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The impact of carbon emission fees on passenger demand and air fares: A game theoretic approach

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ABSTRACT

The implementation of an environmental market-based measure on U.S. aviation industry is studied. Under this policy, each airline pays a carbon fee for the carbon dioxide emissions it generates. The impact on ticket prices and corresponding market shares is investigated via the joint estimation of an air travel demand model and an airlines' behavior model. In the demand model, aggregate air traffic data is used to determine the marginal effects of flight attributes that are specific to itinerary, airline and airport on market share. The airline's behavior model incorporates the carbon fee in the airline marginal cost. After the implementation of the carbon policy, the increased cost forces airlines to adjust ticket prices in order to maximize profits. The results obtained by the proposed model indicate a moderate price increase which strongly depends on the per tonne carbon price. Air travel demand falls from 2.4% to 21% depending on the carbon price level.

1. Introduction

Along with safety and security, environmental protection is in the centre of the aviation industry aims. Recent statistics indicate that, if no mitigation action is taken, carbon dioxide (CO_2) emissions will continue to rise given the increasing trend of air traffic. Technological and operational efficiency improvements and the use of alternative fuels are widely believed to be promising long-term approaches to meet aviation's climate goals. Market-based instruments complement these measures and provide a cost-effective option to reduce emissions in the short term (Lee et al., 2013).

Market-based measures (MBM) put a price on aircraft emissions, with most existing instruments focusing on CO_2 emissions. Existing market-based measures include voluntary carbon offsetting, environmental charges at the airports and cap-and-trade policies. The largest cap-and-trade aviation policy is the European Emissions Trading Scheme (EU ETS), introduced in 2012 (European Union, 2008). Trade disputes at international level and opposition from many non-EU countries led to the amendment of the European regulation in 2014; EU ETS covers flights only within the European Economic Area until 2016 (European Union, 2014). This situation added a pressure on International Civil Aviation Organization (ICAO) to agree on a global market-based measure for aviation as part of a broader package of measures including new technology, more efficient operations and better use of infrastructure (ICAO, 2013).

A number of studies examined the impact of EU ETS on airlines network reconfiguration (Derigs and Illing, 2013; Hsu and Lin, 2005), tourism (Blanc and Winchester, 2012; Peeters and Dubois, 2010; Pentelow and Scott, 2011; Tol, 2007), airline operational characteristics (Brueckner and Zhang, 2010) and airline competition (Barbot et al., 2014). Other studies investigated the impact on ticket prices and demand change. Albers et al. (2009) examined the effect of EU ETS on airfares and passenger demand at individual route level. Assuming a carbon price of €20/tn, they found that additional costs may range from €1.5 to €26.8 per passenger. Under two scenarios of cost pass-through rate (35% and 100%) and using existing values of price elasticity, their results showed moderate price increase which could not initiate major route configuration. EU ETS has also been studied by Scheelhaase and Grimme (2007) and Scheelhaase et al. (2010) in terms of its economic impact on EU and non-EU airlines. The results indicated that EU airlines' environmental costs are higher, due to a wider coverage of operations within the EU region, losing a significant competitive

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advantage as compared to the non-EU airlines. Anger (2010) used a dynamic simulation model to investigate the impact of EU ETS on macroeconomic activity and CO_2 emissions. Under three allowance price scenarios and 100% cost pass-through rate, the author concluded that EU-ETS results in an increase of annual CO_2 emissions at low allowance prices but a fall of 0.30% at an allowance price of €40 in 2020 compared with no action scenarios. Lu (2009) examined the impact of environmental charges on air passenger demand using six intra-European short-haul routes in two city pairs. The potential demand reduction is higher for the low-cost carrier Easyjet compared to that of full service carriers, because of lower fares. Miyoshi (2014) investigated the changes in passenger demand and consumer welfare after the implementation of EU ETS on Annex I and non-Annex I airlines. The author constructed a logit model to estimate the impact of travel costs increase on market shares of a specific route. The results demonstrated that the EU ETS could be an effective instrument except for very low carbon prices. Malina et al. (2012) estimated the economic impact of EU ETS on US airlines. They used price elasticity values derived in other studies and assumed that fuel efficiency, fuel price and carbon price are annually increased. The authors found that under full cost pass-through, the CO_2 emissions from US airlines may increase by 32% between 2011 and 2020 in comparison to 35% for the reference scenario. Hofer et al. (2010) examined the effects of an air travel carbon emissions tax on travel-related carbon emissions in the US and concluded that the emissions tax increases ticket prices under an own-price elasticity value of −1.15. They also considered the air-automobile substitution effect, since some air travelers may divert to automobiles, assuming a cross-elasticity of 0.041. They showed that emission taxes may cause significant air-to-automobile diversion effects.

This paper considers the hypothetical implementation of a market-based environmental policy on U.S. flights, where airlines pay an extra fee, referred to as "carbon fee", based on their CO_2 emissions. The impact of this policy is assessed using an empirical demand and supply model following Berry (1994). The interaction of passengers' behavior and airline decision is taken into account by the joint estimation of demand and supply parameters. The demand side is studied by discrete choice models, using market-level data over a large number of Origin and Destination cities without a need for consumer-level data. On the supply side, airlines offer several differentiated flight connections and set their ticket prices under Bertrand competition. The carbon fee increases airlines costs. If airlines maintain ticket prices levels, profits will fall. However, it is expected that a portion of the carbon cost will be passed onto the passengers, resulting in increased prices and lower demand. Estimation of price and demand adjustments caused by the introduction of the carbon fee is the main objective of this paper. More specifically, aggregate air traffic data is used while air travel demand is modeled by discrete choice models of consumer behavior. Most known aggregate demand models employ linear regression of passenger traffic and thus do not consider travelers' behavioral decisions (Bhadra and Kee, 2008; Kopsch, 2012; Mumbower et al., 2014; Sivrikaya and Tunç, 2013; Wei and Hansen, 2006). This research uses a nested logit model for air travel demand where the utility of the passenger for a specific connection is formed by a number of observed flight characteristics. The model accounts for the fact that not all flight characteristics are observed by the researcher and, thus, a single term capturing unobserved (to the analyst) characteristics is also included. On the supply side, a linear model is assumed for the marginal cost of each airline connection. The marginal cost is determined up to a vector of several cost shifters. After the implementation of the environmental policy, carbon costs are added to the airlines' marginal cost. Contrary to existing studies, the impact of the market-based policy on air travel demand is not based on given values of price elasticity of demand. Posterior policy prices are determined from the computation of the new equilibrium in demand and supply. Then price elasticity and market shares are obtained from the demand model. Airline cost pass-through behavior is an important determinant of the impact of the market-based measures. Most of existing studies assume a fixed percentage of cost pass-through. In this study, cost pass-through rate is determined by the demand and supply model and consequently depends on a number of factors, including market structure and level of competition.

The implementation of a market-based environmental policy is considered on the US airline network and a large number of domestic flight connections. Our results identify the key factors that influence the environmental policy such as itinerary distance and number of stops. Longer flights and indirect flights experience the greatest impact on ticket prices increase and demand fall due to the larger amount of CO_2 emissions.

2. Modeling framework

In this section the proposed modeling framework is described following Berry (1994). Nested logit models are employed for the representation of passenger behavior allowing for unobserved flight characteristics in the utility of travelers. On the supply side, airlines act as profit maximizers that settle over prices given by a Bertrand Nash equilibrium. Carbon fee is introduced as a shifter of marginal cost.

2.1. Passenger perspective

In a given network, there is a set of Origin-Destination (O-D) cities and a set of airlines which link them by direct or indirect itineraries. An O-D city pair is regarded as a "market". Our basic unit of observation is the unique combination of the itinerary and the ticketing carrier, i.e. "Origin-Connecting-Destination airports and ticketing airline" and is referred to as "airline connection". A passenger who wants to travel within a market m may choose to travel by air, travel by another transport mode or not travel. If the passenger decides to travel by air, he/she chooses among several airline connections j ($j = 1, 2, \ldots, n$). If the passenger chooses not to travel by air, we say that the non-air alternative is picked ($j = 0$). The share of passengers choosing the non-air alternative is denoted by MS_0. This choice formulation suggests the use of a nested logit model, where the choice set of a passenger is partitioned into two nests: (i) air and (ii) non-air. The air nest includes all airline connections. The non-air nest includes travelling by other transportation modes (such as car, train, etc) or not travelling at all. The utility U_{ij} that a passenger i obtains when choosing alternative j is given by:

$$U_{ij} = x_j\beta - \alpha p_j + \xi_j + \nu_i(\lambda) + \lambda\varepsilon_{ij} \tag{1}$$

where p_j is the ticket price of connection j and x_j is a vector encompassing all observable characteristics; it includes features associated with the itinerary, the airline and the airport. A detailed description is given in Section 3.2. The scalar term ξ_j includes all characteristics that are unobserved by the analyst (but known to the passenger) such as in-advance ticket purchase, in-flight meal service quality, ticket restrictions etc, factors that give an important explanation for the deviation in ticket prices offered within given routes. The term $\nu_i(\lambda) + \lambda\cdot\varepsilon_{ij}$ is a stochastic term that captures the preferences of passenger i on airline connection j. $\nu_i(\lambda)$ is a random variable that is constant across airline connections (within the air nest) and differentiates them from the non-air alternative. ε_{ij} is an independent and identically distributed random variable across passengers and airline connections following the extreme value distribution. λ is a measure of the degree of independence within market alternatives (high λ means greater independence and less correlation).

The nested-logit can be decomposed in two logit models so that the aggregate market share MS_j of connection j in market m can be expressed as the product of two logit probabilities: the product of the share of air transport MS_g (upper level involving nest choice) and the conditional share of a specific connection j $MS_{j/g}$, given that air transport is chosen (lower level).

$$MS_j = MS_{j/g} \cdot MS_g = \frac{e^{(x_j\beta - \alpha p_j + \xi_j)/\lambda}}{D_g} \cdot \frac{D_g^\lambda}{\sum_g D_g^\lambda} \tag{2}$$

where $D_g = \sum_{j \in J} e^{\frac{x_j\beta - \alpha p_j + \xi_j}{\lambda}}$. Berry (1994) proposes an estimation procedure which transforms Eq. (2) so that parameters enter linearly. The resulting demand equation has the following form:

$$\ln MS_j - \ln MS_0 \;=\; x_j\beta - \alpha p_j + (1-\lambda) \cdot \ln MS_{j/g} + \xi_j \tag{3}$$

Eq. (3) has a linear regression form. The dependent variable is formed by the log difference of market shares minus the non-air option. The explanatory variables include the vector of observed characteristics x_j, the price of flight p_j and the conditional market share. The unobserved characteristic ξ_j acts as the disturbance term. β, α and λ are the unknown parameters that need to be estimated. Notice that standard Ordinary Least Squares (OLS) procedures are not directly applicable because the disturbance and some of the explanatory variables are generally correlated. Indeed, ticket- or flight-level unobserved attributes that are captured by the term ξ_j are correlated with price p_j and with the within-group (conditional) market share $MS_{j/g}$. Thus Eq. (3) suffers from endogeneity since two explanatory variables are correlated with the disturbance. This issue is addressed by the use of Instrumental Variables methods as explained in Section 2.3.

2.2. Airline behavior

Airlines set ticket prices to maximize profits. Following (Berry and Jia, 2010; Gayle and Brown, 2014; Lee, 2013) we assume that ticket prices are determined independently across markets. Each airline f serves a subset J_f of the J total within-market connections. The airline profit is formed by the difference in revenues and cost as follows:

$$\begin{aligned} \pi_f &= \sum_{j \in J_f} \left(\underbrace{p_j \cdot M \cdot MS_j}_{Revenues} - \underbrace{mc_j \cdot M \cdot MS_j}_{Costs} \right) \\ \pi_f &= \sum_{j \in J_f} \left(p_j - mc_j\right) \cdot M \cdot MS_j \end{aligned} \tag{4}$$

where mc_j is the marginal operating cost of connection j and M is the market size, i.e. the potential number of travelers between the O-D cities. The marginal cost is not directly provided by the available aggregate data and thus needs to be estimated. We assume it is given by a linear function of observed cost shifters (w_j) (further detailed in Section 3.2) and an unobserved cost shock (ω_j):

$$\mathrm{mc}_j \;=\; w_j \cdot \gamma \;+\; \omega_j \tag{5}$$

Airlines set their ticket prices under Bertrand competition and product differentiation, taking into account the prices set by competitors. The first order condition yields:

$$\max_p \pi_f \rightarrow MS_j + \sum_{k \in J_f} (p_k - mc_k) \cdot \frac{\partial MS_k}{\partial p_j} = 0, \quad for\ \forall j \in J_f \tag{6}$$

A Bertrand Nash equilibrium is a vector of prices that satisfies Eq. (6). Note that the ticket prices of competitors are contained in the market share marginal effects. Eq. (6) forms a linear system of equations for the prices of all flights of a given airline in a given market. Substituting the marginal cost from Eq. (5), the system of Eq. (6) takes the form:

$$p_f = \left(\underbrace{-D^{-1}_{MS_f, p_f} \cdot MS_f}_{mark-up} \right) + \underbrace{w_f \cdot \gamma + \omega_f}_{marginal\ cost} \tag{7}$$

where vectors p_f, MS_f, w_f, ω_f represent ticket prices, market shares, observed and unobserved cost characteristics of airline f within a market. Note that price is split in two terms: the airline markup and the marginal cost. D_{MS_f, p_f} represents the $J_f \times J_f$ matrix of partial derivatives of MS_j with respect to price.

The above approach relies on a static Nash equilibrium in prices and thus rests upon some simplifying assumptions. First, airline decisions are not confined to price setting but include other important variables such as flight frequencies and hub choice locations. Moreover, under real conditions ticket prices are set using revenue management techniques, which seek to allocate seats across different passenger categories in order to maximize expected revenue (Donovan, 2005). The inclusion of yield management techniques in the above model requires consideration of dynamic aspects that are beyond the scope of this paper and is left for future work.

2.3. Joint estimation of demand and supply

The system of demand and supply Eqs. (3) and (7) forms the basis for the estimation of parameters α, β, σ and γ. Two issues should be pointed out: First, the two equations need to be estimated jointly because demand parameters enter both equations. Moreover due to the presence of the derivative matrix D_{MS_f, p_f} parameters α and σ enter the cost function nonlinearly, while β enters both equations linearly. Secondly, endogeneity of prices and market shares is a critical econometric issue. In the pricing equation, market share and market share derivatives are endogenous. The unobserved cost characteristics affect ticket prices through Eq. (7) and, thus, are correlated with connections' market share and market share derivatives. Thus these variables are endogenous since they are correlated with ω in Eq. (7). The above endogeneity issues may lead to biased parameter estimates if OLS is used. In contrast, Instrumental Variables methods can cope with endogeneity under suitable conditions. Instrumental Variables methods require the existence of proper instruments, i.e. auxiliary variables that are correlated with the explanatory variables but are uncorrelated with the disturbance for both the supply and demand sides. Moreover handling the inherent presence of nonlinearities, requires the use of generalized moments in connection with instruments. In this work the two-step Generalized Method of Moments estimator is used (Hansen, 1982; Hall, 2005). For the two main equations we employ instruments that satisfy the following moment conditions:

$$E\begin{bmatrix} \xi_j Z_1 \\ \omega_j Z_2 \end{bmatrix} = 0 \tag{8}$$

Z_1 and Z_2 are the vectors of instruments for the demand and cost equation respectively. These instruments include the explanatory variables of our system and additional auxiliary variables. A detailed discussion is presented in Section 3.3. We first solve Eqs. (3) and (7) for ξ_j and ω_j respectively. Then the Generalized Method of Moments estimators for demand and supply can be defined by minimizing the quadratic product of the moment conditions (from Eq. (8)) with a symmetric and positive definite weight matrix.

2.4. CO_2 emissions model

To assess the impact of a market-based environmental policy on air transportation we need to calculate the fuel burn and associated emissions for all flights. The fuel mostly used by civil aircraft is kerosene (Lee et al., 2010). Combustion of kerosene produces various emissions including carbon dioxide, water vapor, nitrogen oxides, carbon monoxide, hydrocarbons and soot (Brasseur et al., 1998; IPCC, 2007; Lee et al., 2009, 2010). Of these, carbon dioxide and water vapor are greenhouse gases and directly affect the climate. Carbon monoxide, hydrocarbons and nitrogen oxides are called air pollutants and affect air quality around airports as they are mainly produced when aircraft engines are operating at their lowest combustion efficiency, while the latter also has indirect effect on climate change. Greenhouse gas emissions differ from air pollutants in the fact that the impact of air pollutants is limited to a regional level, while the impact of greenhouse gases expand to global scale due to their long lifetime. In particular, the atmospheric lifetime of CO_2 is on the order of one hundred years, which means that its impact on climate change is long lasting (Schafer et al., 2009). Although water vapor and nitrogen oxides have significant effect on climate, their precise impact is yet uncertain and it depends on several factors, including the prevailing ambient atmospheric conditions and the amount and types of particles formed in the engine exhaust (Schafer et al., 2009). In addition, water vapor emissions at low altitudes have no climate effect. For these reasons, CO_2 which has been widely documented as the dominant greenhouse gas emitted by aircraft (IPCC, 2007; Gudmundsson and Anger, 2012; Scheelhaase et al., 2010) is included in the majority of existing policy measures and will be the focus of this work. The fuel burn and CO_2 emissions computations are conducted flight-by-flight for every itinerary in the traffic sample.

Aircraft fuel burn and CO_2 emissions are influenced by various factors including aircraft and engine type, flight distance, flight mode and time consumed in each mode. Once the aircraft fuel consumption is calculated, CO_2 emissions can be obtained by multiplying fuel burn by the emission factor of 3.157 kg CO_2/kg fuel (ICAO, 2014). Landing and Take-off (LTO) phase, which includes operations below 3000 feet, is separated from operations above 3000 feet which form part of the Climb-Cruise-Descent phase (called cruise thereafter). The LTO fuel burn rate is obtained from the ICAO Engine Exhaust Emissions databank (ICAO, 2016) and the fuel burn rate during the cruise phase is taken from the EMEP CORINAIR database (EEA, 2013).

Air traffic data are obtained from the Airline Origin and Destination Survey (DB1B) available from the U.S. Department of Transportation, as explained in Section 3.1. Table 1 presents the procedure employed in this work and the variables required to compute aircraft fuel consumption and CO_2 emissions for each individual flight. The data required by the CO_2 model include aircraft and engine type, flight distance and LTO times in the study airports. The original flight data is supplemented by two other databases: the T-100 Domestic Segment for U.S. Carriers (T100), which provides us with the aircraft type and the Airline On-Time Performance database (OTP), from which taxiing times at the study airports are derived. Flight distance is given in the original flight data from DB1B, while engine types are assigned to the given aircraft type according to EEA (2013). The exact equations used in this paper for the calculation of fuel burn and CO_2 emissions are given in Pagoni and Psaraki (2014).

3. Data description and estimation

3.1. Description of the dataset

Estimation of the supply and demand model and simulation of the market-based environmental policy, require a rich dataset with information on airline connections, flight passengers, ticket prices and other explanatory attributes that affect passenger demand and airline marginal cost. In addition, aircraft data is needed for the computation of CO_2 emissions. In this study, data available by the U.S. Department of Transportation published in the website of the Bureau of Transportation Statistics (BTS, 2015) are used. In particular, the Airline Origin and Destination Survey (DB1B) reports a 10% sample of domestic airline tickets sold by U.S. airlines. DB1B is used to create the flight itineraries and to generate airline connections' market shares, ticket prices and other itinerary attributes which are presented in Table 2. We merge the above dataset with three additional databases: the T-100 Domestic Segment for U.S. Carriers, the Airline On-Time Performance database and the U.S. Census Bureau. The T-100 Domestic Segment for U.S. Carriers (hereinafter referred to as T100) contains monthly domestic non-stop segment data reported by U.S. air carriers. The variables constructed by T100 include frequency, seat capacity and representative aircraft types as presented in Table 2. Airline On-Time Performance (hereinafter referred to as OTP) contains on-time arrival data for non-stop domestic flights in the U.S. and it is used to create delay and other time-related variables. The U.S. Census Bureau provides us with population data used to construct the market size, as the geometric mean of the populations of origin and destination cities. The construction of the final sample follows a well established procedure (Berry and Jia, 2010; Chi and Koo, 2009; Lee, 2013; Hsaio and Hansen, 2011) consisting of the following steps. We filter DB1B raw data to keep round-trip itineraries with at most two segments per direction and tickets with single itinerary ticketing carrier and credible fares, while we omit open-jaw trips and tickets with very low and very high air fares (we keep tickets in the fare range of $25 and $3000 for a round-trip). In the second step, we process T100 and OTP data to be compatible with the DB1B database. Since T100

Table 1
Procedure for fuel burn and CO_2 emissions calculation.

Flight phase	Fuel burn rate database	Inputs	Source
LTO	ICAO Engine Exhaust Emissions Databank	Aircraft type	T100
		Engine type	EEA (2013)
		Time spent in LTO modes	OTP
Cruise	EMEP CORINAIR	Aircraft type	T100
		Flight distance	DB1B

Notes: See Section 3.1 for the derivation of T100, OTP and DB1B databases.

Table 2
Summary statistics of demand and cost variables.

Variable	Mean	Standard deviation	Minimum	Maximum	Source
Airline-route specific					
Fare [in $100]	4.52	1.41	1.21	16.50	DBIB
Number of stops	1.52	0.79	0	2	DBIB
Round trip distance [in 1000 sm]	3.07	1.56	0.17	10.90	DBIB
Minimum frequency (flights/quarter)	277.78	193.44	13	1992	T100
% of morning departures	0.25	0.17	0	1	OTP
% of late-afternoon departures	0.25	0.16	0	1	OTP
Aircraft size	0.25	0.43	0	1	T100
Per passenger fuel [tn fuel/pax]	0.16	0.06	0.02	0.55	Own-computation
Airport-specific					
Slot control	0.12	0.35	0	3	DB1B
Delays	0.14	0.05	0	0.38	OTP
Alternative airport	0.59	0.49	0	1	Own-computation
Airport-Airline relationship					
Hub	0.63	0.48	0	1	DB1B
Market specific					
Market distance [in 1000 sm]	1.54	0.78	0.09	5.45	DB1B
Airline dummies					
Jet Blue Airways	0.02	0.15	0	1	DB1B
Delta Air Lines	0.20	0.40	0	1	DB1B
American Airlines	0.15	0.35	0	1	DB1B
US Airways	0.13	0.34	0	1	DB1B
Southwest Airlines	0.31	0.46	0	1	DB1B
Other legacy airlines	0.11	0.31	0	1	DB1B
Other low-cost airlines	0.08	0.27	0	1	DB1B
Observations: *19,362*					

and OTP are reported in a monthly basis, and DB1B data are quarterly, we need to aggregate T100 and OTP in a quarterly basis. Once this is done, edited T100 and OTP tables include frequency, seating, aircraft and time-related quarterly data. In the third step, we merge the three databases by flight segment and airline. DB1B and T100 segments are merged by operating airline while DB1B and OTP by reporting airline. Next, we supplement the DB1B-T100-OTP merged data with population data. Finally we filter airline connections so as to include regular scheduled flights (a minimum of 12 flights per quarter and more than fifty passengers in the quarter are chosen as thresholds) and medium to large Metropolitan Statistical Areas (with population greater than 800,000 people). The data are rearranged to create the final data table which includes unique combinations of a round-trip between Origin (O_j), Connecting (C_j), Destination (D_j) airports by Ticketing airline (A_j) during a specific Quarter (Q_j), i.e. "O_j-C_j-D_j/A_j,Q_j" supplemented with demand and cost variables.

Similar to existing econometric studies, we used one-quarter data for model estimates. In particular, our sample period is the first quarter of 2012 (Q1/2012). The database resulting from the above pre-processing has 19,362 airline connections, 3,285 markets (O-D city pairs), 66 origin and destination cities, 99 airports and 10 ticketing airlines. The sample markets consist of 20.4% monopolies, 16.5% duopolies and 63.1% oligopolies. On average, there are 5.9 airlines within each market.

3.2. Demand and cost variables

The most common explanatory variables in air transport demand models are ticket prices, flight frequency, market distance, delays, layovers and dummies for airlines and slot controlled airports. Trip distance, aircraft types, transferring via hub airports and airline dummies have been used in previous studies as cost shifters.

On the demand side an increase in the price of a good will typically lead to a reduction in the quantity demanded, ceteris paribus. This is also applicable to air travel where ticket price is an important determinant of demand. In our work, the *ticket price* of each round-trip is taken as the passenger-weighted average ticket price. The variable "*number of stops*" is included in order to explain the intuition that, all else being equal, a direct air travel connection is more preferable than a connection with intermediate stops. The variable *"number of stops"* is calculated as the number of layovers within the itinerary and takes three values 0, 1 or 2. For a round-trip with both direct outbound and return flight, the variable is equal to zero. *Frequency* is an important factor in passenger's travel decision-making process, since passenger's utility increases with higher flight frequency. Since flight frequency is a segment characteristic, an itinerary may include several frequency variables. The itinerary frequency could be calculated as the average number of segment departures. However, the minimum frequency is more critical than the average and thus the frequency variable is here calculated as the minimum of segment frequencies. Following Hsiao and Hansen (2011), the frequency is introduced in logarithmic form. *Distance* is assumed to affect air travel demand in two ways (Bhadra, 2003): it affects passenger's propensity to travel and passenger's choice on transport mode. In the demand function, distance is defined as the O-D market distance. In the cost function, round-trip distance is used to capture various cost components such as fuel and maintenance costs. The variable *slot-control* captures the potential negative effect of congestion in slot controlled airports on air travel demand. The four U.S. slot-controlled airports are: Newark Liberty International Airport, John F. Kennedy International Airport, LaGuardia airport and Ronald Reagan Washington National Airport (GAO, 2012). On average, each airline connection passes via 0.12 slot-controlled airports. On-time performance is another important factor which influences passenger itinerary choices. Suzuki (2000) notes that market shares may be influenced by passengers' delay experience. Thus, the *delay* variable takes into account the connection's on-time performance during the last quarter of 2011 ie. the quarter prior to decision. Besides, when passengers book their tickets, they are informed on airline delays for the previous quarter. The *delay* variable is equal to 1 if the itinerary arrival was more than 15 min delayed in the previous quarter of the decision quarter. On average, 14% of flights experienced more than 15 min delay during the last quarter of 2011. Finally, we include dummy variables for the ticketing airlines to capture the preference of consumers on specific airlines. Two legacy carriers (Delta and American Airlines) and two low-cost airlines (Southwest and JetBlue) are included. US Airways is used as the base carrier in the estimation against which the other airlines are compared. Airline dummies are also included in the cost function to model airline-specific cost effects. Turning to purely cost variables, aircraft size and transferring via hub airports are selected to explain marginal cost. *Aircraft size* determines a variety of aircraft operating costs, such as rental/ownership and maintenance costs. Other size-related costs include landing fees since they are computed on the basis of the maximum take-off aircraft weight. This dummy variable is equal to 1 if at least one segment of the itinerary is operated by a wide-body aircraft. A variable indicating transfer via hub airports is used to explain if concentration of traffic in hubs affects marginal cost. The dummy *Hub variable* is equal to 1 if the itinerary departs/connects/arrives from/to an airport which is a hub for the ticketing carrier.

In this paper, the above variables are augmented with some additional attributes not formerly used in aggregate models. Intuitively an itinerary is more attractive if it is offered in the morning and afternoon period. Past studies used booking data from computer reservation systems and found that late-evening itineraries are not preferred (Barnhart et al., 2014; Koppelman et al., 2008) while Koppelman et al. (2008) found that mid-morning and late-afternoon itineraries are most preferred. Based on these observational findings, we construct two variables, *morning and late-afternoon departures*, that indicate the percentage of connections offered in the morning period (from 8 a.m. to 12 a.m.) and in the late-afternoon period (from 3 p.m. to 7 p.m.) respectively. In the 1st quarter of 2012, 25% of airline connections are offered in the morning period. Another factor that stands out as helping to explain city-pair travel demand is the presence of *alternative airports* nearby the passenger's origin or destination city. A variable is constructed to control for the possibility that passengers can leave the market and fly from/to other airports. Although several factors may influence airport choice (Malina, 2010), we control for access distance and flight availability. We assume that the distance a traveler is willing to drive to reach an alternative airport is differentiated for short- and medium/long-haul trips. This distance is taken as 60 miles for short-haul flights and 100 miles for medium/long-haul fights. These values are consistent with existing evidence on airport leakage (Leon, 2011; Fuellhart, 2007) and are within the distance range given in the booking system of various U.S. airlines. Our approach differs from existing studies (Ciliberto and Tamer, 2009) in two points: first, access distance is measured from the Metropolitan Statistical Area (MSA) centroid to the candidate airport, since the traveler is assumed to originate his/her trip from this point. Second, a candidate airport is considered as alternative only if it serves the desired destination within the quarter under consideration. In our sample, 59% of the itineraries are served by alternative airports. For a better understanding of the above process, Fig. 1 illustrates the proximity of MSA (indicated by their population-weighted centroids) to alternative airports within 60- and 100-mile radius. It can be seen that passengers at the Northeast and Southwest U.S. have the greatest opportunity to choose alternative airports. Finally, the variable *fuel consumption* captures the impact of fuel cost on airline marginal cost. The variable is computed for every flight according to the emission model outlined in Section 2.4 and represents the amount of fuel consumed per passenger travelled.

Table 2 summarizes the relevant demand and cost variables with descriptive statistics and data source.

3.3. Instrumental variables

The main source of endogeneity in the demand equation comes from the correlation of price and within group market share with the unobserved variable as the latter commonly reflects quality features. Thus we need to instrument for p_j and $MS_{j/g}$. Following the standard practice, we assume that the remaining characteristics x_j are uncorrelated with ξ_j, and thus can be used as valid instruments. We also use additional exogenous variables that are believed to affect ticket prices and within group share but are uncorrelated with ξ_j. We use three groups of instruments for the demand equation related to market- and route-level characteristics and rival attributes. The first group includes market characteristics such as the number of offered connections and the number of airlines in the market. Both instruments indicate the degree of within-market competition a connection is facing, which in turn may affect its ticket price. Route-level characteristics include two instruments of whether the destination or the connecting airports are hubs for the ticketing carrier. The intuition is that airline costs may be affected by hub operation, which may in turn influence ticket prices set by the ticketing airline. In addition, the number of destination cities served by direct flights reflects the airline's size of operation at the origin airport and can be related to its price level at the airport. Finally, rival connections' attributes include the percentage of nonstop rivals' routes and the average number of passengers carried by rivals within the given market. Both variables capture within-market competitiveness and thus overall price level, while the latter additionally predicts within-group market shares. The pricing equation also suffers from endogeneity since the error term (ω) is correlated with market share and market share derivatives. Apart from the demand instruments we include two more instruments which are indicative of the potential passenger traffic of each connection and each airline. In this way, they predict potential market share of each connection and airline. They are defined by the market size divided by the number of connections and by the number of airlines in the market respectively.

To justify the appropriateness of the selected instruments we applied the Hausman test which verifies the endogeneity of prices and market shares and F-statistic test for the relevance of instruments.

3.4. Parameter estimates

The parameter estimates and their standard errors are reported in Table 3. The coefficients associated with the explanatory variables have the expected sign. As expected, the ticket price has negative effect on air travel demand (−0.45). The estimated value of ($1-\lambda$) indicates a correlation of 0.32 in the preferences of passengers for air, which reflects moderate substitution possibility among flight connections. The negative coefficient of the number of stops (−1.00) indicates that passengers do not favor flights via connecting airports. This is partly explained by the extra travel. Market distance has a positive coefficient equal to 0.43 which reflects the fact that aircraft is the preferred long distance transport mode. The frequency coefficient (0.48) indicates that passenger's utility increases with the number of departures. The other two indicators of quality of service namely percentage of morning and late-afternoon departures, have positive coefficients (0.17 and 0.14 respectively). These values indicate that airlines attract more passengers if they offer a large percentage of connections during morning and late-afternoon. On the contrary, market shares are negatively influenced by delays. Arrival delays at the destination airport of more than 15 min significantly affect passenger's utility (−2.07). The variable slot-controlled airports is also negatively weighted (−0.26). Flight delays frequently observed at slot-controlled

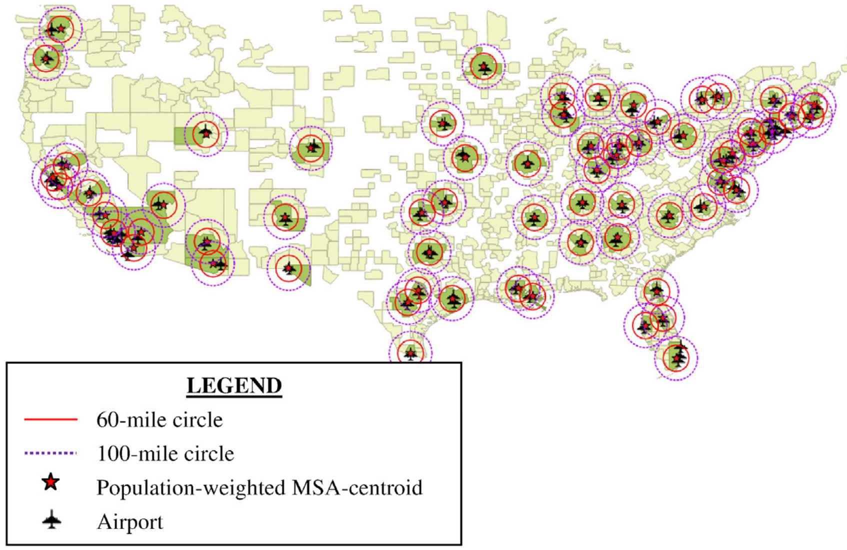

Fig. 1. Proximity of Metropolitan Statistical Areas (MSA) to alternative airports within 60- and 100-mile radius.

Table 3
Estimation results for the demand and cost equations (Q1/2012).

Dependent variable: $\ln MS_j - \ln MS_0$			Dependent variable: p_j (*fare*)		
Demand variables	Coefficient	Std. error	Cost variables	Coefficient	Std. error
Constant	−7.67	0.139	Constant	1.33	0.045
Ticket price	−0.45	0.028	Round-trip distance	0.44	0.016
$\ln(MS_{j/g})$ $(1-\lambda)$	0.32	0.010	Aircraft size	−0.07	0.027
Number of stops	−1.00	0.011	Per passenger fuel	1.57	0.336
Market distance	0.43	0.032	Hub dummy	0.17	0.036
ln(minimum frequency)	0.48	0.012	Jet Blue Airways*	−0.95	0.046
% of morning departures	0.17	0.039	Delta Air Lines*	0.01	0.032
% of late-afternoon departures	0.14	0.044	American Airlines*	−0.30	0.031
Slot control	−0.26	0.022	Southwest Airlines*	−0.41	0.042
Delays	−2.07	0.178	Other low-cost airlines*	−1.07	0.029
Alternative airport	−0.31	0.015	Other legacy airlines*	0.12	0.036
Jet Blue Airways*	0.15	0.057			
Delta Air Lines*	−0.12	0.022			
American Airlines*	−0.15	0.029			
Southwest Airlines*	−0.39	0.023			
Other low-cost airlines*	−0.22	0.044			
Other legacy airlines*	−0.15	0.030			

Observations: 19,362
Note: * US Airways is used as the base carrier in the estimation.

airports may discourage passengers from choosing these airports. The negative coefficient of the variable alternative airport (−0.31) is consistent with our intuition that the existence of an alternative airport reduces passenger's utility for the connection as it can be served by another itinerary.

The estimated cost parameters have also the expected sign. The positive coefficient of round-trip distance (0.44) indicates that cost rises with distance travelled. The aircraft size coefficient (−0.07) implies that using wide-body aircraft may be more cost efficient for an airline. Wide-body aircraft can provide more capacity and thus transfer more passengers, lowering per passenger marginal cost. Cost economies of larger aircraft are documented in (Wei and Hansen, 2003; Ryerson and Hansen, 2013). Our cost estimates show that fuel consumption significantly increases marginal cost. In particular, a 10% increase of per passenger fuel consumption would lead to an increase in marginal cost per passenger of approximately 15.7%. Passing through a hub airport increases airline marginal cost, all else being equal. Hub operations offer economies of density. Airlines may transfer higher traffic flows and thus generate higher load factors, which decrease per-passenger cost (Lee, 2013; Shen, 2012; Ssamula, 2008). On the other hand, traffic concentration in hub airports may cause congestion and flight delays or may increase travel time compared to the corresponding direct flight and ultimately increase marginal costs (Borenstein and Rose, 2007; Gayle and Wu, 2015). The hub dummy coefficient (0.17) indicates that the net effect of these countervailing forces on cost is positive. Finally airline dummies indicate that in general low cost airlines have lower marginal cost (−1.07), with Jet Blue Airways being the most cost efficient (−0.95) followed by Southwest Airlines (−0.41).

In order to measure how well the estimated equations reproduce the observed data, two indicators are compared: the passenger demand, which will reveal the goodness of fit of the demand model and the ticket prices, which reflect the characteristics of the supply side. For each airline connection, the estimated and observed values are plotted in Fig. 2. The line in the figure is indicative of the difference between observed and estimated values. To obtain the estimated data, we substitute the demand and

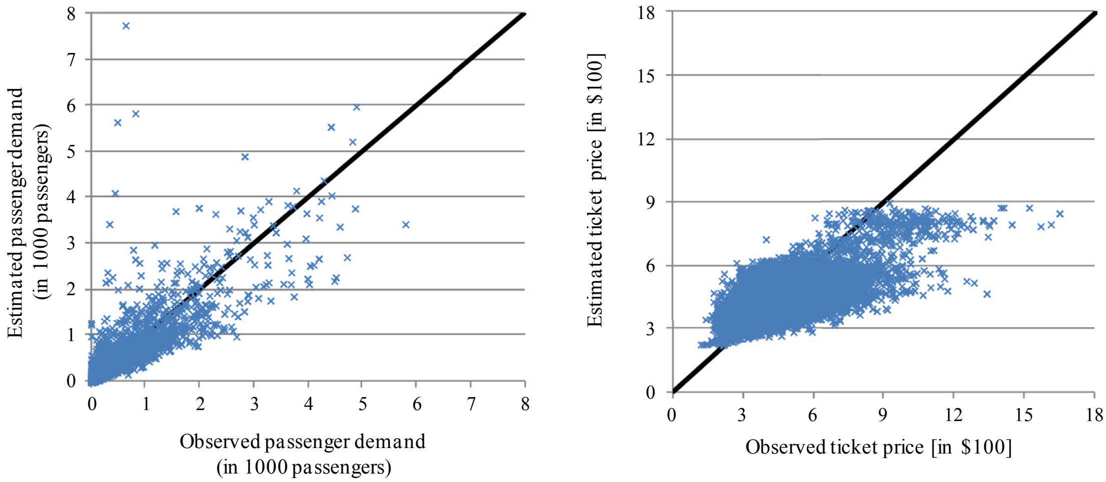

Fig. 2. Comparison of estimated and observed passenger demand and ticket prices.

marginal cost estimates of Table 3 into Eq. (7) and solve the equation for ticket price. Then, the estimated prices are substituted into the market share function (Eq. (2)) to predict market shares. Estimated passenger demand is calculated by multiplying the estimated market shares with the respective market size.

Table 4 provides a comparison of average observed and estimated passenger demand and ticket prices. In addition, a goodness of fit measure, which has been suggested for instrumental variables regressions (Gugler and Yurtoglu, 2004; Pesaran and Smith, 1994; Windmeijer, 1995) is calculated for the demand and the supply model. It is computed as the squared correlation coefficient between predicted and observed values of the passenger demand and ticket prices and ranges from 0 to 1. For the passenger demand, it is 0.66, while for the airline behavior it is equal to 0.45.

Fig. 2 and the findings from Table 4 generally suggest that our model is capable of capturing the dominant effects of passenger demand and ticket prices. Summed across all airline connections, estimated passenger demand is only 1.7% higher than the observed data while modeled ticket prices are only 0.6% lower than the observed. If the outliers observed in Fig. 2 are excluded, the goodness of fit measure rises to 0.70.

4. Simulating a market-based environmental policy

Suppose that a carbon emission fee F (in \$/tn CO_2) is introduced, for every tonne of CO_2 emitted. The pre-policy airline's marginal cost ($mc_{j,pre}$) is increased by the emission fee. The post-policy marginal cost ($mc_{j,post}$) is given by:

$$mc_{j,post} = mc_{j,pre} + F \cdot \sum_{s=2}^{S} \frac{E_{s,j}}{LF_{s,j} \cdot SEAT_{s,j}}, \quad where\ S = \{2,3,4\}\ ,\ j \in J \tag{9}$$

$E_{s,j}$ is the amount of CO_2 (in tn CO_2) emitted by the airline in each segment s of connection j and the product $LF_{s,j} \cdot SEAT_{s,j}$ gives the number of passengers carried by the regulated airline in each segment s of the examined connection j. The resulting emission cost is computed for every connection by summing the per passenger CO_2 emissions for all segments.

Ticket prices will be adjusted as a response to the carbon emission fee. The precise value of the adjustment is determined from the new equilibrium associated with the post policy marginal cost. This new equilibrium is computed iteratively as highlighted in the methodology section.

Setting an effective level of carbon price is essential when designing a market-based policy. In emission trading schemes, carbon price is driven by market conditions. For example, too many allowances will result in a low carbon price but too few allowances will result in a high carbon price. The policy considered in this paper employs a pre-defined carbon unit price. To set a realistic unit carbon price, historical price data from existing policies in aviation as well as values reported in various studies were reviewed. To take into account the uncertainties related to carbon price, three scenarios (low, medium and high) were considered based on different carbon prices: \$10, \$20, \$50 and \$100 per tonne of CO_2. The medium price scenario (\$20/tn CO_2) was chosen in order to reflect the baseline price level used among existing research papers (Albers et al., 2009; Anger and Kohler, 2010; Barbot et al., 2014; Malina et al., 2012; Scheelhaase et al., 2010). The low price was used to approximate the average price of European Union Allowance (EUA) price during 2012. The prices of \$50 and \$100 per tn CO_2 reflect two more aggressive scenarios for aviation emissions abatement.

The simulation results are presented in Table 5. The ticket price increases by 1.18%–11.77% depending on the carbon price set. The change of within-group market shares ($MS_{j/g}$) varies from −0.27% for a carbon price of \$10 to −2.60% for a carbon price of \$100. Overall, the implementation of a market-based policy leads to airfare increase followed by a decrease in air traffic. In particular, our results indicate a 4.65% decrease in air traffic for the medium scenario (\$20 per ton CO_2). This means that 4.65% of passengers will

Table 4
Goodness of fit for the demand and supply model.

	Estimated	Observed	Δ% (Estimated/Observed)	Goodness of fit
All airline connections				
Mean Passengers per connection	100.3	98.6	101.7%	0.66
Mean Ticket price	449.42	452.22	99.4%	0.45

Table 5
Effects of the market-based policy in the US domestic airline industry (Q1 2012).

F [\$/tn CO_2]		Low scenario	Medium scenario	High scenarios	
		F = 10	*F* = 20	*F* = 50	*F* = 100
Average fare increase [%]	$\Delta price$	1.18%	2.35%	5.89%	11.77%
Average air travel demand change [%]	ΔMS_j	−2.36%	−4.65%	−11.18%	−20.94%
Average demand change of within-group connections [%]	$\Delta MS_{j/g}$	−0.27%	−0.54%	−1.33%	−2.60%

choose not to fly as a result of increased prices. Decreased air traffic will lead to lower emission levels for the network under consideration. Some of the passengers will divert to other transport modes, while others may choose not to travel at all. Due to the appearance of this travel mode substitution effect a decrease in the aggregate volume of aviation will cause an increase in the aggregate traffic volume of another mode. This especially applies to short-distance trips where air transport strongly competes with land transport.

The effect of the above changes to different distance groups is illustrated in Fig. 3. Flight connections are grouped in three groups based on their market distance: connections with market distance less than 1250 miles, from 1250 to 2500 miles and greater than 2500 miles. Longer flights experience the greatest impact due to the carbon cost as they generate the largest amount of CO_2 emissions. For the medium scenario (\$ 20/tn CO_2), shorter flights become on average 1.9% more expensive while longer flights' fares increase by about 3.1%.

Another critical observation is that the CO_2 policy affects direct and non-direct flights differently. Fig. 4 shows that on average, a passenger will face a higher price increase on non-direct flights. A one-stop flight includes the fuel consuming parts of landing and take-off at the connecting airports. This results in higher CO_2 emissions in comparison to the corresponding direct flight. Hence, even within the same market, passengers who choose to travel directly between O-D airports will benefit more than those who travel on a one-stop flight. For the high scenario of \$50 per tn CO_2, connecting flights face a 6.3% increase in ticket prices compared to 4.2% for direct flights. Moreover, 12.1% and 7.1% of passengers in connecting and direct flights respectively may choose not to fly after the introduction of carbon policy, due to higher airfare.

5. Conclusions

This paper shows how an airline may adjust its pricing strategy in view of a market-based environmental policy within a competitive airline network. A portion of the induced environmental cost may be passed onto the passengers, resulting in increased ticket prices and lower demand. An empirical demand and supply model for air travel, which considers the interaction of passengers' behavior and airline decision, is presented. One important feature of this paper is that a carbon fee is introduced as a shifter of the airline's marginal cost. The adjustment of ticket prices in response to the carbon fee is determined by a Nash equilibrium in prices.

The key determinants of airlines' demand and cost are identified. On the demand side, apart from ticket price, arrival delays and indirect flights are found to negatively affect air travel demand. Furthermore, travel demand of a specific connection is found to be negatively affected by the presence of an alternative airport. On the other hand, an airline could increase its market share by improving its itinerary's frequency. Contrary to the majority of aggregate studies, which employ linear regression of passenger traffic, air travel demand is modeled by discrete choice models of consumer behavior. On the cost side, itinerary distance and fuel burn are the most significant cost drivers. The two-step Generalized Method of Moments is used for the joint estimation of the nonlinear model bypassing endogeneity issues through the use of proper instruments. One limitation of our analysis is that ticket price is considered as the key decision variable in the airline strategy towards an externally imposed environmental fee. In future research, additional decision variables considered by airlines such as frequency or hub choice location will be examined.

On the whole, our analysis revealed that the implementation of a carbon policy in the U.S. aviation is expected to cause moderate changes on ticket prices and market shares. Ticket prices were found to increase by 1.2%–11.8% depending on the carbon price.

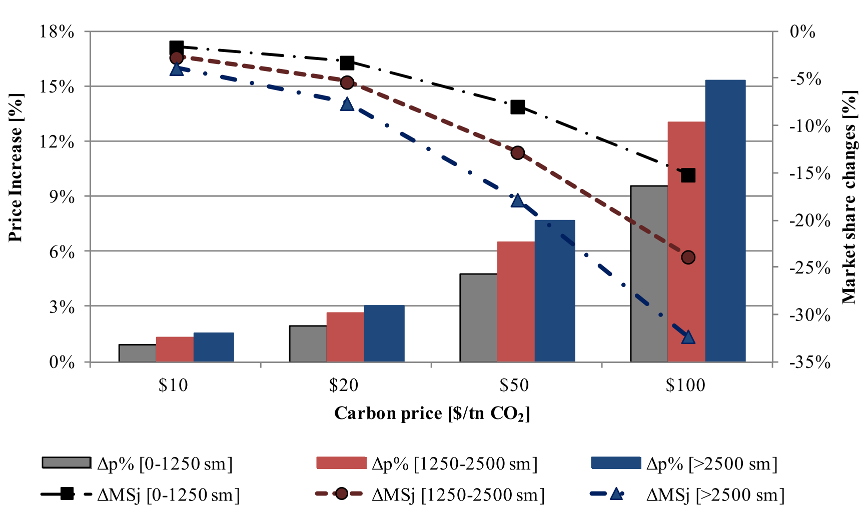

Fig. 3. Changes in ticket prices and market shares compared to actual Q1/2012 values for different distance groups (in statute miles-sm).

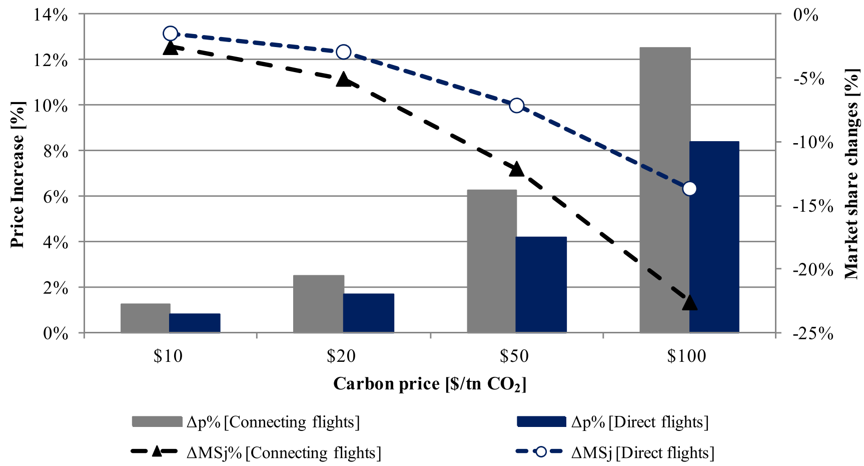

Fig. 4. Changes in ticket prices and market shares compared to actual Q1/2012 for direct and indirect flights.

These changes are more likely to change total air travel demand as opposed to affecting demand shift between airline connections. In particular, within-group air travel demand is found to decrease by only 0.27% for the low scenario and 2.6% for the highest carbon price. This means that competition distortions are expected to be rather low. Our findings augment the concluding remarks of other studies which have investigated environmental policies in European or other markets (Anger, 2010; Malina et al., 2012; Miyoshi, 2014; Scheelhaase et al., 2010).

An examination of the historical data on EU allowances in the context of EU ETS proves that there exists a considerable amount of volatility in the dynamics of the carbon price. If carbon price reaches the highest levels of our assumed unit prices ($50 or $100), air travel demand may decrease by about 11.2% and 20.9% respectively. Thus, airlines and policy makers may need to turn to alternative approaches to ensure economic and environmental sustainability. Finally, policy makers should not ignore the potential passenger shift from air travel to other transport modes, which is modeled in this paper as the non-air option. Hence, the demand decrease resulting by the implementation of a carbon fee (reported in Table 5) should not be interpreted as a proportional reduction in CO_2 emissions. This especially applies to short-distance trips where air transport strongly competes with land transport.

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