the relative vulnerability of FSCs and LFCs with respect to wage premium hikes and sources of competitive advantage stemming from costs in the industry.

Table 5 presents the computed elasticities of marginal costs ($c_j$), prices ($p_j$) and output ($q_j$). We extract elasticities under the following three scenarios of returns to density (RTD): 1. "Base Case" – elasticities are calculated assuming the RTD parameters estimated from data; 2. Weaker than "Base Case" – elasticities are calculated assuming estimated RTD multiplied by 0.90; and 3. "Stronger than Base Case" – elasticities are calculated assuming estimated RTD multiplied by 1.10. With these experiments, we are able to analyze the impact of RTD exhaustion on results. As an illustration, consider marginal costs. In Table 5, the wage-elasticity of this variable is 0.4660 for the FSCs and 0.1557 for the LFCs. Therefore, a 1% increase in wages implies an increase in marginal costs of 0.47% of FSCs and 0.16% of LFCs. Column (1)–(2) computes the difference between the elasticities. Note that the marginal costs of FSCs are considerably more vulnerable to wage premiums than the marginal costs for LFCs. These results are robust to changes in RTD. Table 5 also shows that rising wage premiums produces marginal cost and price increases for both the FSCs and LFCs, as expected. In both cases, the wage-elasticity of FSCs is higher than that of LFCs in all scenarios. With respect to prices, increasing returns to density tend to reduce the difference between the wage-

[22] When using the variable cost function (7) we must adjust the traditional formula to compute returns to density. Caves et al. (1981) suggest using $RTD = (1 - \varepsilon_k)/\varepsilon_y$, where RTD are returns to density, $\varepsilon_k$ is the elasticity of variable cost with respect to capital and $\varepsilon_y$ is the elasticity of variable cost with respect to output. As we do not observe $K_j$, we are unable to estimate $\varepsilon_k$. We therefore employ the estimate of $\varepsilon_k$ from Caves et al. (1984) for their full period sample mean, equal to 0.153 (p. 481). Standard errors of our return to density estimates: 0.1706 (FSC) and 0.3273 (LFC).

[23] Again, we use the adjustment procedure of Caves et al. (1981), this time using $RTS = (1 - \varepsilon_k)/(\varepsilon_y + \varepsilon_p)$, where $\varepsilon_p$ is the elasticity of variable costs with respect to the number of network points – in our case, $\text{nd}_j$. The estimate of $\varepsilon k$ was once again the same of Caves et al. (1984). Standard errors of estimated returns to scale: 0.2613 (FSC) and 0.0880 (LFC).

[24] Price-cost markup is defined as $\text{mpc}_j = (p_j - c_j)/p_j$.

[25] We introduce wage hikes in the system of Equations (6)–(8) by increasing each carrier's intercept $\rho_{0jt}$, in the wage Equation (8). We calculate elasticities by imposing a shift of 0.01% in wages. The wage hike is transmitted to costs according to the entire system of equations. The cost-price pass-through rates are dictated according to the Bertrand–Nash model. For simulation purposes, we calculated the intercepts of the estimated equations by setting all the exogenous variables at the midpoint of the sample.

**Table 5**
Wage premium increase simulations – elasticities.

| Variable | Scenario | | (1) FSC | (2) LFC | (1) – (2) |
|---|---|---|---|---|---|
| $mc_j$ | Returns to Density | Base case (BC) | 0.4660 | 0.1557 | 0.3103 |
| | | Weaker than BC | 0.4665 | 0.1554 | 0.3111 |
| | | Stronger than BC | 0.4656 | 0.1559 | 0.3097 |
| $p_j$ | Returns to Density | Base case (BC) | 0.0512 | 0.0499 | 0.0013 |
| | | Weaker than BC | 0.0562 | 0.0543 | 0.0018 |
| | | Stronger than BC | 0.0470 | 0.0462 | 0.0009 |
| $q_j$ | Returns to Density | Base case (BC) | −0.0227 | 0.0053 | −0.0280 |
| | | Weaker than BC | −0.0253 | 0.0060 | −0.0313 |
| | | Stronger than BC | −0.0205 | 0.0048 | −0.0253 |

Source: authors' own calculations.

elasticities. However, we observe the opposite effect with quantities; in fact, we have positive elasticities for the LFCs, whereas the wage-elasticity of FSCs is negative. The results show, therefore, that the FSCs lose quantities following the wage hike – a fact that may be explained by higher marginal cost vulnerability and consequent higher cost-price pass-through. Although LFCs follow the price increases of FSCs, their demand is not reduced because of a market stealing effect. In this case, it is notable that stronger returns to density tend to soothe the difference between the wage-elasticities of the two groups of carriers.

Table 6 presents the results of the simulations focusing on the price-cost markup ($mpc_j$), which measures the extent of firms' market power. For the Base Case, the average markup of FSCs and LFCs are 0.84 and 0, 69, respectively. In addition, we also created scenarios of price-elasticity of demand and economic activity in the scenarios regarding returns to density described above. We again create scenarios by setting parameters to lower and higher values than Base Case and compute the associated wage-elasticities.[26]

Considering the results for the Base Case (first row of Table 6), we observe that the markup $mpc_j$ of the FSC carriers is considerably more affected by shocks in wage premiums than that of the LFCs. For the base case, we observe that the computed wage-elasticity of markup for the FSCs is −0.0762 whereas it is −0.0451 for the LFCs. This result is caused by the marginal costs and output of FSCs being more vulnerable to wage premium shocks than those of LFCs. The results, therefore, identify a source of competitive advantage for LFCs when the market faces greater bargaining power from labor unions. Our results are consistent with the experiences of the US airline industry. In the US market, Hirsch (2007) shows that the post-deregulation period reveals positive wage premiums for pilots stemming from considerable union bargaining power at the major carriers, but not at small regional carriers. In fact, this author shows that regional carriers wages approximate opportunity costs. Although we have not modeled regional carriers, we believe that our results may show that smaller carriers are less vulnerable to wage shocks than major carriers insofar as differential wage concessions are concerned. FSCs therefore have an incentive to engage in cost reductions and labor force restructuring to face competition stemming from LFCs. These results are consistent with the intense movements of network and cost restructuring by Brazilian FSCs and by major legacy carriers in the rest of the world during the first decade of this century.

[26] For the price-elasticity of demand scenarios, we modify the following components of the elasticity expres-sions: $\beta_g$ and $\gamma_g$. We multiply $\beta_g$ and $\gamma_g$ of both groups of firms by 0.90 ("Lower than Base Case") and 1.10 ("Higher than Base Case"). For the economic activity scenarios, we multiply the gross domestic product ($gdp_t$) by 0.90 ("Lower than Base Case") and 1.10 ("Higher than Base Case") and plug the new values into the demand of FSCs. For the LFCs, we estimate an auxiliary regression of $eap_t$ against $gdp_t$ in order to estimate the effect of an increase in the economic activity ($gdp_t$) in the demand function of those carriers. The sample Pearson correlation of $gdp_t$ and $eap_t$ is 0.6816.

**Table 6**
Wage premium increase simulations – markup elasticities.

| Variable | Scenario | | (1) FSC | (2) LFC | (1) – (2) |
|---|---|---|---|---|---|
| $mpc_j$ | Returns to Density | Base case (BC) | −0.0762 | −0.0451 | −0.0311 |
| | | Lower than BC | −0.0840 | −0.0488 | −0.0352 |
| | | Higher than BC | −0.0697 | −0.0418 | −0.0278 |
| $mpc_j$ | Price elasticity of demand | Lower than BC | −0.0662 | −0.0406 | −0.0256 |
| | | Higher than BC | −0.0861 | −0.0495 | −0.0366 |
| $mpc_j$ | Economic activity | Lower than BC | −0.0864 | −0.0498 | −0.0366 |
| | | Higher than BC | −0.0679 | −0.0410 | −0.0269 |

Source: authors' own calculations.

We check the sensitivity of the results showing the higher $mpc_j$ vulnerability of FSCs by inspecting changes in returns to density, price-elasticities of demand and economic activity. Table 6 permits the observation that exhausting returns to density enhances the difference between the wage-elasticities of groups. Indeed, in the "Lower than BC" scenario, the difference went from −0.0311 ("Base Case") to −0.0352. It is notable that the elasticities of both groups decreased in this case, indicating that lower returns to density increase the vulnerability of all firms to wage hikes. Additionally, higher price-elasticity of demand and lower economic activity tend to produce the same effect, indicating that results are amplified by weaker (more exhausted) economies of density, lower perceived product differentiation and passenger loyalty, and lower economic growth.

In Fig. 2, we simulate a wider range of RTD values and assess the impact on carrier vulnerability of wage premium increases. Again, we allow for asymmetric returns to density and investigate the competitive effects of such asymmetry. Values of RTD are simulated within the interval of 0.5 and 1.5 (with incremental steps of 0.01) for each of the respective carriers to identify patterns of the wage-elasticity of markups – defined here as $\eta_{LFC}$ and $\eta_{FSC}$.[27]

The surfaces of Fig. 2 show the elasticities of markups for LFCs (darker) and FSCs (lighter). In both cases, the surfaces are increasing in own values of RTD. This indicates that returns to density make firms less vulnerable to wage hikes, as discussed before. The elasticities rise from −0.15 (own RTD equal to 0.5) to values close to zero (own RTD equal to 1.5), with slightly lower values for the FSCs. In the case of increases in the RTD of rivals, however, we have the opposite effect and show a decrease in the elasticities. This latter effect is more clearly pronounced for LFCs.

Fig. 3 shows a contour plot with the difference in wage-elasticities of markups, $\eta_{LFC} - \eta_{FSC}$. These differences are plotted against the returns to density of the two groups of carriers ($RTD_{FSC}$ and $RTD_{LFC}$). The greater the difference, the higher the relative vulnerability to shocks in wages and therefore the greater the competitive advantage. It is possible to observe that lighter regions of the graph depict the competitive advantage of LFCs, whereas darker regions portray the competitive advantage of FSCs. Thus, the lighter the graph, the lower the wage-elasticity of the FSCs' markup in relation to LFCs ($\eta_{LFC} > \eta_{FSC}$). The darker the graph, the lower the elasticity of LFCs in relation to FSCs ($\eta_{LFC} < \eta_{FSC}$). The contour plot of Fig. 3 shows the elasticity–equality curve ($\eta_{LFC} = \eta_{FSC}$), contrasted with the line of equality returns to density ($RTD_{FSC} = RTD_{LFC}$). In case of symmetry with equal returns to density among carriers, LFCs have a competitive advantage in a broad range of values, ending only for returns higher than 1.20 (depicted by *A*). At this point, we have the intersection of the curves, with $\eta_{LFC} = \eta_{FSC}$ and $RTD_{FSC} = RTD_{LFC}$. A market with symmetric positions would have FSCs with lower vulnerability to

[27] Assume $\eta_j = (\partial mpc_j/\partial wl_j)(wl_j/mpc_j)$. Here, we compute average wage-elasticities for both groups of carriers ($\eta_{FSC}$ and $\eta_{LFC}$). We employ quantity shares as weights.

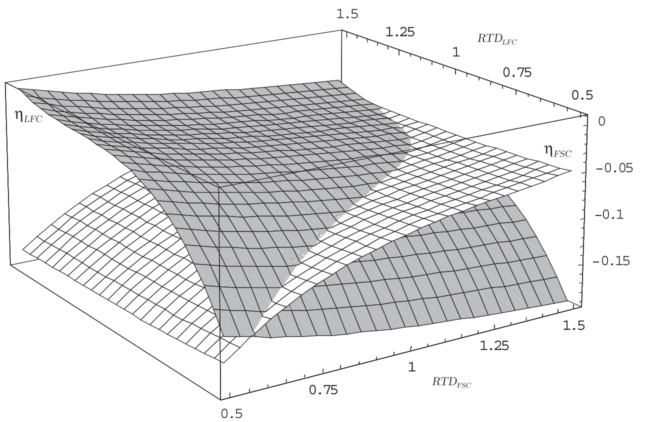


**Fig. 2.** Wage-elasticities of markups for FSCs and LFCs.

wage shocks only at situation *A* and to the right and above. Asymmetric cases would confer LFCs with higher and unexploited returns to density compared to FSCs. Therefore, the main conclusion is that the most likely case to be observed is the situation in which FSCs have larger losses associated with wage hikes, i.e., $\eta_{LFC} < \eta_{FSC}$.

In summary, our main results may be classified in the following way. Consider the following three possibilities: 1. *technological innovation*, 2. *market growth* and 3. *market stealing*.

- *Technological innovation*: A managerial or technological innovation that expands the possibilities of exploitation of returns to density – an increase in RTD – tends to make carriers less vulnerable to shocks in wage premiums. In the case of exclusive innovation – in which rivals are notable to innovate – the associated competitive advantage is higher, as discussed above, and with an impact of an increase in the own RTD;
- *market growth*: The growth of the market, enabling a better use of current seating capacity of carriers through higher load factors, in addition to aircraft size and flight frequency increases, leads to a further exhaustion of economies of density. Thus, the RTD of firms tends to drop. However, more demand is created – primarily for FSCs. This demand effect more than compensates the cost effect on carriers' markups. This situation decreases the vulnerability to wage shocks of both carriers. Larger airlines – who are closer to the rapid exhaustion of economies of density– tend to benefit more;
- *market stealing*: As opposed to market growth, market stealing does not create new demand. To the extent that a group of carriers steals demand from the other group, its economies of density become more exhausted – i.e., the increase in output causes a drop in RTD – and therefore the group becomes more vulnerable to shocks in wages. For example, rapid growth in an LFC resulting from price wars that increase its traffic density may cause a reduction in its RTD. Consequently, its wage-elasticity of markup will fall, increasing its vulnerability to shocks unless new demand is created or price elasticity of demand increases.

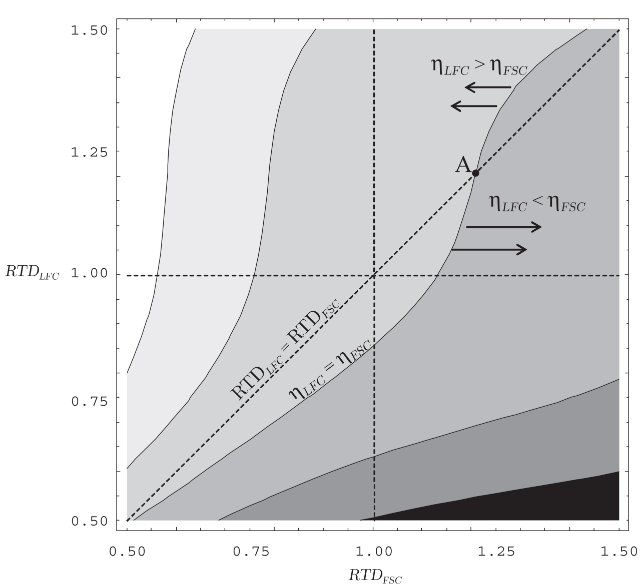


**Fig. 3.** Differences in wage-elasticities of markups between FSCs and LFCs.

Thus, we observe that wage premium increases likely confer LFCs with a competitive advantage stemming from costs. This result may be regarded as positive from the perspective of market competition because FSCs are major carriers with route and airport dominance and because an increase in the bargaining power of labor unions is a major cause of concern with respect to economic welfare in the industry. Conversely, as long as LFCs expand by conquering market share and increasing their traffic density, their returns to density become exhausted and therefore the competitive advantage tends to dissipate unless the price elasticity of demand continues to be stimulated by new demand creation or if economic activity continues to grow.

## 5. Conclusions

In this paper, we analyzed the effects of labor cost hikes caused by stronger union power and qualified labor scarcity in the airline industry and inspected the impact on marginal costs, prices, demand and markups. We used a differentiated product model and a costs-side model allowing for asymmetric economies of density to assess the effects of wage premiums on airline competition. Utilizing this framework, we modeled the competitive interaction of major Full-Service Carriers (FSC) and Low Fare Carriers (LFC) on the densest route in Brazil.

This work contributes to the literature in two ways. First, it applies the existing differentiated oligopoly models to investigate the effect of wage premiums. Second, it evaluates the impact of wage premium hikes on FSCs and LFCs by taking into account the effect of asymmetric economies of traffic density.

This paper's findings suggest that on dense markets FSCs are likely to have their markups more affected by shocks in wage premiums than LFCs. Theses results are mainly driven by the higher estimated economies of density and the lower sensitivity to labor costs of LFCs in our case study. For thinner markets, results may be substantially different and therefore further research is needed. We consider alternative scenarios to check the robustness of our results and find that more exhausted economies of density and higher price-elasticity of demand tend to reinforce and amplify the competitive advantage of LFCs. Technological or managerial innovations and market growth reduce the vulnerability to wage premium shocks, but product homogeneity and market stealing tend to increase such vulnerability. Consistently with the previous literature, financial fragility is likely to force employees to make wage concessions to help reduce vulnerability to cost pressure. Our final conclusions suggest that FSCs have an incentive to engage in cost reductions and labor force restructuring. The competitive advantage of LFCs may be eroded as they expand in the industry or conquer market share, unless they continue to create new demand.

It is important to emphasize that our paper has relevant drawbacks to be mentioned. First, the choice of a sample period of early deregulation (1997–2001) clearly allowed us to avoid more recent (and complex) phenomena such as the emergence of evident airport infrastructure bottlenecks and the effects of the growing of middle class in Brazil. On the other hand, however, our sample is less representative of current market situation, especially after years of quick growth in air travel demand and major changes in market structure and participating firms. Second, the restricted sample period forces our analysis of the asymmetries between airline business models to be restricted to the comparison of FSCs with LFCs, but not with LCCs (genuinely Low Cost Carriers, which are now more commonly found in the industry worldwide). Also, the both LFCs under analysis in this paper actually went bankrupt and left the market, which may be an indication that the most successful, Southwest Airlines-like, LCC business model was not still put in practice in the market. And third, in contrast to the existing incumbents in the industry nowadays, in the analyzed period carriers were still not predominantly focused on strategic cost restructuring. One possible extension that could address all these issues would be to replicate the approach for a more recent period, with application to Brazil or other country, in future research.

## References


Armantier, O., Richard, O., 2008. Domestic airline alliances and consumer welfare. Rand J. Econ. 39 (3), 875–904.

Bai, J., 2009. Panel data models with interactive fixed effects. Econometrica 77 (4), 1229–1279.

Boguslaski, C., Ito, H., Lee, D., 2004. Entry patterns in the Southwest airlines route system. Rev. Ind. Organ. 25, 317–350.

Brueckner, J., Dyer, N., Spiller, P.T., 1992. Fare determination in airline hub-and-spoke networks. Rand J. Econ. 23 (3), 309–333.

Caves, D.W., Christensen, L.M., Swanson, J.A., 1981. Productivity growth, scale economics and capacity utilization in U.S. railroads, 1955-1974. Am. Econ. Rev. 71, 994–1002.

Caves, D., Christensen, L., Tretheway, M., 1984. Economies of density versus economies of scale: why trunk and local service airline costs differ. Rand J. Econ. 15 (4), 471–489.

Fu, X., Dresner, M., Oum, T.H., 2011. Effects of transport service differentiation in the US domestic airline market. Transp. Res. Part 47 (3), 297–305.

Good, D.H., Nadiri, M.I., Sickles, R.C., 1991. The Structure of Production, Technical Change and Efficiency in a Multiproduct Industry: An Application to U.S. Airlines. NBER Working Paper, 3939.

Hirsch, B., 2007. Wage determination in the US airline industry: union power under product market constraints. In: Lee, Darin (Ed.), Advances in Airline Economics, vol. 2, pp. 27–59.

Hirsch, B., Macpherson, D., 2000. Earnings, rents, and competition in the airline labor market. J. Labor Econ. 18 (1), 125–155.

Hofer, C., Windle, R.J., Dresner, M.E., 2008. Price premiums and low cost carrier competition. Transp. Res. E 44, 864–882.

Johnston, A., Ozment, J., 2013. Economies of scale in the US airline industry. Transp. Res. Part 51, 95–108.

Neven, D.J., Röller, L.H., 1996. Rentsharing in the European airline industry. Eur. Econ. Rev. 40 (3–5), 933–940.

Neven, D.J., Röller, L.H., Zhang, Z., 2006. Endogenous costs and price-cost margins: an application to the European airline industry. J. Ind. Econ. 54 (3), 351–368.

Oliveira, A.V.M., 2003. Simulating revenue management in an airline market with demand segmentation and strategic interaction. J. Revenue Pricing Manag. 1 (4), 301–318.

Oum, T.H., Yu, C., 1998. Cost competitiveness of major airlines: an international comparison. Transp. Res. A 32 (6), 407–422.

Salgado, L.H., Vassallo, M.D., Oliveira, A.V.M., 2010. Regulation, policy-making, competitiveness and price formation: considerations for air transport in Brazil. J. Transp. Lit. 4 (1), 7–48.

Silveira, J.M., Oliveira, A.V.M., 2008. An empirical game-theoretical approach to model a price war in the Brazilian airline industry. J. Transp. Lit. 2 (1), 7–20.

Slade, M.E., 1986. Conjectures, firm characteristics, and market structure – an empirical assessment. Int. J. Indus. Organ. 4, 347–369.

Smith, A.S.J., 2012. The application of stochastic frontier panel models in economic regulation: experience from the European rail sector. Transp. Res. E Logist. Transp. Rev. 48 (2), 503–515.

Swan, W.M., Adler, N., 2006. Aircraft trip cost parameters: a function of stage length and seat capacity. Transp. Res. E 42, 105–115.

Turolla, F.A., Lima, M.F., Ohira, T.H., 2011. Public policy to enhance the competitiveness of the Brazilian regional airline industry. J. Transp. Lit. 5 (4), 188–231.