ΕΘΝΙΚΟ ΜΕΤΣΟΒΙΟ ΠΟΛΥΤΕΧΝΕΙΟ

Σχολή Πολιτικών Μηχανικών
Τομέας Μεταφορών και Συγκοινωνιακής Υποδομής

NATIONAL TECHNICAL UNIVERSITY OF ATHENS

School of Civil Engineering
Department of Transportation Planning and Engineering

Διδακτορική Διατριβή

Διερεύνηση των επιλογών των επιβατών και των αποκρίσεων των αεροπορικών εταιρειών σε αγορακεντρικά περιβαλλοντικά μέτρα με τη χρήση προτύπων διακριτής επιλογής και θεωρίας παιγνίων

PhD Dissertation

Passenger travel choices and airline responses under market-based environmental policies using discrete choice modeling and game theory

ΙΩΑΝΝΑ ΠΑΓΩΝΗ
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Αθήνα, Φεβρουάριος 2017

Athens, February 2017

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Διδακτορική Διατριβή
για την απόκτηση διδακτορικού διπλώματος
της Σχολής Πολιτικών Μηχανικών, Εθνικό Μετσόβιο Πολυτεχνείο

ΙΩΑΝΝΑ ΠΑΓΩΝΗ
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PhD Dissertation
for the title of Doctor of Philosophy in Engineering submitted in the
School of Civil Engineering, National Technical University of Athens

IOANNA PAGONI
Diploma in Civil Engineering, NTUA
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Athens, February 2017

To my parents, Panagiotis and Kalliopi
and
To my husband, Thanasis

Στους γονείς μου, Παναγιώτη και Καλλιόπη
και
Στο σύζυγο μου, Θανάση

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Διερεύνηση των επιλογών των επιβατών και των αποκρίσεων των αεροπορικών εταιρειών σε αγορακεντρικά περιβαλλοντικά μέτρα με τη χρήση προτύπων διακριτής επιλογής και θεωρίας παιγνίων

Ιωάννα Π. Παγώνη

Επιβλέπουσα Καθηγήτρια: Παρασκευή Ψαράκη-Καλουπτσίδη, Αναπλ. Καθηγήτρια ΕΜΠ

ΣΥΝΟΨΗ

Στην παρούσα διδακτορική διατριβή διερευνάται η επίδραση ενός αγορακεντρικού περιβαλλοντικού μέτρου στην ανταγωνιστική αγορά των αερομεταφορών. Με την εφαρμογή του μέτρου οι αεροπορικές εταιρείες πληρώνουν ένα επιπλέον κόστος εκπομπών το οποίο εκφράζεται συναρτήσει της ποσότητας διοξειδίου του άνθρακα (CO_2) που εκπέμπουν και του μοναδιαίου κόστους (ανά τόνο CO_2) που καθορίζεται στα πλαίσια της περιβαλλοντικής πολιτικής. Η επίδραση του μέτρου στις τιμές των εισιτηρίων, στα μερίδια αγορών των αεροπορικών εταιρειών και στις συνολικές εκπομπές διοξειδίου του άνθρακα σε ένα αεροπορικό δίκτυο διερευνάται μέσω της ανάπτυξης μιας μεθοδολογίας η οποία περιλαμβάνει ένα πρότυπο μεταφορικής ζήτησης, ένα πρότυπο συμπεριφοράς των αεροπορικών εταιρειών και μια μέθοδο υπολογισμού του κόστους εκπομπών για κάθε αεροπορική εταιρεία και διαδρομή.

Η αεροπορική ζήτηση αναλύεται με τη χρήση προτύπων διακριτών επιλογών (χρησιμοποιώντας αθροιστικά δεδομένα) εντός μιας αγοράς, που ορίζεται ως το ζεύγος πόλεων προέλευσης-προορισμού. Πιο συγκεκριμένα, χρησιμοποιείται το ιεραρχικό πρότυπο logit (nested logit model). Η χρησιμότητα του επιβάτη από την επιλογή μιας αεροπορικής σύνδεσης εκφράζεται ως συνάρτηση των χαρακτηριστικών της σύνδεσης, των αεροδρομίων προέλευσης-προορισμού και της αεροπορικής εταιρείας που εκτελεί το δρομολόγιο. Η συμπεριφορά των εταιρειών βασίζεται στην υπόθεση ότι οι εταιρείες, που δραστηριοποιούνται σε μια αγορά, διαμορφώνουν τις τιμές των εισιτηρίων υπό συνθήκες ολιγοπωλιακού ανταγωνισμού με γνώμονα τη μεγιστοποίηση των κερδών τους. Κάθε εταιρεία διαμορφώνει τις τιμές των εισιτηρίων της ταυτόχρονα με τις άλλες εταιρείες που δραστηριοποιούνται στην ίδια αγορά, αναπτύσσοντας ένα μη συνεργατικό παίγνιο. Μετά την εφαρμογή της περιβαλλοντικής πολιτικής, το πρότυπο συμπεριφοράς των αεροπορικών εταιρειών αναπροσαρμόζεται ώστε στο οριακό κόστος κάθε αεροπορικής εταιρείας να ενσωματωθεί το κόστος εκπομπών. Για τον υπολογισμό των εκπομπών CO_2 και του αντίστοιχου κόστους, κάθε διαδρομή κατατάσσεται σε μοναδικούς συνδυασμούς «αεροσκάφους, απόστασης πτήσης και προσανατολισμού πτήσης». Για κάθε συνδυασμό εκτιμάται το τυπικό μονοπάτι κατακόρυφης πορείας του αεροσκάφους και με τη χρήση του μοντέλου Base of Aircraft Data του EUROCONTROL υπολογίζονται οι εκπομπές CO_2.

Η εφαρμογή του αγορακεντρικού περιβαλλοντικού μέτρου εξετάζεται στο αεροπορικό δίκτυο των Ηνωμένων Πολιτειών για το έτος 2012. Τα αποτελέσματα δείχνουν ότι η αύξηση στις τιμές των εισιτηρίων και η μείωση της αεροπορικής ζήτησης μπορεί να είναι σημαντική αν η τιμή του άνθρακα είναι υψηλή. Για το χαμηλό σενάριο των \$10 ανά τόνο CO_2 που είναι κοντά στην τρέχουσα τιμή άνθρακα η μείωση των συνολικών εκπομπών CO_2 (λόγω μείωσης της αεροπορικής ζήτησης) εκτιμήθηκε ίση με 1,88%. Λαμβάνοντας υπόψη τον στόχο της αεροπορικής βιομηχανίας για μείωση των εκπομπών CO_2 των αεροπορικών μεταφορών κατά 50% μέχρι το 2050 (σε σχέση με τα επίπεδα του 2005), η παρούσα διατριβή δείχνει ότι είναι ανάγκη οι αεροπορικές εταιρείες και οι άλλοι φορείς της βιομηχανίας να στραφούν σε εναλλακτικές προσεγγίσεις για να διασφαλιστεί η οικονομική και περιβαλλοντική βιωσιμότητα των αερομεταφορών. Η ανάλυσή της διατριβής δείχνει ότι η τιμολόγηση των εκπομπών CO_2 συμβάλλει στη μείωση των εκπομπών CO_2. Παρ' όλα αυτά, τα χαμηλά επίπεδα της τιμής του άνθρακα δεν αναμένεται να οδηγήσουν σε σημαντικές αλλαγές στον τομέα των αεροπορικών μεταφορών από την εφαρμογή μόνο ενός περιβαλλοντικού μέτρου. Τέλος, η εφαρμογή της πολιτικής δεν αναμένεται να επηρεάσει τον ανταγωνισμό των αεροπορικών εταιρειών που δραστηριοποιούνται στην ίδια αγορά.

Λέξεις-Κλειδιά: *αγορακεντρικά περιβαλλοντικά μέτρα, αεροπορική ζήτηση, πρότυπα διακριτών επιλογών, ενδογένεια, γενικευμένη μέθοδος των ροπών, κέρδος αεροπορικών εταιρειών, μη συνεργατικό παίγνιο, τυπική κατακόρυφη τροχιά αεροσκάφους, ευθυγράμμιση των καμπυλών με βάση τα σημεία, πρότυπο προσομοίωσης λειτουργίας αεροσκάφους.*

Passenger travel choices and airline responses under market-based environmental policies using discrete choice modeling and game theory

Ioanna P. Pagoni

Supervisor: Paraskevi Psaraki-Kalouptsidi, Associate Professor NTUA

ABSTRACT

In this dissertation, the implementation of a market-based environmental policy on aviation industry is studied. Under this policy, each airline pays a carbon fee, as a function of the carbon dioxide emissions (CO_2) it generates and the pre-defined unit carbon price (per ton CO_2). The impact on ticket prices, airlines' market shares and resulting network-wide carbon emissions is investigated via a methodology which includes an air travel demand model, an airlines' behavior model and a method for estimating carbon emissions costs by airline and itinerary.

The aggregate air travel demand model relies on discrete choice analysis of different airline connections in origin-destination markets. In particular, the Nested Logit model is used. The passengers' utility for each airline connection is expressed as a function of various flight attributes that are specific to the itinerary, the airline and the airport. The airline's behavior model is based on the hypothesis that active airlines set their ticket prices in an origin-destination market under oligopolistic competition with the aim to maximize own profits. Ticket prices are simultaneously set by each airline in the market, which means that airlines play a non-cooperative game. After the implementation of the environmental policy, the airline's behavior model is adjusted so as to incorporate the carbon fee in the airline's marginal cost. For the computation of airline connection's CO_2 emissions and corresponding emissions cost, connections are organized in unique combinations of "aircraft type, flight distance, flight direction". For every combination, the typical altitude profile is estimated and the CO_2 emissions are computed by using the fuel flow coefficients given in the EUROCONTROL's Base of Aircraft Data.

The market-based environmental policy is implemented at the U.S. domestic aviation network for the study year 2012. The simulation analysis revealed that the implementation of the environmental market-based policy in the U.S. aviation could have some significant effects on ticket prices, air travel demand and resulting CO_2 emissions for high ranges of carbon unit price. For the low scenario of \$10 per ton CO_2, which is close to the prevailing carbon price, the network-wide CO_2 emissions are expected to decrease by 1.88% (due to air travel demand decrease). Taking into account the aviation industry ambitious goal to reduce net aviation CO_2 emissions by 50% until 2050 (relative to 2005 levels), this dissertation suggests that airlines and policy makers may need to turn to alternative approaches to ensure economic and environmental sustainability. Although carbon pricing may contribute to CO_2 emissions reduction, it seems that the low levels of carbon price would not trigger more significant changes in the air transport sector so as to act as a stand-alone measure. A combination of different policies (e.g. technological improvements, operational changes etc) could be needed to effectively work towards the environmental target. Finally, our simulation results indicate that airline competition distortions are expected to be rather low.

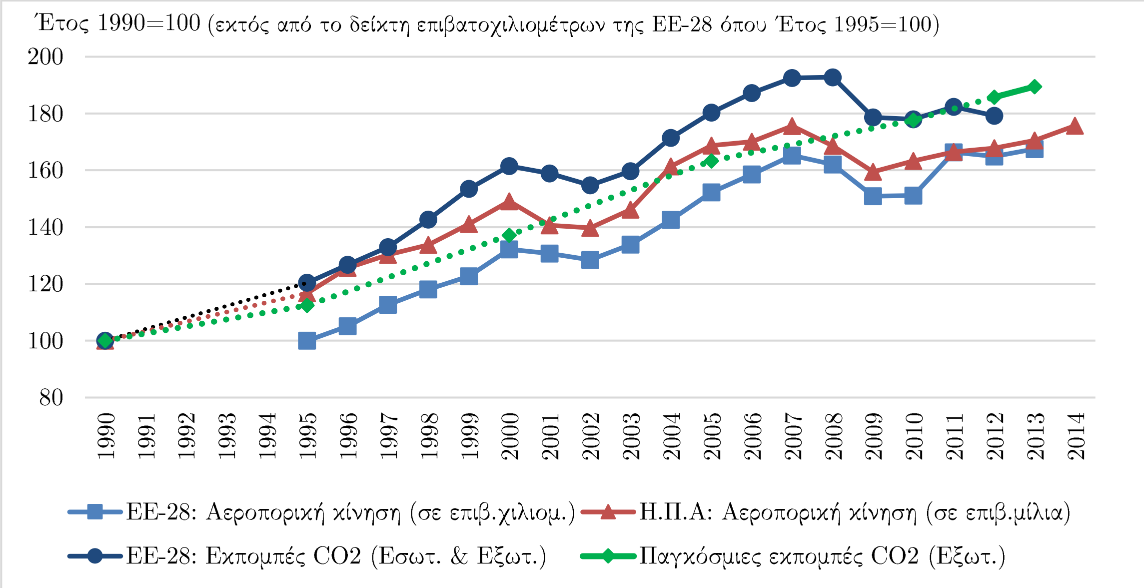
Keywords: *market-based environmental policy, air travel demand, discrete choice model, endogeneity, generalized method of moments, airline profits, non-cooperative game, typical altitude profile, landmark registration, BADA performance model.*

ΕΚΤΕΤΑΜΕΝΗ ΠΕΡΙΛΗΨΗ ΣΤΑ ΕΛΛΗΝΙΚΑ

1. Εισαγωγή

Οι αεροπορικές μεταφορές αποτελούν ουσιαστική συνιστώσα στην κοινωνική και οικονομική, ανάπτυξη ενός τόπου. Τα τελευταία χρόνια οι αεροπορικές μεταφορές έχουν επηρεαστεί από διεθνείς μεταβολές όπως οι συγχωνεύσεις των αεροπορικών εταιρειών και η δημιουργία μεγάλων αεροπορικών συμμαχιών, η ανάπτυξη των κομβικών αεροδρομίων που επιτρέπουν τη μαζική μετακίνηση επιβατών με διαφορετικούς τελικούς προορισμούς προς ένα κοινό κομβικό αεροδρόμιο και είσοδος των εταιρειών χαμηλού κόστους, οι οποίες έχουν οδηγήσει σε αύξηση του ανταγωνισμού. Επίσης, τις τελευταίες δεκαετίες ο τομέας των αερομεταφορών χαρακτηρίζεται από αύξηση της αεροπορικής κίνησης. Από το 2000 έως το 2013, η επιβατική αεροπορική κίνηση (σε μονάδες επιβατοχιλιομέτρων) στην Ευρώπη έχει αυξηθεί κατά 26,8% (European Commission, 2015). Ανάλογη αυξητική τάση παρατηρήθηκε και στις Ηνωμένες Πολιτείες Αμερικής (Η.Π.Α.), όπου τα επιβατοχιλιόμετρα αυξήθηκαν κατά περίπου 17,9% από το 2000 έως το 2014 (BTS, 2016a). Σύμφωνα με προβλέψεις της εταιρείας Boeing (2015), η επιβατική κίνηση αναμένεται να έχει μέσο ετήσιο ρυθμό ανάπτυξης 4,9% μέχρι το 2034. Η αυξητική τάση της κίνησης έχει σαν αποτέλεσμα την αύξηση των εκπομπών διοξειδίου του άνθρακα (CO_2). Επί του παρόντος, οι εκπομπές CO_2 που οφείλονται στις αερομεταφορές κυμαίνονται στο 1,3% των συνολικών εκπομπών CO_2 παγκοσμίως (ITF, 2016). Πρόσφατες μελέτες υποστηρίζουν πως αν δεν ληφθούν μέτρα αντιμετώπισης των περιβαλλοντικών επιπτώσεων από τις αερομεταφορές, το ποσοστό αυτό θα αυξηθεί κατά πολύ τα επόμενα χρόνια (ICAO, 2016a). Στο Σχήμα 1 παρουσιάζεται η αυξανόμενη εξέλιξη της αεροπορικής κίνησης και των εκπομπών CO_2 στην Ευρώπη, τις Η.Π.Α. και παγκοσμίως.

Η αύξηση των εκπομπών από τις αεροπορικές μετακινήσεις έχει οδηγήσει στην υιοθέτηση αγορακεντρικών περιβαλλοντικών μέτρων με στόχο τη μείωση της περιβαλλοντικής επιβάρυνσης. Σύμφωνα με το άρθρο των Kossoy et al. (2015), μέχρι το 2015 σε όλο τον κόσμο είχαν εφαρμοστεί περίπου 60 μέτρα τιμολόγησης του άνθρακα (σε διάφορες βιομηχανίες), άλλα σε εθνικό (περίπου 40) και άλλα σε τοπικό επίπεδο. Στον τομέα των αεροπορικών μεταφορών, παράδειγμα αποτελεί το Σύστημα Εμπορίας Δικαιωμάτων Εκπομπών (ΣΕΔΕ) της Ευρωπαϊκής Ένωσης, το οποίο τέθηκε αρχικά σε ισχύ το 2012. Βάσει Ευρωπαϊκής οδηγίας του 2014, το ΣΕΔΕ πλέον εφαρμόζεται μόνο σε πτήσεις εντός του Ευρωπαϊκού Οικονομικού Χώρου (ΕΟΧ) (δηλαδή μόνο μεταξύ Ευρωπαϊκών αεροδρόμιων). Άλλα μέτρα αφορούν περιβαλλοντικούς/ά φόρους/τέξη σε αεροδρόμια και μέτρα αντιστάθμισης της περιβαλλοντικής επιβάρυνσης. Είναι φανερό πως οι πολιτικές αυτές επιφέρουν ένα επιπλέον κόστος, το οποίο καλείται εφ'εξής «κόστος εκπομπών».



Σχήμα 1. Εξέλιξη της αεροπορικής κίνησης και των εκπομπών CO_2 (με στοιχεία από EC, 2015; BTS, 2016a and IEA, 2015)[1]

Ο κύριος στόχος της παρούσας διδακτορικής διατριβής είναι η ανάπτυξη μιας μεθοδολογικής προσέγγισης για τη πρόβλεψη της συμπεριφοράς των επιβατών, ως προς την επιλογή διαδρομής, και της συμπεριφοράς των αεροπορικών εταιρειών, ως προς τη διαμόρφωση των τιμών, μετά την εφαρμογή ενός αγορακεντρικού περιβαλλοντικού μέτρου. Η διατριβή εστιάζεται σε περιβαλλοντικό μέτρο που «χρεώνει» τις αεροπορικές εταιρείες με βάση τις εκπομπές διοξειδίου του άνθρακα. Η μεθοδολογία που ακολουθείται βασίζεται στην εσωτερίκευση του κόστους εκπομπών στο οριακό κόστος των αεροπορικών εταιρειών. Η επίδραση του αγορακεντρικού περιβαλλοντικού μέτρου διερευνάται με τη χρήση ενός συνόλου τεχνικών οι οποίες περιλαμβάνουν ένα πρότυπο μεταφορικής ζήτησης, ένα πρότυπο συμπεριφοράς των αεροπορικών εταιρειών και μια μέθοδο υπολογισμού του κόστους εκπομπών για κάθε αεροπορική εταιρεία και διαδρομή.

Στο σύνολο της, η παρούσα διατριβή εφαρμόζει οικονομετρικά πρότυπα με στόχο να απαντήσει στην εξής ερευνητική ερώτηση: Ποια θα είναι η επίδραση της εφαρμογής ενός αγορακεντρικού περιβαλλοντικού μέτρου στις τιμές των εισιτηρίων, στα μερίδια αγοράς των αεροπορικών εταιρειών και στις συνολικές εκπομπές CO_2; Για να επιτευχθεί ο ανωτέρω στόχος, η προτεινόμενη μεθοδολογία αποτελείται από τα εξής:

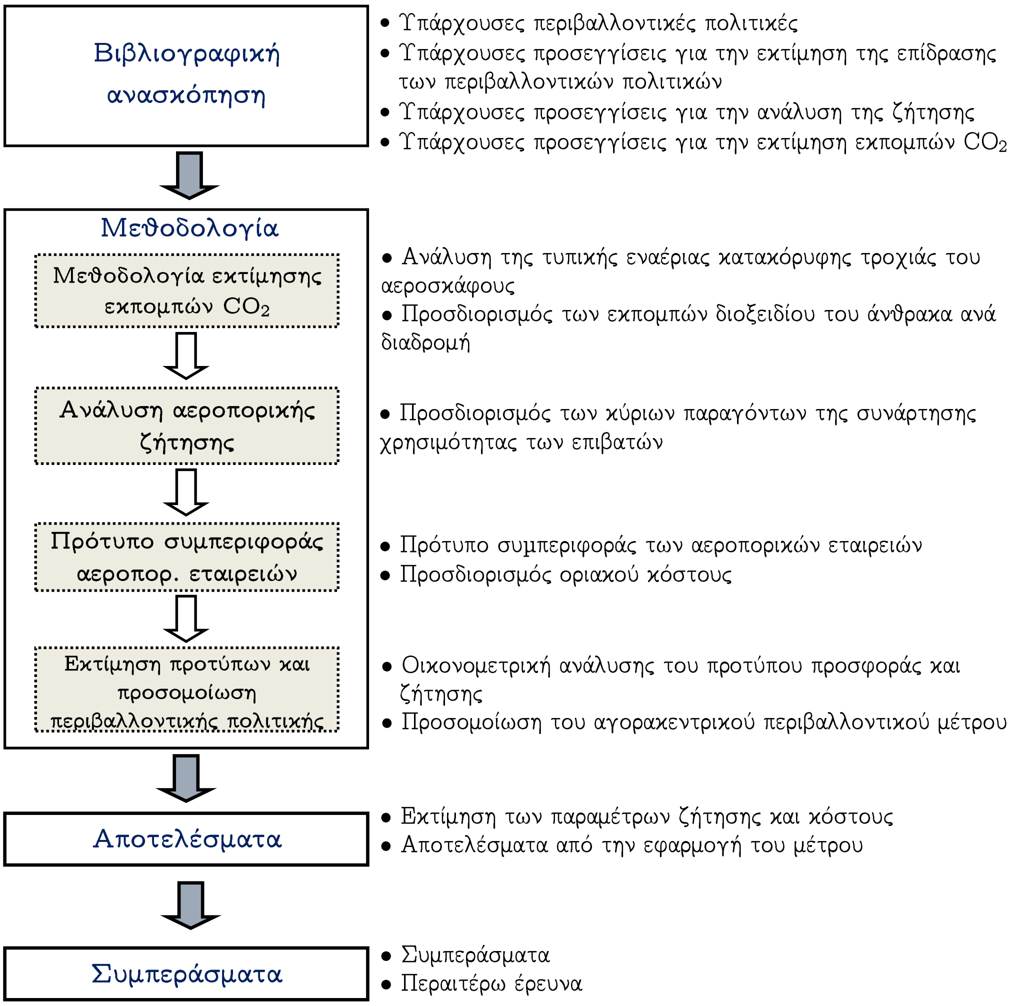
- Ταξινόμηση των πτήσεων σε μοναδικούς συνδυασμούς «απόστασης πτήσης, αεροσκάφους και προσανατολισμού πτήσης» και ανάλυση της τυπικής εναέριας κατακόρυφης τροχιάς του αεροσκάφους για κάθε συνδυασμό. Χρήση κατάλληλων εργαλείων για τον προσδιορισμό των εκπομπών διοξειδίου του άνθρακα ανά διαδρομή.

[1] Οι διακεκομμένες γραμμές προκύπτουν από γραμμική παρεμβολή λόγω έλλειψης πραγματικών στοιχείων.

- Ανάπτυξη οικονομετρικού προτύπου που ενσωματώνει ένα πρότυπο μεταφορικής ζήτησης διακριτής επιλογής, και πρότυπο συμπεριφοράς των αεροπορικών εταιρειών που δραστηριοποιούνται σε μια ολιγοπωλιακή αγορά.
- Προσδιορισμός των κύριων παραγόντων της συνάρτησης χρησιμότητας των επιβατών και της συνάρτησης κόστους των αεροπορικών εταιρειών. Εκτίμηση των παραμέτρων ζήτησης και κόστους με τη χρήση κατάλληλων οικονομετρικών μεθόδων.
- Αναπροσαρμογή του προτύπου συμπεριφοράς των αεροπορικών εταιρειών ώστε στο οριακό κόστος κάθε αεροπορικής εταιρείας να ενσωματωθεί το κόστος εκπομπών διοξειδίου του άνθρακα.
- Προσδιορισμός των μεριδίων αγοράς και των τιμών εισιτηρίων σε ισορροπία ανά αεροπορική σύνδεση μετά την εφαρμογή του αγορακεντρικού περιβαλλοντικού μέτρου. Επίσης, προσδιορίζεται η επίδραση στις συνολικές εκπομπές CO_2.

Η εργασία περιλαμβάνει εφαρμογή στο αεροπορικό δίκτυο των Ηνωμένων Πολιτειών για το οποίο υπάρχει δημόσια διαθέσιμη βάση δεδομένων. Τα δεδομένα παρέχουν στοιχεία αναφορικά με τα χαρακτηριστικά κάθε αεροπορικής σύνδεσης, τα αεροδρόμια προέλευσης-προορισμού και την αεροπορική εταιρεία που εκτελεί το δρομολόγιο. Τα παραπάνω δεδομένα αεροπορικής κίνησης συνδυάζονται με δεδομένα άλλων βάσεων απαραίτητων για τη εφαρμογή της μελέτης και χρησιμοποιούνται μετά από κατάλληλη επεξεργασία.

Στην εργασία αναλύονται οι παράγοντες που επηρεάζουν τις εκπομπές διοξειδίου του άνθρακα των αεροσκαφών και αναπτύσσεται μέθοδος εκτίμησης των σχετικών εκπομπών. Για το σκοπό αυτό αναπτύσσονται δύο προσεγγίσεις: (i) εφαρμογή προτύπου προσομοίωσης της λειτουργίας ενός αεροσκάφους και (ii) υπολογισμός της τυπικής εναέριας τροχιάς του αεροσκάφους μετά από ευθυγράμμιση κατάλληλου δείγματος ιστορικών στοιχείων με βάση τα σημεία (landmark registration). Για την εφαρμογή των δύο προσεγγίσεων απαιτείται εκτενή συλλογή στοιχείων της εναέριας τροχιάς των αεροσκαφών. Επίσης, στην εργασία διερευνώνται τα πρότυπα διακριτής επιλογής που μέχρι σήμερα έχουν εφαρμοστεί στην επιλογή αεροπορικής σύνδεσης. Το ιεραρχικό πρότυπο logit (nested logit model) χρησιμοποιείται για την περιγραφή της αεροπορικής ζήτησης. Η συμπεριφορά των εταιρειών βασίζεται στην υπόθεση ότι οι εταιρείες που δραστηριοποιούνται σε μια αγορά διαμορφώνουν τις τιμές των εισιτηρίων υπό συνθήκες ολιγοπωλιακού ανταγωνισμού και καθορίζεται από ένα μη συνεργατικό παίγνιο. Τέλος, προσομοιώνεται η εφαρμογή αγορακεντρικού περιβαλλοντικού μέτρου και προσδιορίζονται τα μερίδια αγοράς και οι τιμές εισιτηρίων σε ισορροπία ανά αεροπορική σύνδεση, καθώς και η επίπτωση του μέτρου στις συνολικές εκπομπές διοξειδίου του άνθρακα. Η υλοποίηση της μεθοδολογίας πραγματοποιήθηκε αλγοριθμικά σε περιβάλλον MATLAB. Το μεθοδολογικό πλαίσιο της διδακτορικής διατριβής παρουσιάζεται στο Σχήμα 2 και προσδιορίζει τη δομή της παρούσας εκτεταμένης περίληψης.



Σχήμα 2. Μεθοδολογικό πλαίσιο της διδακτορικής διατριβής

2. Βιβλιογραφική Ανασκόπηση

2.1. Υπάρχουσες περιβαλλοντικές πολιτικές

Τα αγορακεντρικά περιβαλλοντικά μέτρα αποτελούνται από μια σειρά πολιτικών οι οποίες βασίζονται στην εσωτερίκευση του εξωτερικού περιβαλλοντικού κόστους στα πλαίσια της αρχής «ο ρυπαίνων πληρώνει» και τη δημιουργία οικονομικών κινήτρων για τη βιώσιμη ανάπτυξη της αεροπορικής βιομηχανίας.

Το πιο γνωστό μέτρο είναι το Σύστημα Εμπορίας Δικαιωμάτων Εκπομπών (ΣΕΔΕ) της Ευρωπαϊκής Ένωσης (Ε.Ε.), το οποίο αποτελεί σύστημα «επιβολής ανώτατου ορίου και εμπορίας». Με οδηγία του Ευρωπαϊκού Κοινοβουλίου (EU, 2008), το ΣΕΔΕ είχε σχεδιαστεί ώστε να περιλαμβάνει αεροπορικές δραστηριότητες τόσο από ενδοκοινοτικές πτήσεις της Ε.Ε. όσο και από πτήσεις (εκτός Ε.Ε.) με την προϋπόθεση ότι αναχωρούν ή φθάνουν σε ευρωπαϊκά αεροδρόμια. Αυτό σήμαινε ότι, για παράδειγμα, μια αμερικανική αεροπορική εταιρεία που εκτελεί πτήση από Νέα Υόρκη προς Λονδίνο θα έπρεπε να ενταχθεί στο ΣΕΔΕ. Λόγω ισχυρών αντιδράσεων από μη-Ευρωπαϊκές χώρες, όπως Ηνωμένες Πολιτείες, Κίνα, Ρωσία, Ινδία κτλ. το 2014, η οδηγία ΣΕΔΕ τροποποιήθηκε ώστε να εφαρμόζεται μόνο σε πτήσεις μεταξύ αεροδρομίων που βρίσκονται στον Ευρωπαϊκό

Οικονομικό Χώρο (EU, 2014). Επίσης, αυτή η τροποποίηση ήταν συνέπεια της αναμένουσας εφαρμογής του αγορακεντρικού περιβαλλοντικού μέτρου σε παγκόσμιο επίπεδο από το Διεθνή Οργανισμό Πολιτικής Αεροπορίας μετά το 2016 (International Civil Aviation Organization-ICAO).

Η δεύτερη μεγαλύτερη πρωτοβουλία είναι το ΣΕΔΕ της Κορέας, το οποίο τέθηκε σε ισχύ το 2015 και είναι το πρώτο εθνικό πρόγραμμα επιβολής ανώτατου ορίου και εμπορίας στην Ανατολική Ασία. Καλύπτει τις αεροπορικές μεταφορές (πτήσεις εσωτερικού) καθώς και άλλους 22 τομείς (ICAP, 2016a). Ένα χαρακτηριστικό γνώρισμα του ΣΕΔΕ της Κορέας είναι η δυνατότητα της κυβέρνησης να αυξήσει την προσφορά των δικαιωμάτων, προκειμένου να σταθεροποιείται η τιμή του δικαιώματος στις 10.000 μονάδες KRW (περίπου €7,9 ή $9).

Το ΣΕΔΕ για τις αερομεταφορές της Σανγκάης αποτελεί ένα από τα επτά πιλοτικά προγράμματα της Κίνας που εφαρμόζονται σε διάφορους τομείς. Τέθηκε σε ισχύ το 2013 και είναι το μόνο πρόγραμμα στην Κίνα, που καλύπτει τις εκπομπές αερίων του θερμοκηπίου από τις αεροπορικές μεταφορές (μόνο πτήσεις εσωτερικού).

Άλλο περιβαλλοντικό μέτρο είναι η επιβολή περιβαλλοντικών χρεώσεων για την ποσότητα των εκπομπών που παράγονται είτε σε ένα αεροδρόμιο κατά τη φάση της προσγείωσης και απογείωσης (airport charge) είτε κατά τη διάρκεια της κύριας πτήσης (en-route charge). Στην Ευρώπη, υπάρχουν αρκετά παραδείγματα τέτοιων εφαρμογών, κυρίως σε χώρες όπως η Ελβετία, η Γερμανία, το Ηνωμένο Βασίλειο, τη Δανία κτλ.

Επίσης, τα προγράμματα αντιστάθμισης του άνθρακα είναι περιβαλλοντικά προγράμματα που εφαρμόζονται, σε εθελοντικό επίπεδο μέχρι στιγμής, από διάφορες αεροπορικές εταιρείες. Έτσι, αν ο επιβάτης το επιθυμεί μπορεί να πληρώσει ένα επιπλέον κόστος ώστε να αντισταθμίσει τις αρνητικές επιπτώσεις του ταξιδιού του. Τα έσοδα αυτά συλλέγονται για τη χρηματοδότηση περιβαλλοντικών έργων. Μέχρι το 2014, πάνω από 35 αεροπορικές εταιρείες είχαν ήδη εφαρμόσει το δικό τους πρόγραμμα αντιστάθμισης άνθρακα (IATA, 2014b).

Τέλος, ο ICAO στη 39η σύνοδο τον Οκτώβριο του 2016, αποφάσισε την ανάπτυξη ενός αγορακεντρικού περιβαλλοντικού μέτρου σε παγκόσμιο επίπεδο, ως μέρος μιας ευρύτερης σειράς μέτρων (ICAO, 2013a). Ο ICAO επέλεξε ένα πρόγραμμα αντιστάθμισης των εκπομπών άνθρακα με στόχο τη σταθεροποίηση των εκπομπών που παράγονται από τις διεθνείς αερομεταφορές (Carbon Offsetting and Reduction Scheme for International Aviation-CORSIA).

2.2. Υπάρχουσες προσεγγίσεις για την εκτίμηση της επίδρασης των περιβαλλοντικών πολιτικών στην αεροπορική βιομηχανία

Η εφαρμογή συστημάτων εμπορίας εκπομπών ή άλλων μέτρων τιμολόγησης των εκπομπών αυξάνει το κόστος των αεροπορικών εταιρειών. Ο βαθμός στον οποίο το κόστος αυτό μπορεί να επηρεάσει τις στρατηγικές των αεροπορικών εταιρειών σχετικά με την τιμολόγηση των εισιτηρίων, την αεροπορική ζήτηση και το γενικό πλαίσιο του δικτύου αερομεταφορών έχει εξεταστεί από διάφορες εργασίες στο παρελθόν. Κάποιες εργασίες εξετάζουν τον αντίκτυπο στην ενδεχόμενη αναπροσαρμογή του δικτύου των αεροπορικών εταιρειών (Derigs and Illing, 2013; Hsu and Lin, 2005), στον τουρισμό (Blanc and Winchester, 2012; Peeters and Dubois, 2010; Pentelow and Scott, 2011; Tol, 2007) και στον ανταγωνισμό (Barbot et al., 2014). Άλλες εργασίες εστιάζονται στην επίδραση των πολιτικών αυτών στις τιμές των εισιτηρίων και τη ζήτηση, με τις περισσότερες από αυτές να αφορούν στην εφαρμογή του ΣΕΔΕ της Ε.Ε. (Albers et al., 2009; Anger, 2010; Mayor and Tol, 2010; Meleo et al., 2016; Miyoshi, 2014; Scheelhaase and Grimme, 2007; Scheelhaase et al., 2010). Άλλες εργασίες αφορούν την εφαρμογή πολιτικών σε χώρες όπου αυτή την στιγμή δεν εφαρμόζονται περιβαλλοντικές πολιτικές για τις αερομεταφορές. Για παράδειγμα οι Malina et al. (2012) και οι Hofer et al. (2010) εξέτασαν τις επιπτώσεις της εφαρμογής ενός τέτοιου μέτρου στις Η.Π.Α., ενώ η εργασία των Gonzalez and Hosoda (2016) αφορούσε την Ιαπωνία.

Η επισκόπηση των ανωτέρω βιβλιογραφικών αναφορών οδήγησε στα παρακάτω συμπεράσματα όσον αφορά τη μεθοδολογία και τις υποθέσεις που χρησιμοποιούν:

- Κατ' αρχάς, η πλειοψηφία των εργασιών στηρίζεται σε υπάρχουσες τιμές ελαστικότητας ζήτησης. Με άλλα λόγια, δε χρησιμοποιούν πρότυπα αεροπορικής ζήτησης αλλά ακολουθούν την εξής προσέγγιση: υπολογισμός εκπομπών CO_2 ανά διαδρομή ή εταιρεία → υπολογισμός αύξησης τιμής εισιτηρίου → υπόθεση ελαστικότητας ζήτησης (από προηγούμενες εργασίες) → εκτίμηση μεταβολής της ζήτησης.
- Επίσης, για τον υπολογισμό της αύξησης της τιμής εισιτηρίου πολλές εργασίες κάνουν απλοποιητικές υποθέσεις ως προς το ποσοστό μετακύλισης του κόστους εκπομπών στον επιβάτη.
- Τρίτον, κάποιες εργασίες δεν περιλαμβάνουν υπολογισμό των εκπομπών ανά διαδρομή κτλ αλλά χρησιμοποιούν μέσες τιμές εκπομπών CO_2.
- Τέλος, ένα ποσοστό των εργασιών περιορίζεται σε ανάλυση συγκεκριμένων διαδρομών ή μικρών αεροπορικών δικτύων. Με αυτόν τον τρόπο δεν είναι εφικτή η ανάλυση σε μακροσκοπικό επίπεδο.

2.3. Υπάρχουσες προσεγγίσεις για την ανάλυση της αεροπορικής ζήτησης

Η ανάλυση της ζήτησης ενός μεταφορικού συστήματος αποτελεί βασικό γνώμονα για τη λήψη αποφάσεων σχετικά με τη λειτουργία του, την ανάπτυξη του, την επένδυση νέων τεχνολογιών και την εφαρμογή πολιτικών σε αυτό. Τα πρότυπα μεταφορικής ζήτησης μπορούν να κατηγοριοποιηθούν: ι) σε εξατομικευμένα και αθροιστικά, όπου ανάλογα με τη λεπτομέρεια των δεδομένων λαμβάνεται υπόψη η μικροσκοπική ή μακροσκοπική θεώρηση του προβλήματος και ιι) σε γραμμικά πρότυπα ή σε πρότυπα διακριτών επιλογών (Hsiao and Hansen, 2011; Ortuzar and Willumsen, 2011; Postorino, 2010). Ανάλογα με τα δεδομένα που χρησιμοποιούνται τα αθροιστικά πρότυπα μπορεί να αφορούν διαστρωματικά στοιχεία, χρονοσειρές και δεδομένα panel. Όσον αφορά τις αεροπορικές μεταφορές, η ανάλυση χρονοσειρών έχει συχνά χρησιμοποιηθεί για την πρόβλεψη της ζήτησης (Carsona et al., 2011; Kopsch, 2012). Οι τεχνικές ανάλυσης χρονοσειρών δεν παρέχουν πληροφορία για την αιτιοκρατική συσχέτιση και ποσοτικοποίηση της εξαρτημένης ως προς τις ανεξάρτητες μεταβλητές και άρα δεν μπορεί να προβλέψει την εξέλιξη της εξαρτημένης μεταβλητής μετά από αλλαγή μιας ανεξάρτητης μεταβλητής. Για το σκοπό αυτό χρησιμοποιούνται οικονομετρικά μοντέλα τα οποία επιτρέπουν τον προσδιορισμό των ανεξάρτητων μεταβλητών, διευκρινίζουν τον τρόπο με τον οποίο πραγματοποιείται η επίδραση και ποσοτικοποιούν την επίδραση αυτή (Abed et al., 2001).

Τα αθροιστικά μοντέλα αναλύουν τα χαρακτηριστικά στο σύνολο του πληθυσμού που εξετάζεται, ενώ τα εξατομικευμένα μοντέλα χρησιμοποιούν δεδομένα για τον κάθε μετακινούμενο. Τα εξατομικευμένα πρότυπα χαρακτηρίζονται από κάποια μειονεκτήματα όπως είναι η δυσκολία εύρεσης αντιπροσωπευτικού δείγματος, το κόστος απόκτησης δεδομένων, καθώς και σε μερικές περιπτώσεις, η αδυναμία συλλογής εξατομικευμένων δεδομένων για κάθε επιβάτη (Garrow, 2010). Αντίθετα, η παροχή αθροιστικών δεδομένων αεροπορικής κίνησης από διάφορους οργανισμούς, όπως είναι το Υπουργείο Μεταφορών των Ηνωμένων Πολιτειών Αμερικής (BTS, n.d.) δίνει τη δυνατότητα στους ερευνητές να αναπτύξουν αθροιστικά μοντέλα ζήτησης. Η παρούσα διατριβή αφορά στην ανάπτυξη προτύπου αεροπορικής ζήτησης χρησιμοποιώντας αθροιστικά διαστρωματικά στοιχεία. Για το λόγο αυτό, η βιβλιογραφική ανασκόπηση επικεντρώνεται στην ανάλυση αθροιστικών προτύπων, ως προς τις μεθοδολογίες και τις ανεξάρτητες μεταβλητές που χρησιμοποιούν. Με βάση την υπάρχουσα βιβλιογραφία, οι κύριοι παράγοντες που επηρεάζουν την αεροπορική ζήτηση είναι η τιμή του εισιτηρίου, η συχνότητα πτήσεων, το μέγεθος του αεροσκάφους, κοινωνικο-οικονομικά χαρακτηριστικά (όπως το εισόδημα, ο πληθυσμός κτλ.), η απόσταση και ο χρόνος πτήσης, το επίπεδο εξυπηρέτησης κτλ.

Από την επισκόπηση της βιβλιογραφίας παρατηρήθηκε ότι τα αθροιστικά μοντέλα ζήτησης βασίζονται, σε μεγάλο βαθμό, σε πρότυπα γραμμικής παλινδρόμησης χωρίς να λαμβάνουν υπόψη την ανθρώπινη συμπεριφορά και άρα χωρίς να ενσωματώνουν μοντέλα διακριτής επιλογής στη μεθοδολογία τους (Bhadra & Kee, 2008; Mumbower et al., 2014; Sivrikaya & Tunç, 2013). Σε αυτά η εξαρτημένη μεταβλητή εκφράζεται ως ο αριθμός των επιβατών ή ο αριθμός των επιβατοχιλιομέτων ανά ζεύγος πόλεων, ανά διαδρομή, ανά εταιρεία κτλ. Λόγω ενδογένειας κάποιας ανεξάρτητης μεταβλητής (συνήθως της τιμής εισιτηρίου) πολλές από τις εργασίες εφαρμόζουν μεθόδους βοηθητικών μεταβλητών (δύο ή τριών σταδίων) για την εκτίμηση των προτύπων. Κάποιες εργασίες αφορούν την κατανομή της ζήτησης σε εναλλακτικές διαδρομές, εταιρίες και άλλα (Barnhart et al., 2014; Coldren et al. 2003; Coldren and Koppelman, 2005; Hsiao and Hansen, 2011; Wei and Hansen, 2005). Αυτές οι εργασίες ενσωματώνουν τη συμπεριφορά των επιβατών μέσω της χρήσης προτύπων διακριτών επιλογών. Σε σύγκριση με τις επίγειες μεταφορές, η χρήση τέτοιων προτύπων για την ανάλυση της συμπεριφοράς των επιβατών των αεροπορικών μεταφορών είναι αρκετά περιορισμένη. Η χρήση των προτύπων σε αθροιστικά δεδομένα οδηγεί στην εκτίμηση των μεριδίων αγοράς μέσα σε ένα σύνολο διαφορετικών διαδρομών, δρομολογίων κτλ. Οι ερμηνευτικές μεταβλητές συνήθως περιλαμβάνουν κοινωνικο-οικονομικά χαρακτηριστικά, αθροιστικά δεδομένα του "μέσου επιβάτη", δεδομένα σχετικά με το επίπεδο εξυπηρέτησης της διαδρομής (όπως η συχνότητα πτήσεων), η τιμή του εισιτηρίου κλπ. Τα δεδομένα που χρησιμοποιούνται συνήθως συλλέγονται από βάσεις δεδομένων των προγραμμάτων πτήσεων ή των συστημάτων ηλεκτρονικών κρατήσεων.

Η επίτευξη ισορροπίας μεταξύ προσφοράς και ζήτησης είναι θεμελιώδης για το σχεδιασμό ενός μεταφορικού συστήματος. Ειδικότερα, για την ανάλυση πολιτικών, είναι αναγκαία η γνώση τόσο της δομής της ζήτησης και της προσφοράς όσο και του μηχανισμού αλληλεπίδρασης τους. Σε γενικές γραμμές, η χρήση προτύπων ζήτησης για την ανάλυση μιας πολιτικής μπορεί να εξάγει ικανοποιητικά αποτελέσματα υπό την προϋπόθεση ότι οι παράγοντες που επηρεάζουν την προσφορά παραμένουν σταθεροί. Όμως, στο περιβάλλον των αεροπορικών μεταφορών, υπάρχει έντονη αλληλεπίδραση μεταξύ προσφοράς και ζήτησης. Κατά τη βιβλιογραφική ανασκόπηση εντοπίστηκε ότι υπάρχει ανάγκη περαιτέρω διερεύνησης της συμπεριφοράς των αεροπορικών εταιρειών, ως προς τη διαμόρφωση των τιμών, και την πρόβλεψη της συμπεριφοράς των επιβατών μετά από την εφαρμογή περιβαλλοντικών μέτρων, υπό το πρίσμα ενός δομικού προτύπου ζήτησης και προσφοράς. Για αυτό το λόγο η παρούσα διατριβή επεκτείνει την εργασία του Berry (1994), η οποία βασίζεται στην ανάπτυξη προτύπων διακριτών επιλογών με χρήση αθροιστικών δεδομένων, ενώ η προσφορά αναλύεται με την παραδοχή ότι οι εταιρείες μεγιστοποιούν τα κέρδη τους εντός μιας ολιγοπωλιακής ανταγωνιστικής αγοράς. Αυτή η προσέγγιση έχει χρησιμοποιηθεί ευρέως στον τομέα της βιομηχανικής οργάνωσης, ενώ μερικές προσπάθειες έχουν σημειωθεί στον τομέα των αεροπορικών μεταφορών μελετώντας (i) τα δικτύα κομβικών αεροδρομίων (Aguirregabiria and Ho, 2012; Berry et al., 2006; Israel et al., 2013), (ii) τη συγχώνευση των αεροπορικών εταιρειών (Chen and Gayle, 2013; Doi and Ohashi, 2015; Lee, 2013a), και (iii) τις αεροπορικές συμμαχίες (Gayle and Brown, 2014), ενώ δεν βρέθηκε κάποια σχετική εργασία που διερευνά μέσω αυτού του προτύπου την εφαρμογή ενός περιβαλλοντικού μέτρου (π.χ. τιμολόγηση των εκπομπών) στο δίκτυο των αερομεταφορών. Όπως υποδεικνύεται από το κεφάλαιο της μεθοδολογίας η χρήση αυτής της προσέγγισης έχει πολλά πλεονεκτήματα που έχουν ενσωματωθεί στην παρούσα διατριβή.

3. Μέθοδος υπολογισμού εκπομπών CO_2 από τα αεροσκάφη

Οι αεροπορικές μεταφορές επηρεάζουν την ατμόσφαιρα με πολλαπλούς τρόπους. Η εκπομπή διοξειδίου του άνθρακα από τα καύσιμα των αεροσκαφών έχει άμεση επίδραση στο περιβάλλον. Επίσης, τα αεροσκάφη εκπέμπουν υδρατμούς οι οποίοι συμβάλλουν στην υπερθέρμανση του πλανήτη όταν εκπέμπονται σε μεγάλα υψόμετρα. Τέλος, εκλύουν οξείδια του αζώτου (που προκαλούν το σχηματισμό του όζοντος στην ανώτερη ατμόσφαιρα) και σωματίδια που οδηγούν στο σχηματισμό νεφών, ενισχύοντας το φαινόμενο του θερμοκηπίου. Οι ρύποι των αεροσκαφών εκπέμπονται κοντά στο έδαφος κατά την προσγείωση και την απογείωση ή σε μεγάλα υψόμετρα κατά την κύρια φάση της πτήσης και οπότε επηρεάζουν την ποιότητα του τοπικού αέρα κοντά στα αεροδρόμια ή συμβάλλουν στην κλιματική αλλαγή αντίστοιχα. Σε αντιστοιχία με τις υπάρχουσες περιβαλλοντικές πολιτικές, η παρούσα διατριβή εστιάζεται στις εκπομπές διοξειδίου του άνθρακα που θεωρείται το σημαντικότερο αέριο του θερμοκηπίου (λόγω της μεγάλης διάρκειας του κύκλου ζωής του).

Η ανησυχία για την επίδραση των αεροπορικών μεταφορών στο περιβάλλον έχει ωθήσει εταιρείες, διεθνείς οργανισμούς καθώς και ερευνητές να αναπτύξουν τρόπους και μεθόδους υπολογισμού των εκπομπών των αεροσκαφών. Στην παρούσα εργασία αναπτύσσεται μια μεθοδολογία για τον υπολογισμό των εκπομπών CO_2 τόσο για τη φάση απογείωσης-προσγείωσης (Landing and Take-off-LTO) όσο και για το κύριο μέρος της πτήσης (Climb-Cruise-Descent-CCD).

Διάφορες εργασίες έχουν δημοσιευτεί σχετικά με την εκτίμηση εκπομπών των αεροσκαφών. Για τη φάση της απογείωσης-προσγείωσης (LTO), η πλειοψηφία των εργασιών επικεντρώνεται στον υπολογισμό αερίων ρύπων που επηρεάζουν την ποιότητα του τοπικού αέρα όπως HC, CO, NO_X. Άλλες εργασίες ασχολούνται επίσης με τον υπολογισμό των εκπομπών CO_2 κατά τη φάση LTO (Alonso et al., 2014; Chao, 2014; Cokorilo, 2016;

Miyoshi and Mason, 2009; Song and Shon, 2012; Symeonidis et al., 2004; Tsilingiridis, 2009; Turgut and Rosen, 2010). Για τους υπολογισμούς κατά τη φάση LTO συνήθως χρησιμοποιείται η βάση δεδομένων Engine Emissions Databank του ICAO, η οποία δίνει το ρυθμό κατανάλωσης καυσίμου για τα τέσσερα διαφορετικά στάδια του κύκλου LTO: προσέγγιση, τροχοδρόμηση, απογείωση και άνοδος στο υψόμετρο πτήσης. Στην παρούσα διατριβή, για την εφαρμογή της μεθοδολογίας χρησιμοποιείται η βάση δεδομένων Engine Emissions Databank του ICAO, με απαιτούμενα στοιχεία τον τύπο του αεροσκάφους και της μηχανής και το χρόνο κάθε φάσης (βλ. επίσης Σχήμα 3). Οι χρόνοι των διαφόρων σταδίων του LTO καθορίζονται ως εξής: για τους χρόνους τροχοδρομήσεων χρησιμοποιούνται στοιχεία από τη βάση δεδομένων Airline On-Time Performance Data που παρέχεται από το Υπουργείο μεταφορών των Η.Π.Α., ενώ για τα άλλα στάδια χρησιμοποιείται ο τυπικός κύκλος απογείωσης-προσγείωσης με βάση τον ICAO (1993). Επειδή η βάση δεδομένων Engine Emissions Databank του ICAO παρέχει ρυθμούς κατανάλωσης καυσίμου μόνο για αεριωθούμενο αεροσκάφη (jet), σε περίπτωση στροβιλοελικοφόρων (turboprop) χρησιμοποιείται η βάση δεδομένων EMEP/CORINAIR (EEA, 2013).

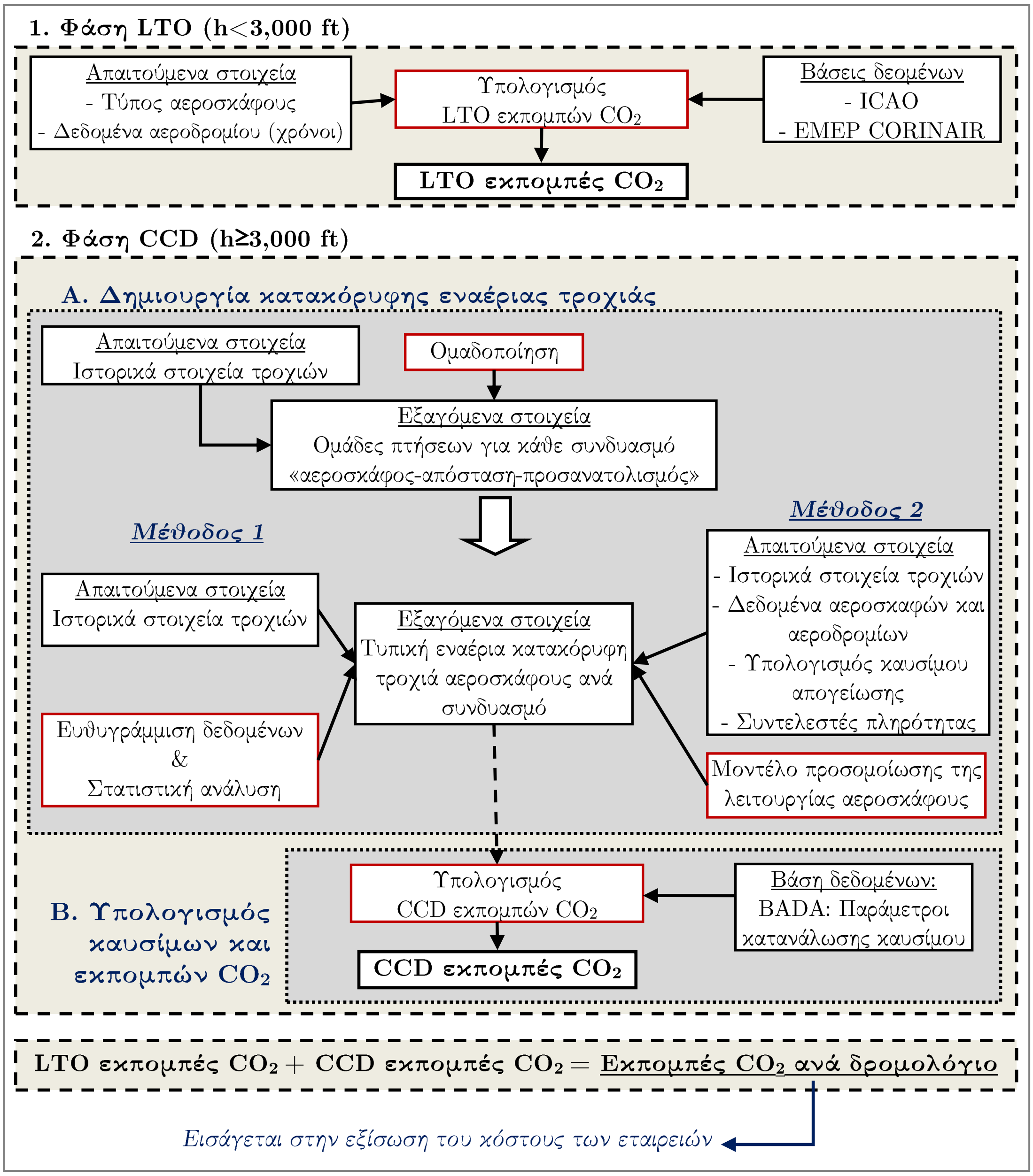
Για τον υπολογισμό των εκπομπών CO_2 κατά τη φάση της κύριας πτήσης (Climb-Cruise-Descent/CCD), η παρούσα εργασία χρησιμοποιεί τη βάση δεδομένων Base of Aircraft Data (BADA) του EUROCONTROL για τον προσδιορισμό του ρυθμού κατανάλωσης καυσίμου. Η συγκεκριμένη βάση έχει χρησιμοποιηθεί ευρέως στη σχετική βιβλιογραφία (Albers et al., 2009; Kim et al., 2007; Schaefer, 2012; Scheelhaase et al., 2010; Wasiuk et al., 2015). Για την εφαρμογή της βάσης δεδομένων BADA είναι απαραίτητη η γνώση της εναέριας κατακόρυφης τροχιάς του αεροσκάφους σε όλη τη διάρκεια της φάσης CCD. Μετά από ανάλυση ιστορικών στοιχείων διαπιστώθηκε ότι στους παράγοντες που καθορίζουν την εναέρια κατακόρυφη τροχιά του αεροσκάφους περιλαμβάνονται ο τύπος αεροσκάφους, η απόσταση πτήσης και ο προσανατολισμός της πτήσης. Άλλοι παράγοντες είναι οι καιρικές συνθήκες, περιορισμοί του ελέγχου εναέριας κυκλοφορίας κτλ. Για να εκτιμηθούν οι εκπομπές CO_2 για ένα ευρύ αεροπορικό δίκτυο με σχετικά ακριβή και γρήγορο τρόπο, θεωρήθηκε σκόπιμο να εκτιμηθεί η τυπική εναέρια κατακόρυφη τροχιά του αεροσκάφους για κάθε συνδυασμό «αεροσκάφος, απόσταση, προσανατολισμός». Στη βιβλιογραφία, η εκτίμηση εναέριας κατακόρυφης τροχιάς του αεροσκάφους έχει προσεγγιστεί βάσει δύο κύριων προσεγγίσεων: χρήση μοντέλων προσομοίωσης της τροχιάς αεροσκάφους και μεθόδων μηχανικής μάθησης.

Η βάση δεδομένων Base of Aircraft Data (BADA) του EUROCONTROL περιλαμβάνει ένα σύνολο αρχείων ASCII τα οποία περιέχουν τιμές των παραμέτρων επίδοσης διαφόρων τύπων αεροσκαφών με σκοπό να χρησιμοποιηθούν για την προσομοίωση της τροχιάς των με βάση τις τυποποιημένες διαδικασίες που συνήθως ακολουθούνται από τις αεροπορικές εταιρείες. Οι παράμετροι αυτές εισάγονται το μοντέλο προσομοίωσης της λειτουργίας του αεροσκάφους (Total Energy Model) το οποίο δίνει τη σχέση μεταξύ τριών βασικών παραμέτρων: την ώθηση (thrust), την πραγματική ταχύτητα (true airspeed) και το ρυθμό ανόδου/καθόδου (rate of climb/descent). Η προσέγγιση αυτή έχει χρησιμοποιηθεί από διάφορους ερευνητές είτε για την δημιουργία της εναέριας τροχιάς ενός αεροσκάφους (Wasiuk et al., 2015; Schaefer; 2012; Simone et al.; 2013) είτε για τον υπολογισμό της κατανάλωσης καυσίμων των αεροσκαφών όταν οι εναέριες τροχιές είναι διαθέσιμες από άλλα στοιχεία (Kim et al., 2007; Pham et al., 2010; Sheng et al., 2015; Turgut et al., 2014; Williams και Noland, 2005).

Στην παρούσα διατριβή χρησιμοποιείται η βάση δεδομένων BADA του EUROCONTROL καθώς και το μοντέλο προσομοίωσης της λειτουργίας του αεροσκάφους (Total Energy Model) ως εξής: Αρχικά, η φάση CCD διαιρείται σε μικρά διακριτά βήματα, για καθένα από τα οποία αρχικά υπολογίζονται η ταχύτητα του αεροσκάφους, το (τρέχον) υψόμετρο, η ώθηση του κινητήρα, η αεροδυναμική αντίσταση και άλλες παράμετροι. Στη συνέχεια, εφαρμόζεται η εξίσωση του μοντέλου προσομοίωσης του αεροσκάφους ώστε να υπολογιστεί ο ρυθμός ανόδου/καθόδου ως συνάρτηση της ώθησης του κινητήρα και της ταχύτητας του αεροσκάφους. Πραγματοποιείται μια επαναληπτική διαδικασία όπου το τρέχον υψόμετρο (κάθε επανάληψης) προσαυξάνεται κατά το υπολογιζόμενο ρυθμό ανόδου/καθόδου. Ως σημείο έναρξης της επαναληπτικής διαδικασίας είναι ο υπολογισμός της μέσης διάρκειας πλεύσης (cruise duration) και του μέσου υψομέτρου πλεύσης (cruise altitude) ανά συνδυασμό «αεροσκάφος, απόσταση, κατεύθυνση» (που προκύπτουν από την ανάλυση μεγάλου εύρους ιστορικών πτήσεων). Επίσης, βασικό απαιτούμενο στοιχείο αποτελεί το αρχικό βάρος του αεροσκάφους πριν την έναρξη της φάσης CCD, το οποίο υπολογίζεται συναρτήσει του ωφέλιμου βάρους ($m_{payload}$), το βάρους καυσίμου (m_{fuel}) και το βάρους άδειου αεροσκάφους (m_{OE}).

Η παραπάνω προσέγγιση βασίζεται σε τυπικές διαδικασίες και άρα ενδέχεται να μην αποτυπώνει την εναέρια τροχιά του αεροσκάφους υπό πραγματικές συνθήκες. Για αυτό το λόγο, η πρόσφατη βιβλιογραφία επικεντρώνεται σε χρήση στατιστικών μεθόδων για την ανάλυση ιστορικών εναέριων τροχιών με σκοπό την εύρεση της τυπικής εναέριας τροχιάς (Hamed, et al., 2013; Hrastovec και Solina, 2014; Nicol, 2013; Tastambekov et al., 2014). Τα αποτελέσματα αυτών των εργασιών δείχνουν ότι τα σφάλματα πρόβλεψης αυτών των μεθόδων είναι μικρότερα σε σχέση αυτών που προκύπτουν από την εφαρμογή του μοντέλου προσομοίωσης λειτουργίας αεροσκάφους με χρήση των παραμέτρων της BADA.

Για αυτό το λόγο, στην παρούσα διατριβή αναπτύσσεται επίσης μια μέθοδος για την εκτίμηση της τυπικής τροχιάς αεροσκάφους με βάση τη στατιστική ανάλυση ιστορικών τροχιών μετά από κατάλληλη ευθυγράμμιση (landmark registration). Για κάθε συνδυασμό «αεροσκάφος, απόσταση, προσανατολισμός», οι καμπύλες (τροχιές αεροσκαφών) που συλλέγονται περιέχουν πληροφορίες σχετικά με το υψόμετρο του αεροσκάφους σε κάθε χρονική στιγμή της πτήσης. Έτσι τα δεδομένα που συλλέγονται αντιμετωπίζονται ως καμπύλες και όχι ως διακριτά δεδομένα. Ένα βασικό πρόβλημα που παρατηρείται σε τέτοιου είδους δεδομένα (functional data) είναι η ύπαρξη διαφοράς φάσης (phase variation). Η εκτίμηση της τυπικής τροχιάς αεροσκάφους μέσω της χρήσης του μέσου όρου των τροχιών θα έδινε μια «μη ρεαλιστική» τροχιά. Για να αντιμετωπιστεί το πρόβλημα αυτό, οι τροχιές (καμπύλες) σε κάθε συνδυασμό «αεροσκάφος, απόσταση, προσανατολισμός» υποβάλλονται σε ευθυγράμμιση (registration) μετά από αντιστοίχιση των χαρακτηριστικών σημείων αναφοράς ή ορόσημων (landmarks) των καμπυλών. Η μέθοδος αυτή ονομάζεται ευθυγράμμιση των καμπυλών με βάση τα σημεία (landmark registration) και βασίζεται στον εντοπισμό χαρακτηριστικών σημείων αναφοράς ή ορόσημων των καμπυλών/τροχιών. Τα ορόσημα είναι σημεία που μπορούν να εντοπιστούν από τον χρήστη με αυτόματο τρόπο και τα οποία αντιστοιχούν σε εμφανή γεωμετρικά χαρακτηριστικά σημεία όπως τοπικά ακρότατα, γωνίες κλπ. Η ευθυγράμμιση γίνεται με χρήση κατάλληλων συναρτήσεων μετασχηματισμού (warping functions). Τελικά, οι ευθυγραμμισμένες τροχιές (registered profiles) πραγματοποιούνται σε κοινή κλίμακα χρόνου ώστε να είναι δυνατή η στατιστική επεξεργασία τους και η εύρεση της τυπικής εναέριας τροχιάς ανά συνδυασμό. Τα βήματα που ακολουθούνται για τον υπολογισμό των εκπομπών CO_2 φαίνονται στο Σχήμα 3.



Σχήμα 3. Μεθοδολογία υπολογισμού εκπομπών CO_2

Οι ανωτέρω προσεγγίσεις εφαρμόζονται σε ένα μεγάλο εύρος πτήσεων, για διαφορετικούς συνδυασμούς τύπων αεροσκαφών, αποστάσεων και διευθύνσεων πτήσεων. Η σύγκριση των εκτιμώμενων χαρακτηριστικών με τις προσεγγίσεις αυτές δείχνουν ότι οι τυπικές τροχιές που προκύπτουν από την ευθυγράμμιση με βάση τα σημεία (registration-based method) παράγει πιο ακριβή αποτελέσματα ως προς τη διάρκεια των διαφόρων φάσεων της πτήσης και το ρυθμό ανόδου και καθόδου. Παρά τις σημαντικές διαφορές στα εκτιμώμενα χαρακτηριστικά πτήσης μεταξύ των τυπικών τροχιών που εξάγονται από τις δύο μεθόδους, η διαφορά στην εκτίμηση των εκπομπών CO_2 είναι λιγότερο έντονη. Οι τυπικές τροχιές χρησιμοποιήθηκαν για την εκτίμηση των συνολικών εκπομπών CO_2 στο αεροπορικό δίκτυο των Η.Π.Α. Με βάση τις εκτιμήσεις της παρούσας εργασίας για το 2012, οι 4,01 εκατ. πτήσεις που αναλύθηκαν είχαν σαν αποτέλεσμα 68,4 εκατ. τόνοι CO_2 που σημαίνει 17,1 τόνοι CO_2 ανά πτήση (ή 5,41 τόνοι καυσίμου). Αυτή η εκτίμηση είναι πολύ κοντά σε υπάρχουσες εκτιμήσεις σε διάφορες γεωγραφικές περιοχές.

4. Μεθοδολογία ανάλυσης της αεροπορικής ζήτησης

Η συνάρτηση ζήτησης συνδέει την εξαρτημένη μεταβλητή (μεταφορική ζήτηση) με κάποιες ερμηνευτικές μεταβλητές, οι οποίες αποτελούν παράγοντες που επηρεάζουν τη ζήτηση. Η αεροπορική ζήτηση θα μπορούσε να εκφραστεί από τον παρακάτω γενικό τύπο:

$$q = f(p, x, \varepsilon) \qquad \textbf{Εξ. 1}$$

όπου q είναι η εξαρτημένη μεταβλητή (αεροπορική ζήτηση), p είναι η τιμή του εισιτηρίου, x είναι οι επεξηγηματικές (ή ανεξάρτητες) μεταβλητές που επηρεάζουν τη ζήτηση, όπως η απόσταση διαδρομής, το επίπεδο εξυπηρέτησης και άλλα χαρακτηριστικά που σχετίζονται με το συγκεκριμένο δρομολόγιο, τον επιβάτη και ε είναι το σφάλμα της εξίσωσης.

Στην παρούσα διατριβή η μεταφορική ζήτηση για κάθε εναλλακτική αναλύεται με πρότυπα διακριτών επιλογών εντός ζευγών πόλεων Προέλευσης-Προορισμού (Π-Π). Σε ένα δεδομένο δίκτυο, υπάρχει ένα σύνολο πόλεων Π-Π, στα οποία κάθε επιβάτης μπορεί να επιλέξει να ταξιδέψει αεροπορικώς, να ταξιδέψει με άλλο μέσο μεταφοράς ή να μην ταξιδέψει. Αν ο επιβάτης επιλέξει να μην ταξιδέψει αεροπορικώς (δηλ. να ταξιδέψει με άλλο μέσο ή να μην ταξιδέψει καθόλου), τότε θεωρούμε ότι επέλεξε τη μη-αεροπορική επιλογή. Ορίζουμε τα εξής:

- «Αγορά» προσδιορίζεται ως το ζεύγος πόλεων Προέλευσης-Προορισμού (Π-Π). Σε μία αγορά οι αεροπορικές εταιρείες προσφέρουν αεροπορικές συνδέσεις που διαφοροποιούνται ως προς τα χαρακτηριστικά τους.
- Κάθε «αεροπορική σύνδεση» προσδιορίζεται ως ο μοναδικός συνδυασμός «Αεροδρόμιο Προέλευσης, Αεροδρόμιο Ανταπόκρισης, Αεροδρόμιο Προορισμού, Αεροπορική εταιρεία, Περίοδος επιλογής». Κάθε επιβάτης επιλέγει να εξυπηρετηθεί από τη σύνδεση που μεγιστοποιεί τη χρησιμότητα του. Επειδή τα διαθέσιμα στοιχεία αφορούν τριμηνιαία στοιχεία τελικά ως αεροπορική σύνδεση θεωρούμε το συνδυασμό «Αεροδρόμιο Προέλευσης, Αεροδρόμιο Ανταπόκρισης, Αεροδρόμιο Προορισμού, Αεροπορική εταιρεία, Τρίμηνο επιλογής».

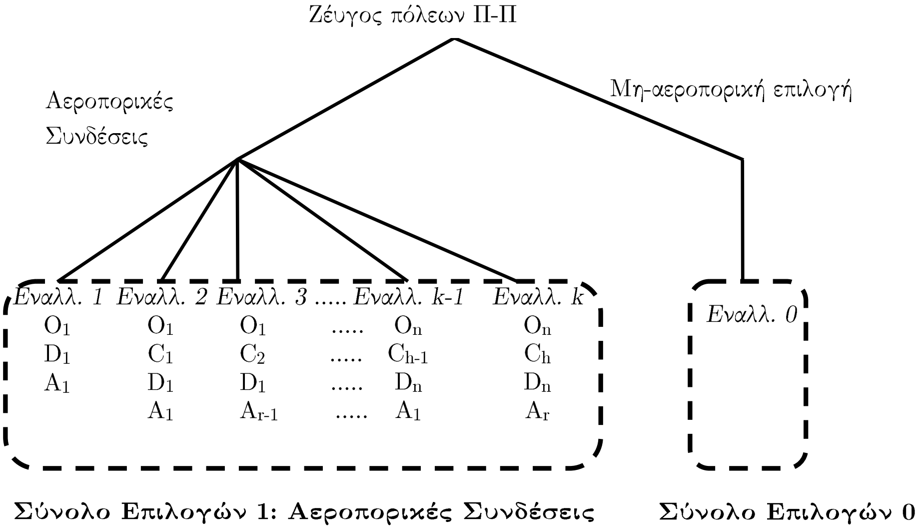
Η ζήτηση μιας αεροπορικής σύνδεσης (q_{jm}) μέσα σε ένα ζεύγος πόλεων (αγορά) m (εκφρασμένη σε αριθμό επιβατών) δίνεται από την Εξ. 2.

$$q_{jm} = Q_m \cdot MS_{jm} \qquad \textbf{Εξ. 2}$$

Ο όρος Q_m αντιπροσωπεύει τον δυνητικό αριθμό των επιβατών μεταξύ των πόλεων Π-Π και μπορεί να προσδιοριστεί με τη χρήση μοντέλων βαρύτητας συναρτήσει δημογραφικών και κοινωνικοοικονομικών χαρακτηριστικών της αγοράς. Μια κοινή προσέγγιση που χρησιμοποιείται είναι να προσδιορίζεται με βάση τον πληθυσμό των δύο πόλεων. Σε αντιστοιχία με την υπάρχουσα βιβλιογραφία, στην διατριβή αυτή λαμβάνεται ότι ο όρος Q_m είναι ίσος με το γεωμετρικό μέσο όρο των πληθυσμών των πόλεων Π-Π. Ο όρος MS_{jm} αποτελεί το μερίδιο αγοράς που έχει κάθε αεροπορική σύνδεση εντός της αγοράς και προσδιορίζεται με τη χρήση προτύπων διακριτών επιλογών. Με βάση αυτά τα πρότυπα ο μετακινούμενος αξιολογεί τις εναλλακτικές διακριτές επιλογές που έχει με βάση τη μεγιστοποίηση της χρησιμότητας που συνδέεται με κάθε επιλογή.

Το πιο διαδεδομένο πρότυπο διακριτών επιλογών είναι το πολυωνυμικό πρότυπο logit (Multinomial Logit model). Η ανεξαρτησία και ταυτοσημία των κατανομών των σφαλμάτων της χρησιμότητας θέτει τον περιορισμό ότι οι εναλλακτικές επιλογές που έχει ο μετακινούμενος πρέπει να είναι ανεξάρτητες. Όταν δεν ισχύει αυτό (δηλαδή υπάρχουν ομάδες που περιέχουν επιλογές που μεταξύ τους είναι πιο όμοιες από ότι με άλλες, όπως για παράδειγμα όλες οι αεροπορικές συνδέσεις σε σχέση με τη μη-αεροπορική επιλογή), τότε εφαρμογή του πολυωνυμικού προτύπου logit θα οδηγήσει σε μη αξιόπιστες εκτιμήσεις των συντελεστών των συναρτήσεων χρησιμότητας.

Το ιεραρχικό πρότυπο logit (nested logit model) θεωρεί ότι ο μμετακινούμενος χωρίζει την μετακίνηση του σε διάφορα στάδια και στην συνέχεια ακολουθεί μια διαδοχική διαδικασία λήψης αποφάσεων, όπως φαίνεται στο Σχήμα 4. Έτσι οι διαφορετικές εναλλακτικές επιλογές που συσχετίζονται, ομαδοποιούνται και αναπαρίστανται με μια σύνθετη μεταβλητή που συνδέεται με μια σύνθετη συνάρτηση ωφέλειας. Στο Σχήμα 4, φαίνεται ότι οι μετακινούμενοι αρχικά επιλέγουν το μέσο μεταφοράς (αεροπορικώς ή μη) και στην συνέχεια αν επιλέξουν το αεροπορικό μέσο, έχουν διάφορες εναλλακτικές αεροπορικές συνδέσεις. Οι αεροπορικές συνδέσεις ομαδοποιούνται σε ένα σύνολο (Σύνολο 1) ενώ η μη-αεροπορική επιλογή είναι η μοναδική του συνόλου 0.



Σημειώσεις: $O_{1,\dots,n}$: Αεροδρόμιο προέλευσης, $C_{1,\dots,h}$: Αεροδρόμιο Ανταπόκρισης, $D_{1,\dots,n}$: Αεροδρόμιο προορισμού, $A_{1,\dots,r}$: Αεροπορική εταιρεία

Σχήμα 4: Δέντρο διαχωρισμού επιλογών του επιβάτη με βάση το ιεραρχικό πρότυπο logit (Nested Logit model)

Η χρησιμότητα ενός επιβάτη i που επιλέγει την αεροπορική σύνδεση j σε μια αγορά (ζεύγος πόλεων Π-Π) δίνεται από την παρακάτω εξίσωση (για ευκολία παραλείπεται ο δείκτης m της αγοράς):

$$U_{ij} = x_j\beta - \alpha p_j + \xi_j + \varepsilon_{ij} \quad \textbf{Εξ. 3}$$

όπου p_j είναι η μέση τιμή εισιτηρίου της αεροπορικής σύνδεσης και x_j είναι τα λοιπά παρατηρούμενα χαρακτηριστικά της αεροπορικής σύνδεσης. Τα παρατηρούμενα χαρακτηριστικά κάθε αεροπορικής σύνδεσης μπορεί να σχετίζονται με την αεροπορική εταιρεία και τη διαδρομή πτήσης (απόσταση, συχνότητα πτήσεων, χωρητικότητα δρομολογίου, τιμή εισιτηρίου), με τα αεροδρόμια που εξυπηρετούνται (καθυστερήσεις, ύπαρξη συντονισμένων αεροδρομίων στο δρομολόγιο) και με δημογραφικά στοιχεία (εισόδημα). Οι παράμετροι α και β είναι παράμετροι του μοντέλου που πρέπει να εκτιμηθούν.

Ο όρος ξ_j περιλαμβάνει τα χαρακτηριστικά της αεροπορικής σύνδεσης που δεν παρατηρούνται από τους ερευνητές (λόγω της φύσης των στοιχείων που υπεισέρχονται στα αθροιστικά μοντέλα) και άρα δεν μπορούν να περιληφθούν στο διάνυσμα x_j, αλλά λαμβάνονται υπόψη από τους επιβάτες κατά τη διαδικασία επιλογής της αεροπορικής σύνδεσης. Σημειώνεται ότι ο όρος ξ_j διαφοροποιείται για κάθε σύνδεση j αλλά όχι για κάθε επιβάτη. Για αυτό μπορεί να θεωρηθεί ότι αντιπροσωπεύει τη μέση τιμή των αποτιμήσεων των επιβατών ως προς τα μη παρατηρούμενα χαρακτηριστικά κάθε σύνδεσης (Berry, 1994). Τέτοια χαρακτηριστικά μπορεί να είναι η ακριβής ώρα αναχώρησης, η ύπαρξη wifi στο αεροπλάνο, η ποιότητα του φαγητού εν πτήσει κτλ.

Το ε_{ij} είναι ένα διάνυσμα όρων σφάλματος της χρησιμότητας του επιβάτη. Με βάση τον Nevo (2011), ο όρος ε_{ij} διαφοροποιεί τους επιβάτες ως προς τις επιλογές που κάνουν ακόμα και αν έρχονται αντιμέτωποι με εναλλακτικές που είναι ίδιες (δηλαδή όλα τα χαρακτηριστικά j είναι ίδια). Για το ιεραρχικό πρότυπο logit ο τυχαίος όρος ε_{ij} έχει την ακόλουθη αθροιστική κατανομή:

$$exp\left(-\sum\nolimits_{k=1}^{K}\left(\sum\nolimits_{j\in B_k} e^{-\varepsilon_{ij}/\lambda_k}\right)^{\lambda_k}\right) \quad \textbf{Εξ. 4}$$

Με βάση τον Berry (1994), ο στοχαστικός όρος ε_{ij} μπορεί να εκφραστεί ως $\varepsilon_{ij}=v_i(\lambda)+\lambda e_{ij}$. Η παράμετρος λ εκφράζει το μέτρο του βαθμού ανεξαρτησίας μεταξύ των αεροπορικών εναλλακτικών επιλογών στο σύνολο επιλογών 1. Παίρνει τιμές από 0 έως 1 και ψηλότερη τιμή του λ σημαίνει μεγαλύτερη ανεξαρτησία και λιγότερη συσχέτιση. Όταν λ=1, τότε η συσχέτιση των αεροπορικών επιλογών πηγαίνει στο μηδέν και το ιεραρχικό πρότυπο logit«ισοδυναμεί» με το πολυωνυμικό πρότυπο logit. Ο όρος $v_i(\lambda)$ είναι μια τυχαία μεταβλητή που είναι σταθερή σε όλες τις αεροπορικές συνδέσεις (μέσα στο σύνολο επιλογών 1) και τις διαφοροποιεί από το σύνολο επιλογών 0. Ο όρος e_{ij} είναι μια ανεξάρτητη και όμοια κατανεμημένη τυχαία μεταβλητή (independent and identically distributed-iid) ως προς τους επιβάτες. Με βάση τους Berry (1994) και Cardell (1991), αν η e_{ij} έχει την ανωτέρω κατανομή, τότε η μεταβλητή $v_i(\lambda)$ ακολουθεί μια κατανομή τέτοια ώστε $\varepsilon_{ij}=v_i(\lambda)+\lambda e_{ij}$ είναι μια τυχαία μεταβλητή ακραίων τιμών (extreme value random variable)

Χρησιμοποιώντας τις εξισώσεις των πιθανοτήτων επιλογής για το ιεραρχικό πρότυπο logit και μετά από διαδοχικές αλγεβρικές πράξεις που παρουσιάζονται στο Παράρτημα Α (χρήση του μεριδίου αγοράς των αεροπορικών συνδέσεων και της μη-αεροπορικής επιλογής και κατάλληλο λογαριθμικό μετασχηματισμό) προκύπτει η παρακάτω εξίσωση, η οποία αποτελεί την τελική εξίσωση της ζήτησης προς εκτίμηση των παραμέτρων α, β και λ.

$$lnMS_j - lnMS_0 = x_j\beta - \alpha p_j + (1-\lambda)\cdot lnMS_{j/g} + \xi_j \qquad \textbf{Εξ. 5}$$

Ο όρος $lnMS_j - lnMS_0$ αποτελεί την εξαρτημένη μεταβλητή της εξίσωσης, όπου MS_j είναι το μερίδιο αγοράς της αεροπορικής σύνδεσης j (ποσοστό των επιβατών που επιλέγουν το j) και MS_0 είναι το ποσοστό των επιβατών που δεν ταξιδεύουν αεροπορικώς (είτε επιλέγουν άλλο μεταφορικό μέσο είτε δεν ταξιδεύουν καθόλου). Με τη χρήση της Εξ. 5 και των διαθέσιμων στοιχείων (μερίδιο αγοράς και τιμές των χαρακτηριστικών) μπορούν να εκτιμηθούν οι συντελεστές β, α και λ.

Η διαμόρφωση της Εξ. 5 όπου ο όρος ξ_j είναι ο διαταρακτικός όρος της εξίσωσης ζήτησης δημιουργεί το πρόβλημα της ενδογένειας. Αυτό το πρόβλημα μπορεί να προκύψει με τη χρήση αθροιστικών μοντέλων και απορρέει από το γεγονός ότι μία ή περισσότερες ανεξάρτητες μεταβλητές του μοντέλου μπορεί να συσχετίζονται με το διαταρακτικό όρο. Αυτές οι ανεξάρτητες μεταβλητές λέγονται ενδογενείς και στο συγκεκριμένο μοντέλο είναι η τιμή του εισιτηρίου p_j και το εξαρτημένο μερίδιο αγοράς $MS_{j/g}$. Αυτό συμβαίνει γιατί στον διαταρακτικό όρο ξ_j της εξίσωσης ενδέχεται να περιλαμβάνονται παράγοντες τους οποίους λαμβάνουν υπόψη οι επιβάτες όταν κάνουν τις διακριτές επιλογές τους (και άρα διαμορφώνουν τα μερίδια αγοράς) αλλά δεν παρατηρούνται από τους ερευνητές. Το πρόβλημα της ενδογένειας αντιμετωπίζεται με την εκτίμηση της εξίσωσης με μεθόδους βοηθητικών μεταβλητών (Instrumental Variables methods). Η εκτίμηση της Εξ. 5 με την μέθοδο των ελαχίστων τετραγώνων (Ordinary Least Squares-OLS) θα έδινε μη συνεπείς εκτιμήσεις. Στην διατριβή αυτή χρησιμοποιείται η Γενικευμένη Μέθοδος των Ροπών (Generalized Method of Moments-GMM) για την εκτίμηση των παραμέτρων ζήτησης, όπως αναλύεται στο Κεφάλαιο 6 της παρούσας περίληψης. Οι μεταβλητές x_j που χρησιμοποιήθηκαν ως ερμηνευτικές μεταβλητές στην συνάρτηση ζήτησης αναλύονται στο Κεφάλαιο 8 της περίληψης.

5. Μεθοδολογία ανάλυσης της συμπεριφοράς των αεροπορικών εταιρειών

Σε κάθε αγορά (ζεύγος πόλεων προέλευσης-προορισμού), ο αριθμός των αεροπορικών εταιρειών είναι σχετικά μικρός. Υποθέτουμε ότι κάθε εταιρεία διαμορφώνει τις τιμές των εισιτηρίων της ταυτόχρονα με τις άλλες εταιρείες που δραστηριοποιούνται στην ίδια αγορά (ταυτόχρονο παίγνιο). Οπότε οι τιμές που διαμορφώνονται εξαρτώνται όχι μόνο από τις αποφάσεις της ίδιας εταιρείας αλλά και τις αποφάσεις των ανταγωνιστών της. Υπό συνθήκες ολιγοπωλιακού ανταγωνισμού, υποθέτουμε ότι οι τιμές των εισιτηρίων διαμορφώνονται με βάση το υπόδειγμα Bertrand.

Σε κάθε αγορά (ζεύγος πόλεων Π-Π), υπάρχουν διάφορες αεροπορικές εταιρείες που δραστηριοποιούνται. Αυτές οι αεροπορικές εταιρείες προσφέρουν διαφοροποιημένες αεροπορικές συνδέσεις και ανταγωνίζονται μεταξύ τους, προκειμένου να προσελκύσουν περισσότερους επιβάτες και να έχουν περισσότερα έσοδα και κέρδη. Το τελικό όφελος μιας αεροπορικής εταιρίας εξαρτάται όχι μόνο από τις δικές της αποφάσεις, αλλά και τις αποφάσεις των ανταγωνιστών της. Ανάλογα με τη δομή της αγοράς, οι αγορές μπορούν να διακριθούν σε μονοπώλια, ολιγοπώλια, αγορές με τέλειο ανταγωνισμό και αγορές με μονοπωλιακό ανταγωνισμό. Η διάκριση αυτή γίνεται με βάση τον αριθμό των παικτών στην αγορά, την ισχύ κάθε παίκτη, το βαθμό διαφοροποίησης των προϊόντων κ.λπ. Στην αγορά με τέλειο ανταγωνισμό υπάρχει ένας μεγάλος αριθμός επιχειρήσεων που παράγουν το ίδιο προϊόν (ονομάζεται επίσης τυποποιημένο ή ομοιογενές προϊόν). Στο μονοπώλιο υπάρχει μόνο μία εταιρεία και παράγει ένα μοναδικό προϊόν που δεν έχει άμεσα υποκατάστατα. Ο μονοπωλιακός ανταγωνισμός είναι ένα είδος ατελούς ανταγωνισμού, όπου υπάρχει ένας μεγάλος αριθμός επιχειρήσεων που παράγουν διαφοροποιημένα προϊόντα και ως εκ τούτου δεν είναι τέλεια υποκατάστατα. Τέλος, σε ένα ολιγοπώλιο υπάρχουν λίγες επιχειρήσεις που παράγουν είτε ένα τυποποιημένο προϊόν ή διαφοροποιημένα προϊόντα. Κάθε επιχείρηση επηρεάζει την αγορά (σε αντίθεση με τον τέλειο ανταγωνισμό), αλλά επηρεάζεται επίσης από τις ενέργειες των άλλων επιχειρήσεων στην αγορά (σε αντίθεση με τα μονοπώλια).

Η αεροπορική βιομηχανία, ιδιαίτερα αυτή των Η.Π.Α., ακολουθεί τη δομή μιας ολιγοπωλιακής αγοράς για τους εξής λόγους. Πρώτον, το μεγαλύτερο μερίδιο αγοράς κατέχεται από μια μικρή ομάδα αεροπορικών εταιρειών. Με βάση στοιχεία του 2015, εννέα μεγάλες αεροπορικές εταιρείες κατείχαν το 83,5% από το σύνολο των εσόδων που προέρχονται από πτήσεις εσωτερικού (MIT, 2016a). Δεύτερον, οι αεροπορικές εταιρείες προσφέρουν διαφοροποιημένα προϊόντα. Παρά το γεγονός ότι οι αεροπορικές συνδέσεις μπορεί να φαίνονται ότι έχουν όμοια χαρακτηριστικά, οι αεροπορικές εταιρείες σε μια προσπάθεια να προσελκύσουν μεγαλύτερο μερίδιο αγοράς διαφοροποιούν τα «προϊόντα» τους ως προς το επίπεδο εξυπηρέτησης (π.χ. συχνότητα πτήσεων, υπηρεσίες προς επιβάτες κτλ). Τρίτον, η είσοδος μιας νέας εταιρείας στην αεροπορική βιομηχανία είναι σχετικά δύσκολη λόγω υψηλού κόστους εκκίνησης, νομικές διαδικασίες κτλ. Το βασικό γνώρισμα μιας ολιγοπωλιακής αγοράς είναι το γεγονός ότι οι αποφάσεις μιας εταιρείας εξαρτώνται άμεσα με τις αποφάσεις των ανταγωνιστών της.

Το πρότυπο συμπεριφοράς των αεροπορικών εταιρειών που αναπτύσσεται σε αυτή τη διατριβή στηρίζεται στην υπόθεση ότι οι εταιρείες που δραστηριοποιούνται εντός μιας ολιγοπωλιακής αγοράς αλληλοεπιδρούν με άλλους ανταγωνιστές μέσω μη-συνεργατικών παιγνίων. Καθεμία από τις εταιρείες καθορίζουν τις τιμές εισιτηρίων τους (υπόδειγμα ανταγωνισμού Bertrand) με στόχο να μεγιστοποιήσουν τα κέρδη τους. Λόγω του ανταγωνισμού, οι τιμές που διαμορφώνονται εξαρτώνται όχι μόνο από τις αποφάσεις της ίδιας εταιρείας αλλά και τις αποφάσεις των ανταγωνιστών της. Σύμφωνα με το βασικό υπόδειγμα Bertrand, αν οι αεροπορικές συνδέσεις ήταν ομοιογενείς τότε η τιμή θα ήταν το μοναδικό κριτήριο επιλογής των επιβατών. Οπότε, οι εταιρείες θα διαμόρφωναν την ίδια τιμή εισιτηρίου, η οποία θα ήταν ίση με το οριακό κόστος της εξυπηρέτησης ενός ακόμα επιβάτη και άρα τα κέρδη τους θα ήταν μηδενικά. Αυτό ονομάζεται το παράδοξο του Bertrand. Το παράδοξο αποτέλεσμα του Bertrand εξαρτάται από τις υποθέσεις του υποδείγματος. Η άρση κάποιας από τις υποθέσεις του υποδείγματος, όπως για παράδειγμα υπόθεση διαφοροποιημένων και όχι ομοιογενών προϊόντων, συνεπάγεται ότι το παράδοξο του Bertrand παύει να ισχύει. Όπως προαναφέρθηκε, σε μια αεροπορική αγορά οι αεροπορικές συνδέσεις είναι διαφοροποιημένες, οι επιβάτες δεν ενδιαφέρονται μόνο για την τιμή αλλά και για τα άλλα χαρακτηριστικά τους, οπότε οι εταιρείες μπορούν να θέσουν τιμές εισιτηρίων πάνω από το οριακό κόστος.

Τα κέρδη μιας εταιρείας f που προσφέρει την αεροπορική σύνδεση j εντός της αγοράς προκύπτουν ως συνάρτηση των εσόδων και του κόστους (Εξ. 6).

$$\pi_f = \sum_{j \in J_f} (p_j \cdot M \cdot MS_j - c_j \cdot M \cdot MS_j) - FC_f \Rightarrow$$
$$\pi_f = \sum_{j \in J_f} (p_j - c_j) \cdot M \cdot MS_j - FC_f \qquad \textbf{Εξ. 6}$$

όπου c_j είναι το οριακό κόστος της αεροπορικής σύνδεσης j, FC_f είναι το σταθερό κόστος. Το μερίδιο αγοράς MS_j προσδιορίστηκε στο μοντέλο της ζήτησης ενώ ο όρος M είναι το μέγεθος της αγοράς ώστε το γινόμενο $M{\cdot}MS_j$ να υποδηλώνει τον αριθμό των επιβατών που επιλέγουν τη σύνδεση j.

Για να βρούμε την ισορροπία Nash στο υπόδειγμα Bertrand χρησιμοποιούμε τη συνθήκη πρώτης τάξης στην Εξ. 6 ως προς την τιμή του εισιτηρίου. Για κάθε σύνδεση j, η εταιρεία f επιλέγει την τιμή p_j ώστε να μεγιστοποιήσει το κέρδος της π_f. Όπως φαίνεται στην Εξ. 7 οι αεροπορικές εταιρείες επιλέγουν τιμή εισιτηρίου μεγαλύτερη από το οριακό κόστος κατά ένα ποσό που προσδιορίζει το περιθώριο κέρδους τους.

$$\frac{\partial \pi_f}{\partial p_j} = 0 \Rightarrow \sum_{k \in J_f} \left(\frac{\partial p_k}{\partial p_j} \cdot M \cdot MS_k + p_k \cdot M \cdot \frac{\partial MS_k}{\partial p_j} - c_k \cdot M \cdot \frac{\partial MS_k}{\partial p_j} \right) + \frac{\partial FC_f}{\partial p_j} = 0 \Rightarrow$$
$$p_f = \left(\underbrace{-D^{-1}_{MS_f, p_f} \cdot MS_f}_{\text{περιθώριο κέρδους}} \right) + \underbrace{c_f}_{\text{οριακό κόστος}} \qquad \textbf{Εξ. 7}$$

Ο όρος D_{MS_f, p_f} αντιπροσωπεύει τον πίνακα διαστάσεων $J_f \times J_f$ των μερικών παραγώγων του μεριδίου αγοράς MS_j ως προς την τιμή ως ακολούθως (Εξ. 8):

$$D_{MS_f, p_f} = \begin{bmatrix} \frac{\partial MS_1}{\partial p_1} & \cdots & \frac{\partial MS_J}{\partial p_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial MS_1}{\partial p_J} & \cdots & \frac{\partial MS_J}{\partial p_J} \end{bmatrix} \qquad \textbf{Εξ. 8}$$

Η παραπάνω προσέγγιση βασίζεται σε μια στατική ισορροπία Nash στις τιμές και, επομένως, στηρίζεται σε μερικές απλοποιητικές υποθέσεις. Πρώτον, υποθέτουμε ότι οι παίκτες έχουν πλήρη πληροφόρηση (δηλαδή γνωρίζουν τα χαρακτηριστικά του παιχνιδιού). Δεύτερον, στην πραγματικότητα οι αεροπορικές εταιρείες δεν έχουν μόνο μια μεταβλητή απόφασης (την τιμή εισιτηρίου). Για παράδειγμα άλλη μεταβλητή απόφασης μπορεί να είναι η συχνότητα των δρομολογίων τους. Στην παρούσα διατύπωση του παιγνίου θεωρούμε ότι οι λοιπές αποφάσεις (εκτός από την τιμή) είναι εξωγενείς και δεν λαμβάνονται υπόψη κατά τη διαδικασία απόφασης της εταιρείας. Επιπλέον, στην πραγματικότητα οι τιμές των εισιτηρίων δεν διαμορφώνονται ως συνάρτηση του κόστους αλλά προκύπτουν μέσω διαχείρισης των εσόδων (revenue management) με πιο πολύπλοκες τεχνικές προκειμένου να μεγιστοποιήσουν τα αναμενόμενα έσοδα και να αντιμετωπίσουν την αβεβαιότητα της ζήτησης (Donovan, 2005). Η ενσωμάτωση τέτοιων τεχνικών στο παραπάνω πρότυπο απαιτεί πιο λεπτομερή δεδομένα, όπως στοιχεία ιστορικών κρατήσεων ανά πτήση και κατηγορία ναύλου για κάθε ημερομηνία αναχώρησης, έτσι ώστε να λαμβάνουν πλήρως υπόψη τους περιορισμούς του εισιτηρίου (π.χ. ημερομηνία κράτησης του εισιτηρίου, ακυρώσεις εισιτηρίων). Εξέταση των δυναμικών πτυχών της διαχείρισης των εσόδων είναι πέρα από το πεδίο εφαρμογής της παρούσας διατριβής και προτείνεται για περαιτέρω έρευνα. Επίσης, σε αντιστοιχία με τις παραδοχές του βασικού υποδείγματος Bertrand και τις παραδοχές της υπάρχουσας βιβλιογραφίας, η παρούσα διατύπωση υποθέτει ότι δεν υπάρχει περιορισμός χωρητικότητας. Σε πραγματικά αεροπορικά δίκτυα, η περιορισμένη χωρητικότητα κάποιων δρομολογίων μπορεί να είναι (σε ορισμένες αγορές) δεσμευτική για κάποιες αεροπορικές εταιρείες, με αποτέλεσμα τα αποτελέσματα να διαφοροποιούνται σε σχέση με το παραπάνω υπόδειγμα. Ωστόσο, τα αθροιστικά δεδομένα που χρησιμοποιεί η παρούσα διατριβή δεν παρέχουν πληροφορία σε αυτό το επίπεδο των μεμονωμένων πτήσεων σε μια συγκεκριμένη ημέρα και ώρα, και, ως εκ τούτου, δεν μπορεί να ληφθεί υπόψη ο περιορισμός χωρητικότητας. Τέλος, το υπόψη παίγνιο αφορά σε ένα μη-συνεργατικό παίγνιο (non-cooperative) ταυτόχρονων κινήσεων (one-shot). Υποθέτουμε ότι οι αεροπορικές εταιρείες (παίκτες) αποφασίζουν ταυτόχρονα και δεν μορφώνουν συνασπισμούς.

Το οριακό κόστος κάθε αεροπορικής σύνδεσης δεν είναι διαθέσιμο από τα αθροιστικά δεδομένα που χρησιμοποιούνται στην παρούσα εργασία. Για το λόγο αυτό είναι αναγκαία η εκτίμηση τους με τη χρήση ενός οικονομετρικού προτύπου. Συγκεκριμένα, η εκτίμηση του οριακού κόστους γίνεται με τη χρήση γραμμικής παλινδρόμησης όπως φαίνεται στην Εξ. 9

$$c_j = w_j \cdot \gamma + \omega_j \qquad \textbf{Εξ. 9}$$

Με αντικατάσταση της Εξ. 9 στην Εξ. 7 προκύπτει η τελική εξίσωση της τιμής του εισιτηρίου συναρτήσει των μεταβλητών του οριακού κόστους και του περιθωρίου κέρδους.

$$p_j = \left(\underbrace{-D_{MS_f,p_f}^{-1} \cdot MS_j}_{\text{περιθώριο κέρδους}} \right) + \underbrace{w_j \cdot \gamma + \omega_j}_{\text{οριακό κόστος}} \qquad \textbf{Εξ. 10}$$

όπου w_j είναι τα χαρακτηριστικά που επηρεάζουν το οριακό κόστος μιας αεροπορικής σύνδεσης και ω_j είναι ο διαταρακτικός όρος της παλινδρόμησης και περιλαμβάνει τα χαρακτηριστικά κόστους των συνδέσεων που δεν παρατηρούνται από τους ερευνητές. Ο συντελεστής γ είναι προς εκτίμηση. Οι μεταβλητές w_j που χρησιμοποιούνται ως ερμηνευτικές μεταβλητές στην συνάρτηση κόστους αναλύονται στο Κεφάλαιο 8 της παρούσας περίληψης.

6. Εκτίμηση των οικονομετρικών προτύπων

Από τη διαμόρφωση της εξίσωσης ζήτησης και της εξίσωσης τιμής των αεροπορικών εταιρειών, προκύπτει το σύστημα που αποτελείται από τις εξισώσεις Εξ. 5 και Εξ. 10, με την εκτίμηση των οποίων θα προκύψουν οι εκτιμώμενες τιμές των συντελεστών α, β, λ και γ. Τρία σημαντικά σημεία πρέπει να ληφθούν υπόψη κατά την εκτίμηση των εξισώσεων:

- Ταυτόχρονη εκτίμηση προσφοράς και ζήτησης: Μία προσέγγιση είναι να εκτιμηθεί αρχικά η εξίσωση της ζήτησης και στη συνέχεια να χρησιμοποιηθούν οι εκτιμώμενες παράμετροι της ζήτησης (α, β και λ) στη συνάρτηση της τιμής εισιτηρίων (μέσω του όρου D_{MS_f,p_f}), προκειμένου να εκτιμηθεί η παράμετρος γ. Επειδή οι παράμετροι της ζήτησης υπεισέρχονται και στις δύο εξισώσεις (Εξ. 5 και Εξ. 10) προτιμάται η ταυτόχρονη εκτίμηση των εξισώσεων.
- Μη γραμμικότητα του συστήματος: Υπενθυμίζεται ότι ο όρος D_{MS_f,p_f} (Εξ. 8) αντιπροσωπεύει τον πίνακα των μερικών παραγώγων του MS_j ως προς την τιμή εισιτηρίου. Οπότε, οι παράμετροι α και λ εισέρχονται στην εξίσωση της τιμής των εταιρειών (Εξ. 10) με μη γραμμικό τρόπο. Έτσι, η μέθοδος υπολογισμού θα πρέπει να λαμβάνει υπόψη το ζήτημα αυτό.
- Ενδογένεια: Η ενδογένεια είναι ένα σημαντικό οικονομετρικό πρόβλημα, το οποίο θα πρέπει να λαμβάνεται υπόψη κατά την εκτίμηση των οικονομετρικών προτύπων. Στα οικονομετρικά πρότυπα της παρούσας εργασίας, η ενδογένεια προκύπτει για δύο λόγους. Κατ' αρχάς, ο διαταρακτικός όρος ξ_j της συνάρτησης ζήτησης (το οποίο εκφράζει διάφορα ποιοτικά χαρακτηριστικά των αεροπορικών συνδέσεων) μπορεί να συσχετίζεται με την τιμή του εισιτηρίου p_j και το (δεσμευμένο) μερίδιο αγοράς $MS_{j/g}$. Για παράδειγμα στον όρο ξ_j μπορεί να περιλαμβάνονται χαρακτηριστικά όπως η ακριβής ώρα αναχώρησης, η διαθεσιμότητα wi-fi κατά την πτήση, περιορισμοί κατά την κράτηση των εισιτηρίων. Επειδή αυτά τα χαρακτηριστικά λαμβάνονται υπόψη από τους επιβάτες (κατά τη λήψη απόφασης της διαδρομής) επηρεάζουν την τελική τους απόφαση και για αυτό συμπεριλαμβάνονται στην εξίσωση ζήτησης. Από την άλλη πλευρά, τα χαρακτηριστικά αυτά συσχετίζονται με την τιμή του εισιτηρίου και άρα με το μερίδιο αγοράς $MS_{j/g}$. Για παράδειγμα, εισιτήρια με πολλούς περιορισμούς κατά την κράτηση τους (π.χ. μη επιστρεψιμότητα των χρημάτων) αναμένεται να έχουν χαμηλότερη τιμή σε σχέση με άλλα εισιτήρια. Δεύτερον, ο όρος ω_j περιλαμβάνει χαρακτηριστικά της αεροπορικής σύνδεσης που μπορεί να επηρεάζουν την τιμή εισιτηρίου αλλά να μην συμπεριλαμβάνονται στην Εξ. 10, λόγω έλλειψης των αντίστοιχων δεδομένων. Λόγω της συσχέτισης της τιμής εισιτηρίου με τα μερίδια αγοράς, ο διαταρακτικός όρος ω_j ενδέχεται και αυτός να συσχετίζεται με το μερίδιο αγοράς. Άρα το μερίδιο αγοράς MS_j θεωρείται ενδογενής μεταβλητή στην Εξ. 10.

Τα παραπάνω ζητήματα καθιστούν αναγκαία την εκτίμηση του συστήματος ζήτησης και προσφοράς με μια μέθοδο η οποία θα αντιμετωπίζει τα ζητήματα ενδογένειας και μη γραμμικότητας. Στην παρούσα εργασία το σύστημα εκτιμάται με τη Γενικευμένη Μέθοδο των Ροπών σε δύο βήματα (Two-step Generalized method of moments-GMM) (Hansen, 1982). Έτσι με τη χρήση έγκυρων βοηθητικών μεταβλητών οι εκτιμητές του μοντέλου είναι αμερόληπτοι και συνεπείς.

Για την επίλυση του προβλήματος της ενδογένειας πρέπει να χρησιμοποιηθούν βοηθητικές μεταβλητές (instrumental variables) για κάθε «υποψήφια» ενδογενή μεταβλητή. Οι βοηθητικές μεταβλητές είναι εξωγενείς μεταβλητές που δεν περιλαμβάνονται στο αρχικό μοντέλο και πρέπει να είναι έγκυρες, δηλαδή να έχουν τις εξής ιδιότητες: (i) να μην συσχετίζονται με το διαταρακτικό όρο του μοντέλου και (ii) να συσχετίζονται με τις ενδογενείς μεταβλητές που αντιπροσωπεύουν. Στην παρούσα εργασία εφαρμόζονται διάφοροι στατιστικοί έλεγχοι ώστε να βεβαιωθεί η χρήση έγκυρων βοηθητικών μεταβλητών. Αρχικά, οι βοηθητικές μεταβλητές ελέγχονται ως προς τη συσχέτιση τους με τις ενδογενείς μεταβλητές. Για το λόγο αυτό, αρχικά καταστρώνεται μια γραμμική παλινδρόμηση όπου η εξαρτημένη μεταβλητή είναι η ενδογενής μεταβλητή. Ως ανεξάρτητες μεταβλητές περιλαμβάνονται όλες οι εξωγενείς μεταβλητές του προτύπου (ανεξάρτητες ερμηνευτικές μεταβλητές που από την αρχή περιλαμβάνονταν στην εξίσωση και πρόσθετες βοηθητικές μεταβλητές). Στη συνέχεια ελέγχονται ο συντελεστής προσδιορισμού R^2 και το στατιστικό μέγεθος F της παλινδρόμησης ώστε να διαπιστωθεί αν οι βοηθητικές μεταβλητές συσχετίζονται με τις ενδογενείς μεταβλητές που αντιπροσωπεύουν. Σύμφωνα με τον Baum et al. (2003) σε περίπτωση ύπαρξης παραπάνω από μιας ενδογενούς μεταβλητής η ανωτέρω διαδικασία δεν είναι κατάλληλη για να ανιχνεύσει «ασθενείς» βοηθητικές μεταβλητές. Σε τέτοιες περιπτώσεις, ο στατιστικός έλεγχος ασθενών βοηθητικών μεταβλητών των Stock and Yogo (2005) είναι κατάλληλος και εφαρμόζεται στην παρούσα διατριβή. Δεύτερον, η εξωγένεια των βοηθητικών μεταβλητών ανιχνεύεται με τον J-έλεγχο έλεγχο υπέρ-ταυτοποίησης των περιορισμών (J-test of overidentifying restrictions). Για τον έλεγχο J θα πρέπει αρχικά να κατασκευαστούν τα κατάλοιπα από τις εκτιμήσεις των αρχικών υποδειγμάτων (με τις ενδογενείς μεταβλητές ως ανεξάρτητες μεταβλητές). Στη συνέχεια παλινδρομούνται τα κατάλοιπα σε όλες τις ερμηνευτικές και τις βοηθητικές μεταβλητές του υποδείγματος και ελέγχεται η μηδενική υπόθεση που ισοδυναμεί με την υπόθεση ότι οι βοηθητικές μεταβλητές δεν σχετίζονται από κοινού με τα κατάλοιπα του υποδείγματος και άρα είναι έγκυρα όργανα ελέγχου. Αν απορριφθεί η μηδενική υπόθεση (δηλ. π.χ. το p-value$<$0,05 ή 0,10), τότε οι βοηθητικές μεταβλητές συσχετίζονται με το διαταρακτικό όρο, άρα δεν είναι εξωγενείς. Τέλος, εφαρμόζεται ο έλεγχος των Durbin-Wu-Hausman ώστε να ελεγχθεί η ενδογένεια των μεταβλητών που θεωρούνται (από τον ερευνητή) ως ενδογενείς, όπως για παράδειγμα η τιμή εισιτηρίου και το μερίδιο αγοράς. Η μηδενική υπόθεση του ελέγχου Durbin-Wu-Hausman είναι ότι στο υπόδειγμα υπάρχει εξωγένεια, δηλαδή οι ερμηνευτικές μεταβλητές δεν συσχετίζονται με τον διαταρακτικό όρο. Απόρριψη της μηδενικής υπόθεσης (δηλ. π.χ. το p-value$<$0,05 ή 0,10), σημαίνει ότι στο υπόδειγμα υπάρχει ενδογένεια.

Για την εφαρμογή της Γενικευμένης Μεθόδου των Ροπών είναι απαραίτητη η διαμόρφωση των ροπών οι οποίες προκύπτουν από την προϋπόθεση ότι οι ερμηνευτικές μεταβλητές του προτύπου (μη συμπεριλαμβανομένων των ενδογενών μεταβλητών) και οι πρόσθετες βοηθητικές μεταβλητές δεν συσχετίζονται με τα κατάλοιπα των προτύπων. Δηλαδή ότι για τα πρότυπα ζήτησης και προσφοράς ισχύουν:

$$m(\widehat{\theta_d}, \hat{\gamma}) = E\begin{bmatrix} {z_1}'\xi \\ {z_2}'\omega \end{bmatrix} = 0 \qquad \textbf{Εξ. 11}$$

όπου με $\widehat{\theta}_d$ σημειώνονται οι παράμετροι του προτύπου ζήτησης (α, β και λ), z_1 και z_2 είναι το σύνολο των εξωγενών μεταβλητών (ερμηνευτικών μεταβλητών του προτύπου-μη συμπεριλαμβανομένων των ενδογενών μεταβλητών- και βοηθητικών μεταβλητών) για το πρότυπο της ζήτησης και της προσφοράς αντίστοιχα. Με την εφαρμογή της Γενικευμένης Μεθόδου των Ροπών, εκτιμώνται οι παράμετροι α, β, γ και λ έτσι ώστε να ελαχιστοποιείται η παρακάτω αντικειμενική συνάρτηση.

$$J(\hat{\theta}_d,\hat{\gamma}) = m(\hat{\theta}_d,\hat{\gamma})' W_{opt} m(\hat{\theta}_d,\hat{\gamma}) \\ = u' z W_{opt} z' u \qquad \textbf{Εξ. 12}$$

Όπου u είναι το διάνυσμα των καταλοίπων $u = \begin{bmatrix} \xi \\ \omega \end{bmatrix}$ και W_{opt} είναι ένας συμμετρικός και θετικά ορισμένος πίνακας στάθμισης (weight matrix), όπως εξηγείται παρακάτω.

Τελικά, η μέθοδος GMM επιλύει το παρακάτω πρόβλημα βελτιστοποίησης:

$$\min_{\hat{\theta}_d,\hat{\gamma}} \left[\underbrace{m(\hat{\theta}_d,\hat{\gamma})'}_{1\times k} \underbrace{W_{opt}}_{k\times k} \underbrace{m(\hat{\theta}_d,\hat{\gamma})}_{k\times 1} \right] \qquad \textbf{Εξ. 13}$$

Η μέθοδος GMM υλοποιείται σε δύο βήματα. Αρχικά υπολογίζονται τα κατάλοιπα των Εξ. 5 και Εξ. 10, ως ακολούθως.

$$u = \begin{bmatrix} \xi \\ \omega \end{bmatrix} = \begin{bmatrix} lnMS_j - lnMS_0 - x_j\hat{\beta} + \hat{\alpha}p_j - (1-\hat{\lambda}) \cdot MS_{j/g} \\ p_j - w_j \cdot \hat{\gamma} + D^{-1}_{MS_f,p_f} \cdot MS_j \end{bmatrix} \qquad \textbf{Εξ. 14}$$

Στη συνέχεια χρησιμοποιούνται οι βοηθητικές μεταβλητές z_1 και z_2 των υποδειγμάτων και σχηματίζονται οι ροπές της Εξ. 11. Αυτές εισέρχονται στην Εξ. 13 με αρχικό πίνακα στάθμισης τον $W = (z'z)^{-1}$. Έτσι εκτιμώνται οι παράμετροι του πρώτου βήματος της μεθόδου GMM: $\hat{\theta}_{d,1step}$ και $\hat{\gamma}_{1step}$.

Στο δεύτερο βήμα της μεθόδου GMM, επαναυπολογίζονται τα κατάλοιπα $\hat{u}_1^2, \ldots, \hat{u}_j^2, \ldots \hat{u}_{2n}^2$ των προτύπων με τη βοήθεια των οποίων υπολογίζεται ο τελικός πίνακας στάθμισης $W_{opt} = (z'\hat{\Omega}z)^{-1}$ όπου $\hat{\Omega} = diag(\hat{u}_1^2, \ldots, \hat{u}_j^2, \ldots \hat{u}_{2n}^2)$. Τελικά, από την ελαχιστοποίηση της αντικειμενικής συνάρτησης GMM (Εξ. 13) προκύπτουν οι τελικοί εκτιμητές $\hat{\theta}_{d,2step}$ και $\hat{\gamma}_{2step}$. Επειδή οι παράμετροι α και λ εισέρχονται στη συνάρτηση της τιμής με μη γραμμικό τρόπο, η ανάκτηση των εκτιμητών γίνεται με τη εφαρμογή κατάλληλου αλγορίθμου σε περιβάλλον MATLAB.

7. Προσομοίωση της περιβαλλοντικής πολιτικής

Στην παρούσα διατριβή εξετάζεται η εφαρμογή ενός αγορακεντρικού περιβαλλοντικού μέτρου το οποίο επιβάλλει ένα επιπλέον κόστος, που ονομάζεται κόστος εκπομπών, στις αεροπορικές εταιρείες που δραστηριοποιούνται στο δίκτυο των Η.Π.Α. Το κόστος αυτό είναι συνάρτηση της ποσότητας εκπομπών CO_2 από τις πτήσεις εσωτερικού και του μοναδιαίου κόστους ανά τόνο CO_2.

Σε μια ολιγοπωλιακή αγορά, οι αεροπορικές εταιρείες ενδέχεται να ανταποκριθούν στην εφαρμογή του περιβαλλοντικού μέτρου χρησιμοποιώντας διαφορετικές στρατηγικές. Στην εργασία αυτή, εξετάζεται αν και κατά πόσο οι αεροπορικές εταιρείες θα αναπροσαρμόσουν τις τιμές εισιτηρίων υποθέτοντας ότι αυτές καθορίζουν τις τιμές τους ίσες με τις τιμές ισορροπίας κατά Nash κατά το υπόδειγμα Bertrand. Μετά την εφαρμογή του μέτρου, το οριακό κόστος κάθε εταιρείας $c_{j,pre}$ αυξάνεται κατά το κόστος των εκπομπών. Έτσι, το νέο οριακό κόστος δίνεται από την Εξ. 15.

$$c_{j,post} = c_{j,pre} + F \cdot \sum_{s=2}^{S} \frac{E_{s,j}}{LF_{s,j} \cdot SEAT_{s,j}}, where\ S = \{2,3,4\}, j \in J \qquad \textbf{Εξ. 15}$$

όπου $E_{s,j}$ είναι η ποσότητα CO_2 (in tn CO_2) της εταιρείας για κάθε τμήμα s της αεροπορικής σύνδεσης j και το γινόμενο $LF_{s,j} \cdot SEAT_{s,j}$ είναι ο αριθμός των επιβατών που μεταφέρονται από την εταιρεία στο τμήμα s της σύνδεσης j. Το συνολικό κόστος εκπομπών ανά επιβάτη προκύπτει ως το γινόμενο του μοναδιαίου κόστους εκπομπών F επί το σύνολο των εκπομπών CO_2 (ανά επιβάτη) για όλα τα τμήματα της αεροπορικής σύνδεσης.

Η τιμή ισορροπίας βρίσκεται με επαναληπτικό τρόπο, μέσω μιας διαδικασίας προσαρμογής των τιμών μέχρι να ικανοποιηθεί ένα καθορισμένο κριτήριο σύγκλισης. Με άλλα λόγια, οι τιμές εισιτηρίων της κάθε αεροπορικής εταιρείας αναπροσαρμόζονται λαμβάνοντας υπόψη τις τιμές των άλλων εταιρειών που δραστηριοποιούνται στην ίδια αγορά. Οι τιμές ισορροπίας βρίσκονται όταν η τιμή κάθε εταιρείας είναι βέλτιστη και καμία εταιρεία δεν θέλει να αποκλίνει από αυτή την τιμή. Αφού βρεθούν οι τιμές ισορροπίας (μετά την επιβολή του κόστους εκπομπών) υπολογίζονται τα νέα μερίδια αγοράς (από το πρότυπο ζήτησης).

Βασική υπόθεση για την εφαρμογή αυτής της πολιτικής είναι το επίπεδο του μοναδιαίου κόστους εκπομπών CO_2. Για την παρούσα εργασία, έγινε επισκόπηση των τιμών CO_2 από διάφορα μέτρα τιμολόγησης άνθρακα ανά τον κόσμο. Λόγω της αβεβαιότητας που παρατηρήθηκε στις τιμές του άνθρακα η παρούσα εργασία στηρίζεται σε τρία σενάρια: i) Χαμηλό σενάριο: $10 ανά τόνο CO_2, (ii) Μεσαίο σενάριο, $20 ανά τόνο CO_2 (iii) Υψηλό σενάριο, $50 και $100 ανά τόνο CO_2.

8. Ανάλυση δεδομένων και αποτελέσματα

8.1. Ανάλυση δεδομένων

Για την εκτίμηση των προτύπων ζήτησης και προσφοράς καθώς και την προσομοίωση του περιβαλλοντικού μέτρου χρησιμοποιούνται μια σειρά βάσεων δεδομένων με στατιστικά στοιχεία κίνησης για το αεροπορικό δίκτυο των Η.Π.Α. Η επιλογή του συγκεκριμένου δικτύου έγινε για διάφορους λόγους. Πρώτον, αποτελεί ένα μεγάλο μέρος των διεθνών αερομεταφορών, αφού για το 2012 τα επιβατοχιλόμετρα στις Η.Π.Α. αποτέλεσαν το 27% της παγκόσμιας αεροπορικής κίνησης (ICAO, 2013c). Τα περισσότερα ζεύγη πόλεων Π-Π (αγορές) του δίκτυο των Η.Π.Α. εξυπηρετούνται από περισσότερο από δύο εταιρείες, πράγμα που έρχεται σε συμφωνία με το υπόδειγμα της παρούσας εργασίας που βασίζεται σε ολιγοπωλιακές αγορές. Τέλος, οι Η.Π.Α. είναι από τις λίγες χώρες για τις οποίες είναι διαθέσιμα στο κοινό αθροιστικά στοιχεία πραγματοποιούμενων δρομολογίων. Τα στοιχεία αυτά καταρτίζονται από το Υπουργείο Μεταφορών των Η.Π.Α. (BTS, n.d.) και δημοσιεύονται στην ιστοσελίδα του τμήματος στατιστικών για τις μεταφορές (Bureau of Transportation Statistics). Τρεις βάσεις δεομένων με στατιστικά στοιχεία αεροπορικής κίνησης χρησιμοποιούνται: Airline Origin and Destination Survey (DB1B), T-100 Domestic Segment for U.S. Carriers (T-100) και On-Time Performance (OTP). Η βάση δεδομένων DB1B χρησιμοποιήθηκε για την δημιουργία των δρομολογίων και των μεριδίων αγοράς. Επίσης, περιλαμβάνει στοιχεία όπως είναι η τιμή εισιτηρίου, οι εταιρείες που εξυπηρετούν το δρομολόγιο κτλ. Τα στοιχεία αυτά δίνονται σε τριμηνιαία βάση. Οι βάσεις δεδομένων T-100 και OTP χρησιμοποιήθηκαν για να συμπληρωθεί το δείγμα με άλλα χαρακτηριστικά των συνδέσεων, όπως συχνότητα πτήσεων, καθυστερήσεις, τύποι αεροσκαφών. Για να διαμορφωθούν οι ανωτέρω βάσεις δεδομένων σε μια κοινή βάση, ακολουθήθηκε κατάλληλη επεξεργασία η οποία περιγράφεται στο Παράρτημα C-1.

Για τη διατριβή χρησιμοποιήθηκαν δεδομένα για το 2012. Το τελικό δείγμα είχε 89667 αεροπορικές συνδέσεις, 13432 αγορές (ζεύγη πόλεων Π-Π), 67 πόλεις, 91 αεροδρόμια και 11 αεροπορικές εταιρείες. Ο Πίνακας 1 παρουσιάζει τις μεταβλητές των προτύπων υποδεικνύοντας με D ή C το μοντέλο ζήτησης (D) ή προσφοράς (C), όπου υπεισέρχεται κάθε μεταβλητή.

Πίνακας 1. Περιγραφικά στατιστικά των μεταβλητών

Μεταβλητή	Πρότυπο[a]	Μέση τιμή (Τυπ. απόκλ.)	[Ελαχ., Μέγ.]	Πηγή προέλευσης
Τιμή εισιτηρίου [σε $100]	D	4,573 (1,35)	[1,16, 13]	DBIB
Αριθμός στάσεων	D	1,556 (0,77)	[0, 2]	DBIB
Απόσταση δρομολογίου μετ' επιστροφής [σε 1000 sm]	C	3,146 (1,49)	[0,17 , 10,43]	DBIB
Συχνότητα (πτήσεις/τρίμηνο)	D	279,89 (191,4)	[12, 1992]	T-100
% πρωινών αναχωρήσεων	D	0,245 (0,17)	[0, 1]	OTP
Μέγεθος αεροσκάφους	C	0,269 (0,44)	[0, 1]	T-100
Ύπαρξη συντονισμένου αεροδρομίου	D	0,130 (0,36)	[0, 3]	DB1B
Καθυστερήσεις	D	0,176 (0,07)	[0, 1]	OTP
Ύπαρξη εναλλακτικού αεροδρομίου	D	0,604 (0,49)	[0, 1]	Υπολογισμός
Ύπαρξη κομβικού αεροδρομίου	C	0,630 (0,48)	[0, 1]	DB1B
Απόσταση μεταξύ πόλεων [σε 1000 sm]	D	1,572 (0,74)	[0,09 , 5,22]	DB1B
Jet Blue Airways	D και C	0,021 (0,14)	[0,1]	DB1B
Delta Air Lines	D και C	0,208 (0,41)	[0,1]	DB1B
American Airlines	D και C	0,128 (0,33)	[0,1]	DB1B
Southwest Airlines	D και C	0,311 (0,46)	[0,1]	DB1B
Άλλες «παραδοσιακές» εταιρείες (legacy)	D και C	0,133 (0,34)	[0,1]	DB1B
Άλλες εταιρείες χαμηλού κόστους	D και C	0,074 (0,26)	[0,1]	DB1B
Ζεύγη πόλεων Π-Π:		13432		
Αεροπορικές συνδέσεις (παρατηρήσεις):		89667		
Έτος έρευνας: 2012				

Σημειώσεις: [a] D: Μεταβλητή ζήτησης, C: Μεταβλητή κόστους

Μεταβλητές Ζήτησης:

- Τιμή εισιτηρίου: Από την πλευρά της ζήτησης, η αύξηση στην τιμή ενός αγαθού κατά κανόνα οδηγεί σε μείωση της ζητούμενης ποσότητας. Αυτό ισχύει επίσης και για τις αεροπορικές μεταφορές, όπου η τιμή του εισιτηρίου είναι ένας καθοριστικός παράγοντας της ζήτησης. Σε αυτή την εργασία η μέση τιμή του εισιτηρίου (σταθμισμένη με τον αριθμό των επιβατών) έχει υπολογιστεί για κάθε αεροπορική σύνδεση σε κάθε τρίμηνο του 2012. Εντός του 2012, η μέση τιμή εισιτηρίου ήταν $457,3.
- Αριθμός στάσεων: Η μεταβλητή αυτή περιλαμβάνεται προκειμένου να εξηγήσει την διαίσθηση ότι μια απευθείας αεροπορική σύνδεση είναι προτιμότερη από μια σύνδεση με ενδιάμεσες στάσεις. Ο «αριθμός των στάσεων» υπολογίζεται ως ο αριθμός των μετεπιβιβάσεων σε κάθε δρομολόγιο μετ' επιστροφής και μπορεί να λάβει τρεις τιμές: 0 αν οι πτήσεις μετάβασης και επιστροφής είναι απευθείας, 1 εάν είτε η πτήση μετάβασης ή η πτήση επιστροφής έχουν μια ενδιάμεση στάση, και 2 αν και οι δύο πτήσεις δεν είναι απευθείας. Το 2012, κάθε σύνδεση είχε κατά μέσο όρο 1,56 στάσεις.

- Απόσταση: Η απόσταση των πόλεων Π-Π αναμένεται να επηρεάσει τη ζήτηση ως εξής. Από τη μια πλευρά, όσο αυξάνεται η απόσταση τόσο μπορεί να μειώνεται η προθυμία των επιβατών για ταξίδια. Από την άλλη, όσο αυξάνεται η απόσταση τότε το αεροπορικό μέσο γίνεται όλο και πιο ανταγωνιστικό σε σχέση με τα άλλα μέσα μεταφοράς, οπότε αναμένεται αύξηση της αεροπορικής ζήτησης. Η μέση απόσταση πόλεων που διανύθηκε αεροπορικώς το 2012 ήταν 1572 μίλια.
- Συχνότητα: Η συχνότητα είναι ένας σημαντικός παράγοντας στη λήψη αποφάσεων του επιβάτη, αφού η χρησιμότητα των επιβατών αναμένεται να είναι αυξημένη για πτήσεις με μεγαλύτερη συχνότητα (αφού αυξάνονται οι επιλογές των επιβατών ως προς την ώρα αναχώρησης). Στην παρούσα εργασία, η συχνότητα εισέρχεται στο πρότυπο ζήτησης σε λογαριθμική μορφή (Ben-Akiva και Lerman, 1985; Hansen, 1990).
- Ύπαρξη συντονισμένου αεροδρομίου: Η μεταβλητή αυτή χρησιμοποιείται στο μοντέλο της ζήτησης, προκειμένου να διαφοροποιήσει τα συντονισμένα αεροδρόμια (που ενδέχεται να έχουν μεγαλύτερη συμφόρηση) από τα υπόλοιπα αεροδρόμια. Η μεταβλητή λαμβάνεται ίση με τον αριθμό των συντονισμένων αεροδρομίων στο μετ' επιστροφής δρομολόγιο.
- Καθυστερήσεις: Με την εισαγωγή αυτή της μεταβλητής αναμένεται να δειχθεί η επίδραση των καθυστερήσεων άφιξης στο αεροδρόμιο προορισμού στην χρησιμότητα του επιβάτη. Πιο συγκεκριμένα, η μεταβλητή αφορά στις καθυστερήσεις του δρομολογίου για το προηγούμενο τρίμηνο από αυτό της λήψης απόφασης. Το 2012, 17,6% των συνδέσεων είχαν καθυστέρηση άφιξης μεγαλύτερη των 15 λεπτών.
- Ψευδομεταβλητές των αεροπορικών εταιρειών: Οι ψευδομεταβλητές αυτές περιλαμβάνονται στο πρότυπο ζήτησης έτσι ώστε να εξεταστεί η επίδραση της φήμης μιας εταιρείας στις προτιμήσεις των επιβατών. Για την εκτίμηση ως εταιρεία βάσης (base airline) λαμβάνεται η US Airways.
- Ύπαρξη εναλλακτικού αεροδρομίου: Ένας παράγοντας που πιστεύεται πως καθορίζει τη ζήτηση για ένα συγκεκριμένο δρομολόγιο είναι η παρουσία εναλλακτικών αεροδρομίων κοντά στο αεροδρόμιο προέλευσης ή προορισμού του επιβάτη. Για παράδειγμα, αν υπάρχει αεροδρόμιο το οποίο να είναι κοντά στον προορισμό του επιβάτη, και, επίσης, προσφέρει δρομολόγιο από το αεροδρόμιο προέλευσης, τότε ενδέχεται ο επιβάτης να προτιμήσει να προσγειωθεί στο ενναλακτικό αεροδρόμιο αν όλα τα άλλα χαρακτηριστικά είναι ίδια. Η μεταβλητή είναι ίση με τη μονάδα αν υπάρχει εναλλακτικό αεροδρόμιο σε ακτίνα 60 ή 100 μιλίων από το κεντροειδές της πόλης προέλευσης ή προορισμού (Π/Π). Η ακτίνα των 100 μιλίων λαμβάνεται για δρομολόγια μεσαίων/μακρινών αποστάσεων (>750 μίλια), ενώ η ακτίνα των 60 μιλίων για δρομολόγια κοντινών αποστάσεων (<750 μίλια).
- Ώρα αναχώρησης: Η εν λόγω μεταβλητή χρησιμοποιείται για να εκτιμηθεί η ελκυστικότητα μιας αεροπορικής σύνδεσης με βάση την ώρα αναχώρησης. Με βάση τη βιβλιογραφία (Barnhart et al, 2014; Koppelman et al, 2008), δρομολόγια τα οποία προσφέρονται είτε πρωί είτε αργά το απόγευμα προτιμώνται περισσότερο. Η μεταβλητή γίνεται ίση με τη μονάδα, αν η σύνδεση εξυπηρετείται από δρομολόγια κατά τις πρωινές ώρες (από τις 8 π.μ. έως 12 π.μ.).

Μεταβλητές κόστους

- Απόσταση μετ' επιστροφής δρομολογίου: Μια αύξηση στην απόσταση της πτήσης μπορεί να οδηγήσει σε αύξηση σε διάφορες συνιστώσες του μεταβλητού κόστους, όπως το κόστος των καυσίμων. Επιπλέον, μια μεγαλύτερη διαδρομή μπορεί να συνεπάγεται περισσότερες προσγειώσεις και απογειώσεις, οδηγώντας σε αύξηση του κόστους των καυσίμων και των αερολιμενικών τελών. Στη συνάρτηση του οριακού κόστους, η απόσταση του μετ' επιστροφής δρομολογίου χρησιμοποιείται ως ερμηνευτική μεταβλητή. Η μέση απόσταση μετ' επιστροφής που διανύθηκε αεροπορικώς το 2012 ήταν 3146 μίλια.
- Μέγεθος αεροσκάφους: Το μέγεθος του αεροσκάφους επηρεάζει διάφορες συνιστώσες του λειτουργικού κόστους των αεροσκαφών, όπως το κόστος των καυσίμων, τα έξοδα συντήρησης κτλ. Άλλες δαπάνες που μπορεί να σχετίζονται με το μέγεθος αεροσκάφους περιλαμβάνουν τα τέλη προσγείωσης δεδομένου ότι υπολογίζονται με βάση το μέγιστο βάρος απογείωσης. Συνδυαστικά, το μέγεθος του αεροσκάφους μαζί με την απόσταση του δρομολογίου μπορεί να χρησιμοποιηθούν ως μεταβλητές ώστε να εκφράσουν έμμεσα το κόστος των καυσίμων, το οποίο είναι σημαντικός παράγοντας του οριακού κόστους μιας σύνδεσης. Η μεταβλητή λαμβάνεται ίση με ένα αν τουλάχιστον ένα τμήμα της διαδρομής πραγματοποιείται από αεροσκάφη ευρείας ατράκτου. Το 2012 το 26,9% των συνδέσεων πραγματοποιούνταν (έστω και σε ένα τμήμα του δρομολογίου) από αεροσκάφος ευρείας ατράκτου.
- Κομβικά αεροδρόμια: Σύμφωνα με την εργασία του SSamula (2008), μεταξύ των πλεονεκτημάτων των κομβικών αεροδρομίων είναι οι οικονομίες κλίμακας, οι υψηλότερες συχνότητες πτήσεων και το χαμηλότερο κόστος του ταξιδιού. Ως εκ τούτου, η εν λόγω μεταβλητή χρησιμοποιείται για να εξηγήσει εάν η συγκέντρωση της κυκλοφορίας σε κομβικά αεροδρόμια επηρεάζει το οριακό κόστος. Η μεταβλητή είναι ίση με 1 αν το αεροδρόμιο προέλευσης/ενδιάμεσης στάσης/προορισμού είναι κομβικό για την εταιρεία της σύνδεσης.
- Ψευδομεταβλητές των αεροπορικών εταιρειών: Χρησιμοποιούνται έτσι ώστε να εξηγηθεί η ενδεχόμενη συσχέτιση της αεροπορικής εταιρείας με το κόστος της σύνδεσης. Κατ' αντιστοιχία με το πρότυπο ζήτησης, ως εταιρεία βάσης (base airline) λαμβάνεται η US Airways.

Οι βοηθητικές μεταβλητές που χρησιμοποιήθηκαν στην παρούσα εργασία φαίνονται παρακάτω (Πίνακας 2), μαζί τα περιγραφικά στατιστικά τους.

Πίνακας 2. Περιγραφικά στατιστικά των βοηθητικών μεταβλητών

Βοηθητικές μεταβλητές	Πρότυπο[a]	Μέση τιμή	Τυπ. απόκλ	Ελαχ.	Μεγ.
Ένδειξη κομβικού αεροδρομίου (=1 αν το αεροδρόμιο προορισμού είναι κομβικό για την αεροπορική εταιρεία)	D	0,103	0,304	0	1
Ένδειξη κομβικού αεροδρομίου (=1 αν το αεροδρόμιο μετεπιβίβασης είναι κομβικό για την αεροπορική εταιρεία)	D	0,476	0,499	0	1
Αριθμός αεροπορικών συνδέσεων στην αγορά	S	17,720	18,778	1	124
Αριθμός εταιρειών στην αγορά	D and S	4,833	2,024	1	10
Ποσοστό απευθείας πτήσεων των ανταγωνιστών στο σύνολο των πτήσεων της αγοράς	D and S	0,259	0,290	0	1
Μέσος αριθμός επιβατών που εξυπηρετούνται από τους ανταγωνιστές στην αγορά	S	100,2	171,89	0	4037
Αριθμός πόλεων που συνδέονται με απευθείας πτήσεις από το αεροδρόμιο προέλευσης με την συγκεκριμένη εταιρεία	D and S	12,376	13,070	0	60
Μέγεθος αγοράς ανά αεροπορική σύνδεση (σε εκατομμύρια)	S	0,384	0,407	0,02	9,29
Μέγεθος αγοράς ανά αεροπορική εταιρεία (σε εκατομμύρια)	S	0,790	0,476	0,20	9,29

<u>Σημειώσεις</u>: [a] D: Πρότυπο ζήτησης, S: Πρότυπο προσφοράς

8.2. Αποτελέσματα εκτίμησης των οικονομετρικών προτύπων

Τα πρότυπα ζήτησης και προσφοράς εκτιμήθηκαν με το συνδυασμό διαφορετικών ερμηνευτικών μεταβλητών. Το σύνολο των τελικών μεταβλητών επιλέγονται με βάση τα αποτελέσματα εκτίμησης, κατάλληλους στατιστικούς ελέγχους και με βάση την υφιστάμενη βιβλιογραφία. Μετά την εκτίμηση διαφορετικών μορφών του προτύπου ζήτησης (με εκτίμηση μόνο τη συνάρτησης ζήτησης) και με διαφορετικές μεθόδους τα παρακάτω συμπεράσματα μπορούν να εξαχθούν.

<u>Σύγκριση εκτιμητών με τη μέθοδο Ελαχίστων Τετραγώνων (OLS) και με τη μέθοδο των Ελαχίστων Τετραγώνων σε Δύο Στάδια (2SLS)</u>

Στο πρότυπο της ζήτησης, η τιμή του εισιτηρίου και το μερίδιο αγοράς $MS_{j/g}$ είναι πιθανό να συσχετίζεται με το διαταρακτικό όρο. Η εκτίμηση του οικονομετρικού προτύπου με τη μέθοδο Ελαχίστων Τετραγώνων (OLS) αγνοεί την ύπαρξη ενδογένειας και, επομένως, οι εκτιμητές δεν είναι αμερόληπτοι. Τα αποτελέσματα από τη μέθοδο OLS δείχνουν αρνητική επίδραση της τιμής του εισιτηρίου (-0,175) στη χρησιμότητα του επιβάτη. Όμως, η εκτίμηση με τη μέθοδο 2SLS εκτιμά συντελεστή με μεγαλύτερη απόλυτη τιμή (-0,481) από ότι με την OLS. Αυτό υποδηλώνει ότι η ενδογένεια οδηγεί σε μεροληψία της εκτίμησης του συντελεστή τιμής εάν δεν χρησιμοποιούνται βοηθητικές μεταβλητές για την εκτίμηση του προτύπου.

<u>Σύγκριση εκτιμητών με το Πολυωνυμικό Πρότυπο Logit (MNL) και το Ιεραρχικό Πρότυπο Logit (NL)</u>

Ο εκτιμώμενος συντελεστής της τιμής του εισιτηρίου για το Πολυωνυμικό Πρότυπο Logit (MNL) είναι ίσος με -0,032 ενώ για το Ιεραρχικό Πρότυπο Logit (NL) είναι -0,175. Οι εκτιμήσεις που προκύπτουν είναι παρόμοιες για τα δύο πρότυπα για τις περισσότερες μεταβλητές της ζήτησης. Όμως, τα πρόσημα μερικών μεταβλητών δεν είναι σε συνέπεια με τα αναμενόμενα με βάση την θεωρία της ζήτησης (όπως για παράδειγμα ο αρνητικός συντελεστής για τη μεταβλητή των πρωινών αναχωρήσεων, ο θετικός εκτιμητής για τη μεταβλητή της καθυστέρησης άφιξης).

Τελικό πρότυπο: Ζήτηση με βάση το Ιεραρχικό Πρότυπο logit (NL) και εκτίμηση με τη μέθοδο GMM

Ο Πίνακας 3 περιλαμβάνει τις εκτιμήσεις των παραμέτρων του τελικού προτύπου στο οποίο η ζήτηση ακολουθεί το Ιεραρχικό Πρότυπο logit (NL) και γίνεται ταυτόχρονη εκτίμηση της συνάρτησης ζήτησης και προσφοράς με τη χρήση της μεθόδου GMM.

Όπως είναι αναμενόμενο, η τιμή του εισιτηρίου έχει αρνητική επίδραση στη ζήτηση μιας αεροπορικής σύνδεσης (-0,46). Η εκτιμώμενη τιμή του *(1-λ)* σημαίνει ότι η συσχέτιση στις προτιμήσεις των επιβατών για τις αεροπορικές συνδέσεις είναι 0,347. Αξίζει να σημειωθεί ότι τα προϊόντα εντός του ίδιου συνόλου, όπως είναι στην περίπτωση μας οι αεροπορικές συνδέσεις, είναι τέλεια υποκατάστατα όταν το *(1-λ)* είναι ίσο με τη μονάδα. Η τιμή 0,347 υποδεικνύει μέτρια δυνατότητα υποκατάστασης μεταξύ των αεροπορικών συνδέσεων. Ο συντελεστής της συχνότητας είναι 0,473 που σημαίνει ότι όσο αυξάνεται η συχνότητα των πτήσεων αυξάνεται και η ζήτηση. Ο συντελεστής της καθυστέρησης άφιξης παίρνει τις αναμενόμενες τιμές. Η χρησιμότητα ενός επιβάτη μειώνεται όσο αυξάνεται η καθυστέρηση άφιξης. Οι εκτιμήσεις δείχνουν ότι οι επιβάτες προτιμούν να ταξιδεύουν με απευθείας πτήσεις ($\beta_{αριθμός\_στάσεων}$=-0,991), ενώ η χρησιμότητα τους μειώνεται όταν η σύνδεση εξυπηρετείται από συντονισμένα αεροδρόμια ($\beta_{slot\_control}$=-0,278). Οι εκτιμώμενες παράμετροι των εταιρειών δείχνουν τις προτιμήσεις των επιβατών σχετικά με την αεροπορική εταιρεία. Η παράμετρος του *«εναλλακτικού αεροδρομίου»* (-0,196) δηλώνει ότι η ύπαρξη εναλλακτικού αεροδρομίου μειώνει τη χρησιμότητα του επιβάτη για τη συγκεκριμένη σύνδεση αφού μπορεί να εξυπηρετηθεί και από άλλο δρομολόγιο μεταβάλλοντας έτσι τα μερίδια αγοράς. Τέλος, η ύπαρξη δρομολογίων σε πρωινές ώρες έχει θετική επίδραση στη χρησιμότητα του επιβάτη ($\beta_{dm\_daytime}$=0,158).

Όσον αφορά το κόστος της εταιρείας, όσο αυξάνεται η απόσταση (0,48) τόσο αυξάνεται το κόστος εξυπηρέτησης ενός ακόμα επιβάτη. Η εκτίμηση αυτή αντικατοπτρίζει σε κάποιο βαθμό και το κόστος καυσίμων ενός αεροσκάφους, το οποίο αυξάνεται όσο αυξάνεται η απόσταση της πτήσης. Από την άλλα μεριά, το μέγεθος του αεροσκάφους δείχνει να συμβάλλει στη μείωση του οριακού κόστους (-0,148), με τον πιθανότερο λόγο να είναι οι οικονομίες κλίμακας που προσφέρει. Η θετική παράμετρος για τη μεταβλητή «κομβικό αεροδρόμιο» δείχνει ότι η επίδραση της πιθανής συμφόρησης σε κομβικά αεροδρόμια είναι ισχυρότερη από τις οικονομίες κλίμακας που προσφέρουν οι αεροπορικές συνδέσεις μέσω κομβικών αεροδρομίων. Τέλος, η παράμετρος της εταιρείας JetBlue (-0,837) δείχνει ότι η εταιρεία έχει χαμηλότερο οριακό κόστος σε σχέση με άλλες εταιρείες που μπορεί να εξηγηθεί από το γεγονός ότι είναι εταιρεία χαμηλού κόστους.

Πίνακας 3. Εκτίμηση των παραμέτρων των τελικών οικονομετρικών προτύπων

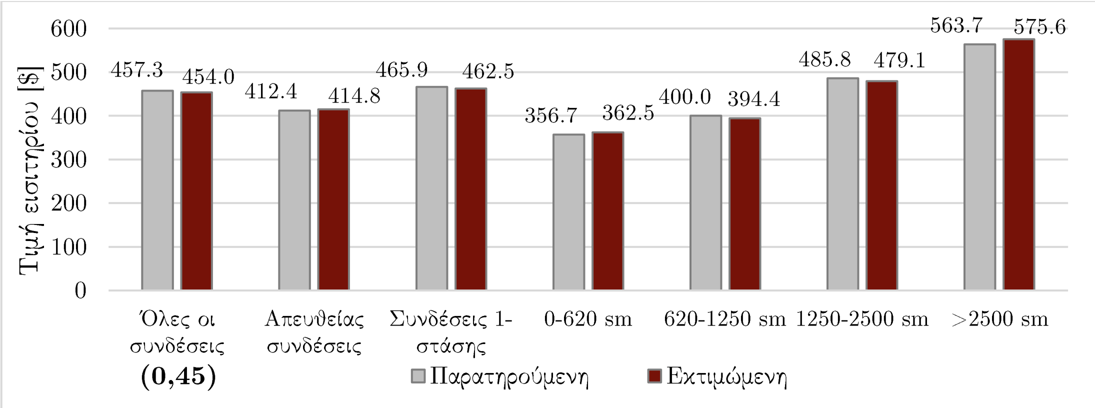
Εξαρτημένη μεταβλητή: $\ln MS_j - \ln MS_0$			**Εξαρτημένη μεταβλητή: p_j (fare)**		
Μεταβλητή ζήτησης	Εκτίμηση (τυπ. σφάλμα)	t-value	Μεταβλητή κόστους	Εκτίμηση (τυπ. σφάλμα)	t-value
Σταθερός όρος	**-7,687*** (0,065)	-117,742	Σταθερός όρος	**1,651*** (0,024)	68,913
Τιμή εισιτηρίου	**-0,460*** (0,013)	-34,179	Απόσταση μετ'επιστροφής	**0,480*** (0,004)	136,798
$\ln(MS_{j/g})$ *(1-λ)*	**0,347*** (0,005)	74,228	Μέγεθος αεροσκάφους	**-0,148*** (0,014)	-10,36
Αριθμός στάσεων	**-0,991*** (0,006)	-163,194	Κομβικό αεροδρόμιο	**0,053*** (0,020)	2,673
Απόσταση μεταξύ πόλεων	**0,360*** (0,014)	24,909	Jet Blue Airways	**-0,837*** (0,027)	-29,89
ln(Συχνότητα)	**0,473*** (0,006)	76,687	Delta Air Lines	**-0,095*** (0,018)	-5,405
% πρωινών αναχωρήσεων	**0,158*** (0,021)	7,537	American Airlines	**-0,162*** (0,017)	-9,314
Συντονισμένο αεροδρόμιο	**-0,278*** (0,011)	-25,170	Southwest Airlines	**-0,360*** (0,023)	-15,820
Καθυστερήσεις	**-0,246*** (0,057)	-4,289	Άλλες εταιρείες LCC	**-1,082*** (0,016)	-66,630
Εναλλακτικό αεροδρόμιο	**-0,196*** (0,009)	-22,762	Άλλες «παραδοσιακές» εταιρείες (legacy)	**0,085*** (0,020)	4,315
Jet Blue Airways	**0,178*** (0,029)	6,176			
Delta Air Lines	**-0,077*** (0,013)	-6,133			
American Airlines	**-0,156*** (0,016)	-9,717			
Southwest Airlines	**-0,246*** (0,012)	-20,528			
Άλλες εταιρείες LCC	**-0,183*** (0,022)	-8,244			
Άλλες «παραδοσιακές» εταιρείες (legacy)	**-0,092*** (0,016)	-5,746			

Στατιστικοί έλεγχοι:	
Τιμή εισιτηρίου: $R^2_{adjusted}$ 1st stage	0,415
F-stat. 1st stage (p-value)	2305,2 (0.00)
$\ln(MS_{j/g})$: $R^2_{adjusted}$ 1st stage	0,665
F-stat. 1st stage (p-value)	6565,3 (0.00)
Τιμή αντικειμ. Συνάρτησης GMM	1020,9
Έλεγχος Cragg-Donald F-statistic	806,4 (>Stock-Yogo$_{0,05}$=19,45)
Overid. test p-value (10% επίπ. σημαντικ.)	0,00
Έλεγχος Durbin-Wu-Hausman p-value	0,00
Αριθμός παρατηρήσεων: 89667	

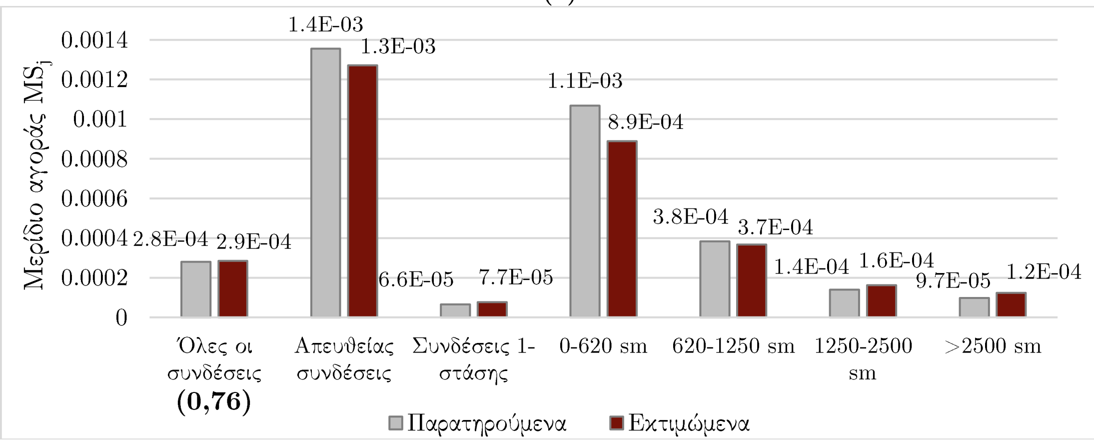
Notes: Ο Πίνακας 2 παρουσιάζει τις βοηθητικές μεταβλητές που εισέρχονται στην εκτίμηση
*: στατιστικά σημαντικό σε επίπεδο σημαντικότητας 1%
US Airways: εταιρεία αναφοράς για την εκτίμηση
LCC: εταιρείες χαμηλού κόστους (Low cost airlines)

Επίσης, ο Πίνακας 3 παρουσιάζει τους στατιστικούς ελέγχους που πραγματοποιούνται για την επικύρωση των προτύπων. Πιο συγκεκριμένα, οι στατιστικοί έλεγχοι δείχνουν ότι οι βοηθητικές μεταβλητές που χρησιμοποιήθηκαν στα πρότυπα είναι έγκυρες (συσχετίζονται με τις ενδογενείς μεταβλητές και δεν συσχετίζονται με τα κατάλοιπα των προτύπων), καθώς και ότι η τιμή εισιτηρίου και το μερίδιο αγοράς είναι ενδογενείς μεταβλητές.

Τέλος, η επικύρωση των προτύπων ολοκληρώνεται με τη σύγκριση των εκτιμώμενων και των παρατηρούμενων μεγεθών, έτσι ώστε να ελεγχθεί η προσαρμογή των προτύπων στις πραγματικές τιμές των εξαρτημένων μεταβλητών. Πιο συγκεκριμένα στο Σχήμα 5 παρουσιάζονται τα σχετικά αποτελέσματα για τον έλεγχο καλής προσαρμογής του προτύπου προσφοράς (τιμές εισιτηρίου) και ζήτησης (μερίδιο αγοράς). Στο σύνολο όλων των αεροπορικών συνδέσεων, τα εκτιμώμενα μερίδια αγοράς είναι μόλις 1,86% υψηλότερα από τα παρατηρούμενα δεδομένα, ενώ οι εκτιμώμενες τιμές των εισιτηρίων είναι μόνο 0,72% χαμηλότερες από τις παρατηρούμενες. Επίσης, το μέτρο καλής προσαρμογής, που έχει προταθεί από τους Gugler και Yurtoglu (2004), Pesaran και Smith (1994), Windmeijer (1995) για πρότυπα που εκτιμώνται με μεθόδους βοηθητικών μεταβλητών, είναι ίσο με 0,76 για τα μερίδια αγοράς και 0,45 για τις τιμές των εισιτηρίων. Το μέτρο αυτό υπολογίζεται ως το τετράγωνο του συντελεστή συσχέτισης μεταξύ των εκτιμώμενων και παρατηρούμενων τιμών και κυμαίνεται από 0 έως 1. Τα ευρήματα αυτά υποδηλώνουν γενικά ότι το μοντέλο είναι ικανό να περιγράψει την αεροπορική ζήτηση και τις τιμές εισιτηρίων.



(a)



(b)

Σχήμα 5. Σύγκριση εκτιμώμενων και παρατηρούμενων τιμών εισιτηρίου(a) και μεριδίων αγοράς (b)

8.3. Αποτελέσματα προσομοίωσης του αγορακεντρικού περιβαλλοντικού μέτρου

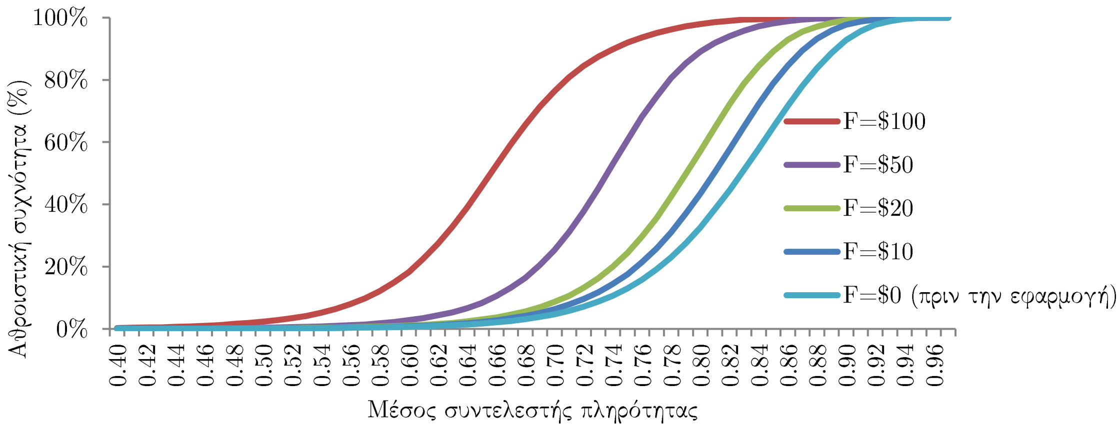
Τα αποτελέσματα μετά την προσομοίωση της περιβαλλοντικής πολιτικής παρουσιάζονται στον παρακάτω πίνακα (Πίνακας 4). Κατά μέσο όρο η αύξηση της τιμής εισιτηρίου κυμαίνεται από 1,07% έως 10,73% ανάλογα με το ύψος της τιμής άνθρακα. Για τη χαμηλή τιμή άνθρακα (F=$10), το κόστος εκπομπών που επιβάλλεται σε μια αεροπορική εταιρεία ανά επιβάτη είναι κατά μέσο όρο $4,75, ενώ αυτό αυξάνεται σε $23,77 για το σενάριο υψηλής τιμής του άνθρακα των $50 ανά τόνο CO_2. Η διαμόρφωση του μοντέλου ζήτησης και προσφοράς επιτρέπει τη μεταβολή τόσο της αεροπορικής ζήτησης στο σύνολο της (μεταβολή του MS_j) όσο και του δεσμευμένου μεριδίου αγοράς (μεταβολή του $MS_{j/g}$). Μετά την εφαρμογή της περιβαλλοντικής πολιτικής, κατά μέσο όρο ένα δρομολόγιο μπορεί να χάσει από 0,22% (για τιμή άνθρακα $10) έως 2,23% (για τιμή άνθρακα των $100) από το δεσμευμένο μερίδιο του εντός της αγοράς των αεροπορικών συνδέσεων. Αυτό σημαίνει ότι η εφαρμογή ενός τέτοιου περιβαλλοντικού μέτρου δεν αναμένεται να προκαλέσει στρεβλώσεις του ανταγωνισμού. Το αποτέλεσμα αυτό έρχεται σε συμφωνία με τα ευρήματα άλλων εργασιών που έχουν διερευνήσει τις περιβαλλοντικές πολιτικές σε ευρωπαϊκές ή άλλες αγορές (Anger, 2010; Malina et al., 2012; Miyoshi, 2014; Scheelhaase et al., 2010). Επίσης, τα αποτελέσματά δείχνουν ότι κατά μέσο όρο το 2,91% των επιβατών μπορεί να επιλέξουν να μην πετάξουν, ως αποτέλεσμα της αύξησης των τιμών για το μέσο σενάριο ($20 ανά τόνο CO_2). Συνολικά, τα αποτελέσματα της προσομοίωσης δείχνουν ότι η συνολική επιβατική κίνηση θα μειωθεί κατά 1,47% για το σενάριο χαμηλής τιμής άνθρακα, ενώ μια σχετικά υψηλή μείωση της ζήτησης (13,5%) μπορεί να προκύψει για το υψηλό σενάριο των $100 ανά τόνο CO_2.

Πίνακας 4. Επιπτώσεις του αγορακεντρικού περιβαλλοντικού μέτρου στο αεροπορικό δίκτυο των Η.Π.Α.

		Σενάρια τιμής άνθρακα (ανά τόνο CO_2)			
		F=$10	F=$20	F=$50	F=$100
Μέση επίπτωση ανά αεροπορική σύνδεση					
Μέσο κόστος εκπομπών ανά σύνδεση [$]	Δcost	4.75	9.51	23.77	47.53
Μέση αύξηση τιμής ανά σύνδεση [%]	%Δprice	1.07%	2.15%	5.36%	10.73%
Μέση μείωση (δεσμευμένου) μεριδίου αγοράς εντός του συνόλου αεροπ. συνδέσεων [%]	%$\Delta MS_{j/g}$	-0.22%	-0.45%	-1.13%	-2.23%
Συνολική επίπτωση στο αεροπορικό δίκτυο					
Μείωση της συνολικής ζήτησης [%]	%Δpassengers	-1.47%	-2.91%	-7.07%	-13.50%
Μείωση των εκπομπών CO_2 [%]	%ΔCO_2	-1.88%	-3.73%	-9.02%	-17.05%

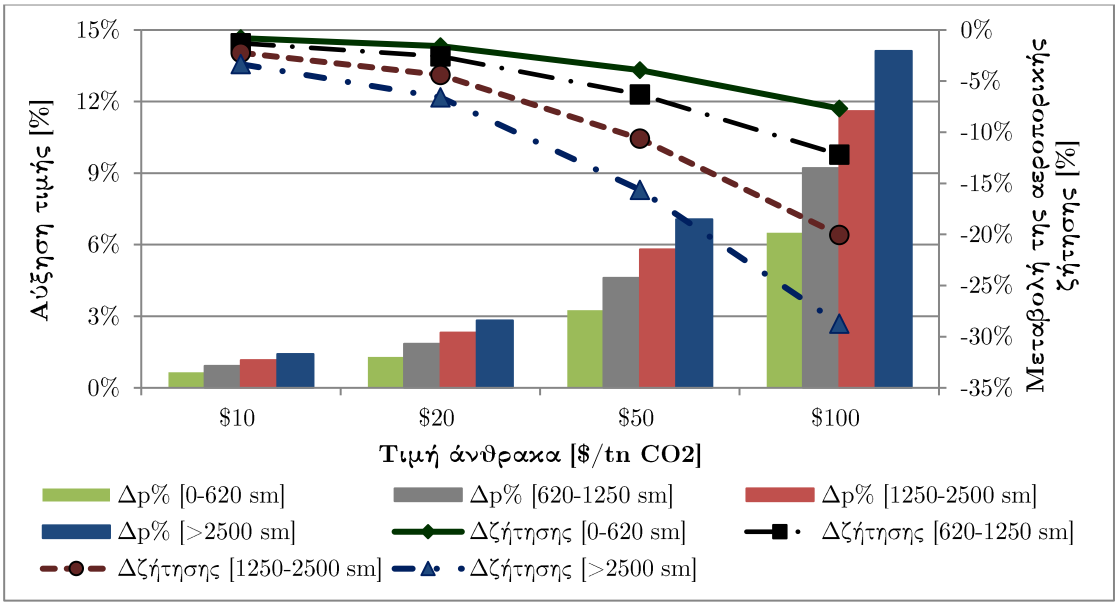
Η μείωση της αεροπορικής ζήτησης θα οδηγήσει σε μειωμένα επίπεδα εκπομπών διοξειδίου του άνθρακα στο εξεταζόμενο δίκτυο. Για να υπολογιστεί με ακρίβεια η εν λόγω μείωση, είναι απαραίτητη η γνώση του αριθμού επιβατών που «φεύγουν» από το αεροπορικό μέσο λόγω της αύξησης της τιμής εισιτηρίου για κάθε μεμονωμένη πτήση της αεροπορικής εταιρείας. Για παράδειγμα, η αυξημένη τιμή εισιτηρίου μπορεί να οδηγήσει σε τέτοια αλλαγή της ζήτησης ώστε οι αεροπορικές εταιρείες να αλλάξουν τη συχνότητα των πτήσεων τους ή να στραφούν σε μεγαλύτερα ή μικρότερα αεροσκάφη σε συγκεκριμένες διαδρομές. Ωστόσο, τα διαθέσιμα αθροιστικά δεδομένα που χρησιμοποιεί η παρούσα διατριβή δεν είναι τόσο λεπτομερή ώστε να γνωρίζουμε τη μείωση των επιβατών σε επίπεδο μεμονωμένων πτήσεων ανά διαδρομή και άρα να μπορούμε να προβλέψουμε ενδεχόμενες αλλαγές στη συχνότητα πτήσεων κτλ. Ωστόσο, γίνεται η απλουστευτική παραδοχή ότι οι εκπομπές CO_2 του δικτύου μειώνονται λόγω της μείωσης της ζήτησης κατά την ακόλουθη ποσότητα: αριθμός των επιβατών που «φεύγουν» από το αεροπορικό μέσο × εκπομπές CO_2 ανά επιβάτη. Αξίζει να σημειωθεί ότι η προσέγγιση αυτή αναμένεται να οδηγήσει σε υπερεκτίμηση της μείωσης των εκπομπών CO_2. Με βάση τα παραπάνω, τα αποτελέσματα δείχνουν ότι οι εκπομπές CO_2 ενδέχεται να μειωθούν κατά -1,88% έως -17,05%, ανάλογα με την τιμή άνθρακα λόγω μείωσης της αεροπορικής ζήτησης.

Το περιβαλλοντικό κόστος αποτελεί μέρος της δομής του κόστους των αεροπορικών εταιρειών και κατά συνέπεια επηρεάζει την κερδοφορία τους. Σε αυτή την εργασία γίνεται η υπόθεση ότι, τουλάχιστον ένα μέρος του, μετακυλύεται στους επιβάτες, με αποτέλεσμα μείωση της αεροπορικής ζήτησης. Στην πραγματικότητα οι αεροπορικές εταιρείες ενδέχεται να αντιδράσουν και προς άλλες κατευθύνσεις έτσι ώστε να περιορίσουν την απώλεια κέρδους. Γίνεται η απλουστευτική παραδοχή ότι η μείωση της ζήτησης θα αντικατοπτριστεί βραχυχρόνια στο συντελεστή πληρότητας των πτήσεων. Αν υποθέσουμε ότι η μείωση της ζήτησης αποδίδεται ομοιόμορφα σε μείωση του συντελεστή πληρότητας, το Σχήμα 6 παρουσιάζει την αθροιστική κατανομή των συντελεστών πληρότητας μετά την περιβαλλοντική πολιτική για τα διάφορα σενάρια της τιμής άνθρακα. Για λόγους σύγκρισης, απεικονίζεται επίσης η αντίστοιχη καμπύλη των συντελεστών πληρότητας πριν την εφαρμογή της πολιτικής. Με βάση τα αποτελέσματα, πριν από την εφαρμογή της περιβαλλοντικής πολιτικής ο μέσος συντελεστής πληρότητας ήταν 0,84, ενώ οι μισές αεροπορικές συνδέσεις είχαν συντελεστή φορτίου μεγαλύτερη από 0,83. Στην τιμή του άνθρακα των \$20 ανά τόνο CO_2, ο μέσος συντελεστής πληρότητας ήταν 0,78. Οι αλλαγές γίνονται ιδιαίτερα έντονες στην τιμή των \$100 ανά τόνο CO_2, όπου ο μέσος συντελεστής πληρότητας πέφτει στο 0,66.



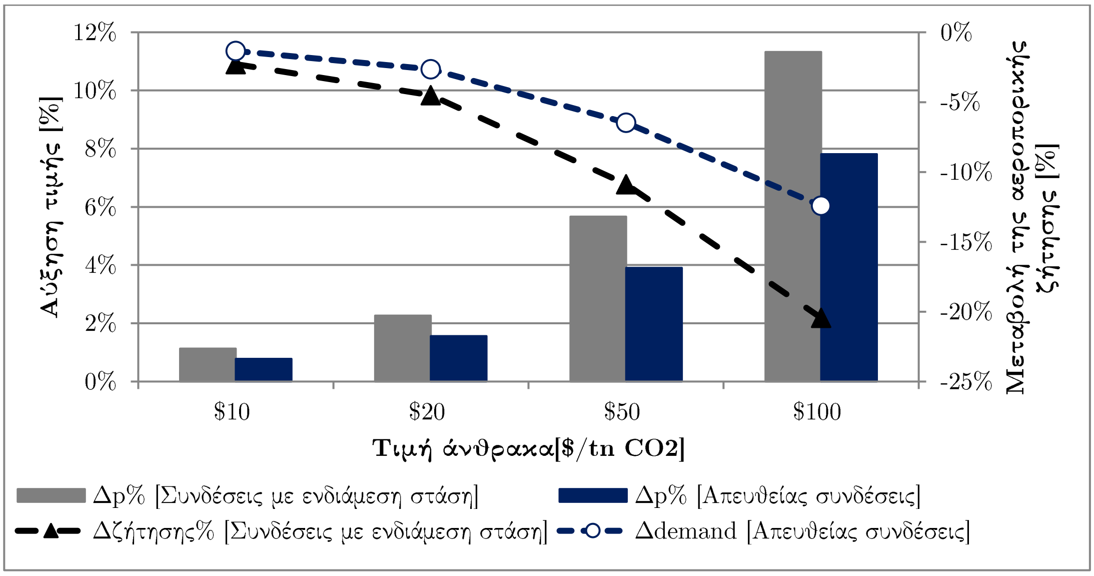
Σχήμα 6. Μεταβολές στην αθροιστική συχνότητα του συντελεστή πληρότητας

Επίσης, εξετάζεται η επίδραση του περιβαλλοντικού μέτρου σε αεροπορικές συνδέσεις με διαφορετικά χαρακτηριστικά (για παράδειγμα απευθείας συνδέσεις ή συνδέσεις με ενδιάμεση στάση, συνδέσεις διαφορετικών αποστάσεων). Στο Σχήμα 7 οι αεροπορικές συνδέσεις ομαδοποιούνται σε τέσσερις ομάδες με βάση την απόστασή των πόλεων Π-Π: συνδέσεις με απόσταση λιγότερη από 620 μίλια (≅1000 km), 620-1250 μίλια (≅1000-2000 km), 1250-2500 μίλια (≅2000-4000 km) και μεγαλύτερη από 2500 μίλια (≅4000 km). Για το μεσαίο σενάριο (\$20/tn CO_2), οι κοντινότερες πτήσεις γίνονται κατά μέσο όρο 1,3% πιο ακριβές, ενώ οι μακρινότερες πτήσεις έχουν αύξηση τιμής κατά περίπου 2,83%. Η μεταβολή της ζήτησης κυμαίνεται από -1,59% έως -6,58% για τις κοντινότερες και τις μακρινότερες πτήσεις αντίστοιχα (για το σενάριο των \$20/tn CO_2). Συνολικά, όπως αναμενόταν, οι πιο μακρινές πτήσεις αναμένεται να υποστούν μεγαλύτερες επιπτώσεις λόγω του αυξημένου κόστους άνθρακα.



Σχήμα 7. Μεταβολή της τιμής εισιτηρίου και της αεροπορικής ζήτησης για δρομολόγια διαφορετικών αποστάσεων

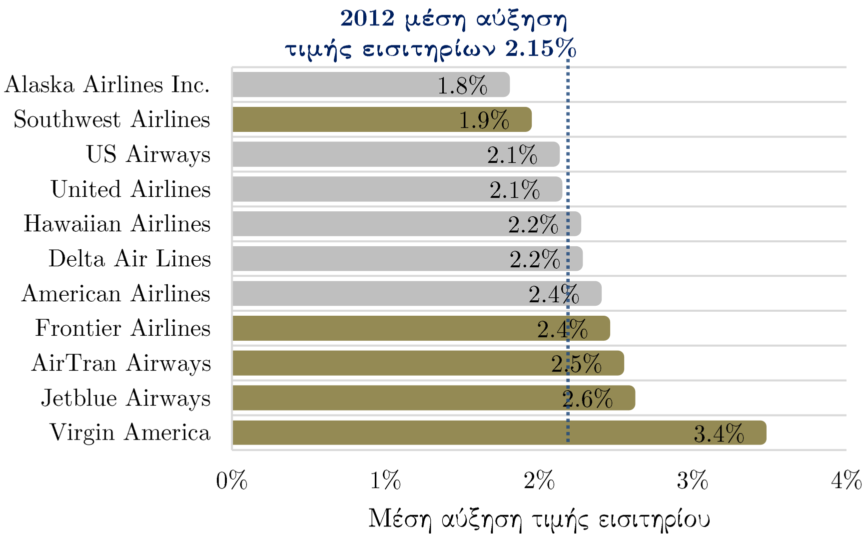
Τα απευθείας δρομολόγια αναμένεται να έχουν διαφορετικές επιπτώσεις από τα δρομολόγια με ενδιάμεση στάση. Τα αποτελέσματα απεικονίζονται στο Σχήμα 8, όπου παρουσιάζεται ότι ένας επιβάτης θα αντιμετωπίσει μεγαλύτερη αύξηση της τιμής εισιτηρίου στις πτήσεις με ενδιάμεση στάση. Αυτό είναι αποτέλεσμα των υψηλότερων εκπομπών CO_2 σε σύγκριση με τα αντίστοιχα απευθείας δρομολόγια. Ως εκ τούτου, ακόμη και εντός της ίδιας αγοράς, οι επιβάτες που επιλέγουν να ταξιδεύουν απευθείας μεταξύ των αεροδρομίων Π-Π θα ωφεληθούν περισσότερο από εκείνους που ταξιδεύουν με ενδιάμεση στάση. Για την υψηλή τιμή άνθρακα των $50 ανά tn CO_2, οι πτήσεις με ανταπόκριση αντιμετωπίζουν κατά μέσο όρο αύξηση 5,7% στην τιμή εισιτηρίου σε σύγκριση με 3,9% για τα απευθείας δρομολόγια.



Σχήμα 8. Μεταβολή της τιμής εισιτηρίου και της αεροπορικής ζήτησης ανά τύπο δρομολογίου

Η ανάλυση σε επίπεδο αγοράς έδειξε ότι η περιβαλλοντική πολιτική αναμένεται να έχει διαφορετικές επιπτώσεις σε αγορές με διαφορετικό επίπεδο ανταγωνισμού. Πιο συγκεκριμένα, στην εργασία εξετάζεται αν ο αριθμός των ανταγωνιστών σε μια αγορά μπορεί να επηρεάσει το μέγεθος της αύξησης της τιμής του εισιτηρίου μετά την εφαρμογή της περιβαλλοντικής πολιτικής. Μετά από σύγκριση αγορών με παρόμοια χαρακτηριστικά διαπιστώνεται πως η αύξηση της τιμής εισιτηρίου έχει πτωτική τάση, όταν κινούμαστε σε μεγαλύτερο αριθμό παικτών (αεροπορικές εταιρείες) στην αγορά. Δηλαδή, όσο μεγαλύτερος είναι ο αριθμός των παικτών σε μία αγορά, τόσο μικρότερη είναι η αύξηση της τιμής του εισιτηρίου.

Η ανάλυση σε επίπεδο αεροπορικής εταιρείας έδειξε ότι το περιβαλλοντικό μέτρο αναμένεται να έχει διαφορετικές επιπτώσεις ανάλογα με τον τύπο της αεροπορικής εταιρείας. Οι επιπτώσεις του μέτρου στην τιμή εισιτηρίου για τιμή του άνθρακα ίση με F=$20 ανά τόνο CO_2 φαίνονται στο Σχήμα 9. Οι επιπτώσεις στις «παραδοσιακές» εταιρείες απεικονίζονται με γκρι, ενώ για τις αεροπορικές εταιρείες χαμηλού κόστους με ανοιχτό καφέ. Παρατηρούμε ότι οι αεροπορικές εταιρείες χαμηλού κόστους αντιμετωπίζουν τη μεγαλύτερη αύξηση τιμών, εκτός από τη Southwest Airlines. Με βάση τα αποτελέσματα της ανάλυσης, οι τιμές της Virgin America είναι πιθανό να αυξηθούν κατά 3,4%, ακολουθούμενη από τρεις άλλες εταιρίες LCC: JetBlue, AirTran και Frontier. Η εντονότερη αύξηση για τις εταιρείες χαμηλού κόστους μπορεί να εξηγηθεί από τις επικρατούσες τιμές των εισιτηρίων πριν την επιβολή του μέτρου καθώς και από το επιβαλλόμενο κόστος άνθρακα. Για παράδειγμα, με βάση τα αποτελέσματα της παρούσας εργασίας, οι εταιρείες Frontier και AirTran έχουν σχετικά χαμηλό κόστος άνθρακα σε σύγκριση με άλλες αεροπορικές εταιρείες. Ωστόσο, λόγω των χαμηλών τιμών εισιτηρίων την περίοδο πριν την εφαρμογή του περιβαλλοντικού μέτρου (οι Frontier και AirTran έχουν κατά μέσο όρο τις χαμηλότερες τιμές, $365,6 και $347,6 αντίστοιχα), η ποσοστιαία αύξηση των τιμών (2,4% και 2,5% αντίστοιχα), μετά την περιβαλλοντική πολιτική είναι υψηλότερη από ό,τι σε άλλες αεροπορικές εταιρείες. Για τις περιπτώσεις της Virgin America και της Southwest Airlines, οι υψηλές και χαμηλές επιπτώσεις αντίστοιχα μπορεί να εξηγηθούν τόσο από το υψηλό/χαμηλό κόστος άνθρακα όσο και από τις αρχικές τιμές των εισιτηρίων.



Σχήμα 9. Μεταβολές της τιμής εισιτηρίου ανά αεροπορική εταιρεία (για το τιμή άνθρακα ίση με F=$20 ανά τόνο CO_2)

9. Συμπεράσματα

Η παρούσα διδακτορική διατριβή αναλύει διαφορετικές πτυχές της αεροπορικής βιομηχανίας, συμπεριλαμβανομένων των επιλογών των επιβατών, των αποφάσεων των αεροπορικών εταιρειών, του ανταγωνισμού στην αγορά, και των εκπομπών διοξειδίου του άνθρακα των αεροσκαφών και του συνεπαγόμενου κόστους άνθρακα σε ένα ρυθμιστικό περιβάλλον χαμηλών εκπομπών. Ειδικότερα, δείχνει πώς οι αεροπορικές εταιρείες ενδέχεται να αναπροσαρμόσουν την τιμή εισιτηρίου και πώς οι επιβάτες ενδέχεται να αλλάξουν τις αεροπορικές επιλογές τους μετά την εφαρμογή μιας περιβαλλοντικής πολιτικής. Για το σκοπό αυτό, μια μεθοδολογική προσέγγιση, που χρησιμοποιείται κυρίως στη βιομηχανική οργάνωση, επεκτείνεται στο τομέα του συγκοινωνιολόγου μηχανικού, έτσι ώστε να περιγράψει με κατάλληλο τρόπο την εφαρμογή του περιβαλλοντικού μέτρου στις αερομεταφορές και τις ενδεχόμενες αλλαγές που θα επιφέρει. Ένα σημαντικό χαρακτηριστικό αυτής της διατριβής είναι ότι, μετά τον υπολογισμό των εκπομπών διοξειδίου του άνθρακα για τις «καλυπτόμενες από το περιβαλλοντικό μέτρο» αεροπορικές εταιρείες, το αντίστοιχο κόστος άνθρακα εισάγεται ως τμήμα του οριακού κόστους της αεροπορικής εταιρείας. Ένα τμήμα αυτού του κόστους μπορεί να μετακυλήσει στους επιβάτες, με αποτέλεσμα την αύξηση της τιμής εισιτηρίου. Η νέα τιμή εισιτηρίου (σε απάντηση του επιπρόσθετου κόστους άνθρακα) διαμορφώνεται από την εταιρεία ως η Ισορροπία Nash με βάση το υπόδειγμα Bertrand. Τέλος, ενδεχόμενες αλλαγές στις αεροπορικές επιλογές των επιβατών αναλύονται με τη χρήση προτύπων διακριτών επιλογών.

Σχετικά με τη μεθοδολογική προσέγγιση που χρησιμοποιήθηκε στην παρούσα διατριβή μπορούν να εξαχθούν διάφορα συμπεράσματα. Κατ' αρχάς, σε αντίθεση με την πλειοψηφία των υπαρχουσών εργασιών με αθροιστικά δεδομένα, οι οποίες κυρίως εφαρμόζουν γραμμικά μοντέλα παλινδρόμησης, η παρούσα εργασία αναλύει τα μερίδια αγοράς των αεροπορικών συνδέσεων με ένα ιεραρχικό πρότυπο logit διακριτής επιλογής (Nested Logit model). Η συμπεριφορά των αεροπορικών εταιρειών διαμορφώνεται από το πρόβλημα μεγιστοποίησης κέρδους σε μια ανταγωνιστική αγορά με αρκετούς παίκτες. Έτσι, προσδιορίζονται οι κύριοι παράγοντες της συνάρτησης χρησιμότητας των επιβατών και της συνάρτησης κόστους των αεροπορικών εταιρειών. Διάφορες μακροσκοπικές μεταβλητές που εντοπίστηκαν στη βιβλιογραφία προσαρμόζονται ή τροποποιούνται ώστε να συμπεριληφθούν στο μοντέλο της ζήτησης, όπως η τιμή του εισιτηρίου, η συχνότητα σύνδεσης, οι καθυστερήσεις άφιξης, ενώ επιπλέον χρησιμοποιούνται ερμηνευτικές μεταβλητές που δεν έχουν χρησιμοποιηθεί στο παρελθόν σε αθροιστικά μοντέλα, όπως η παρουσία εναλλακτικού αεροδρόμιου σε κοντινή απόσταση από την προέλευση ή τον προορισμό του επιβάτη και η αναχώρηση κατά τις πρωινές ώρες. Τα οικονομετρικά πρότυπα που αναπτύσσονται εκτιμώνται με τη Γενικευμένη Μέθοδο των Ροπών ώστε να ληφθεί υπόψη το πρόβλημα ενδογένειας. Κατάλληλοι στατιστικοί έλεγχοι εφαρμόζονται για τη χρήση έγκυρων βοηθητικών μεταβλητών.

Για τον υπολογισμό των εκπομπών CO_2 ανά αεροπορική σύνδεση χρησιμοποιήθηκαν δεδομένα της εναέριας κατακόρυφης τροχιάς για ένα ευρύ φάσμα πτήσεων εσωτερικού των Η.Π.Α. Μετά από εκτενή ανάλυση αυτών των δεδομένων έγινε ταξινόμηση των πτήσεων σε μοναδικούς συνδυασμούς «απόστασης πτήσης, αεροσκάφους και προσανατολισμού πτήσης» και αναλύθηκε η τυπική εναέρια κατακόρυφη τροχιά του αεροσκάφους για κάθε συνδυασμό με την εφαρμογή δύο διαφορετικών προσεγγίσεων: i) εφαρμογή προτύπου προσομοίωσης της λειτουργίας ενός αεροσκάφους και (ii) υπολογισμός της τυπικής εναέριας τροχιάς του αεροσκάφους μετά από ευθυγράμμιση κατάλληλου δείγματος ιστορικών στοιχείων. Στη συνέχεια με βάση τις τυπικές κατακόρυφες τροχιές που εξάγονται η βάση δεδομένων Base of Aircraft Data (BADA) του EUROCONTROL χρησιμοποιήθηκε για τον υπολογισμό της κατανάλωσης καυσίμου και των εκπομπών CO_2.

Η εφαρμογή των παραπάνω προσεγγίσεων για την τυπική τροχιά αεροσκάφους εφαρμόστηκαν στο αεροπορικό δίκτυο των Η.Π.Α. Η σύγκριση των δύο μεθόδων έδειξε ότι η μέθοδος που βασίζεται στην ευθυγράμμιση του δείγματος των στοιχείων (registration-based method) παράγει πιο ακριβή αποτελέσματα ως προς τη διάρκεια των διαφόρων φάσεων της πτήσης και το ρυθμό ανόδου και καθόδου. Παρά τις σημαντικές διαφορές στα εκτιμώμενα χαρακτηριστικά πτήσης μεταξύ των τυπικών τροχιών που εξάγονται από τις δύο μεθόδους, η διαφορά στην εκτίμηση των εκπομπών CO_2 είναι λιγότερο έντονη.

Τα αποτελέσματα από την εφαρμογή του περιβαλλοντικού μέτρου δείχνουν ότι ανάλογα με την τιμή άνθρακα που εφαρμόζεται οι επιπτώσεις στις τιμές των εισιτηρίων, στην αεροπορική ζήτηση και στις συνεπαγόμενες εκπομπές CO_2 μπορεί να είναι σημαντικές. Σε αυτή την διατριβή, διαφορετικά σενάρια τιμής άνθρακα (\$10, \$20, \$50, \$100 ανά τόνο CO_2) χρησιμοποιήθηκαν έτσι ώστε να απεικονίσουν διαφορετικές καταστάσεις της αγοράς άνθρακα. Με βάση την παρούσα ανάλυση, για το σενάριο χαμηλής τιμής άνθρακα (\$10), που είναι κοντά στην τιμή άνθρακα που επικρατεί σήμερα, οι τιμές των εισιτηρίων μπορεί να αυξηθούν κατά μέσο όρο κατά 1,07%. Αυτό θα μειώσει τη συνολική αεροπορική ζήτηση κατά 1,47% και τις συνολικές εκπομπές CO_2 κατά 1,88%.

Για το σενάριο υψηλής τιμής άνθρακα (\$ 100), οι τιμές των εισιτηρίων μπορεί να αυξηθούν κατά περίπου 10,7%, ενώ η αεροπορική βιομηχανία ενδέχεται να αντιμετωπίσει σημαντικές απώλειες ζήτησης (απώλεια περίπου 13,5%). Επί του παρόντος οι επικρατούσες τιμές άνθρακα είναι πολύ χαμηλές σε διάφορες αγορές (λίγο κάτω από το 10\$ ανά τόνο CO_2), όπως στα ΣΕΔΕ της ΕΕ και της Σαγκάης. Παρά τη σημαντική διακύμανση που παρατηρήθηκε τα τελευταία χρόνια στην τιμή του άνθρακα, η υιοθέτηση των υψηλών σεναρίων των \$50 και \$100 ανά τόνο CO_2 δεν φαίνεται πιθανή με βάση τις τρέχουσες τάσεις στη τιμή άνθρακα.

Λαμβάνοντας υπόψη τα αποτελέσματα της προσομοίωσης για το χαμηλό σενάριο τιμής άνθρακα \$ 10 ανά τόνο CO_2 (που είναι κοντά στην σημερινή τιμή άνθρακα) και τον στόχο της αεροπορικής βιομηχανίας (ICAO, 2016a) για μείωση των εκπομπών CO_2 των αεροπορικών μεταφορών κατά 50% μέχρι το 2050 (σε σχέση με τα επίπεδα του 2005), η παρούσα διατριβή δείχνει ότι είναι ανάγκη οι αεροπορικές εταιρείες και οι άλλοι φορείς της βιομηχανίας να στραφούν σε εναλλακτικές προσεγγίσεις για να διασφαλιστεί η οικονομική και περιβαλλοντική βιωσιμότητα των αερομεταφορών. Η ανάλυσή της διατριβής δείχνει ότι η τιμολόγηση των εκπομπών CO_2 συμβάλλει στη μείωση των εκπομπών CO_2. Παρ' όλα αυτά, τα χαμηλά επίπεδα της τιμής του άνθρακα δεν αναμένεται να οδηγήσουν σε σημαντικές αλλαγές στον τομέα των αεροπορικών μεταφορών. Ο συνδυασμός διαφόρων περιβαλλοντικών πολιτικών (π.χ. βελτίωση της τεχνολογίας και του ελέγχου εναέριας κυκλοφορίας, αγορακεντρικά περιβαλλοντικά μέτρα) μπορεί να ήταν πιο αποτελεσματικός.

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Abbreviations

The abbreviations used throughout this dissertation are listed below in alphabetical order. In the text, they are presented by their full name when they are first used but are later on referred to by their abbreviation.

Abbreviation	Description
2SLS	Two-Stage Least Squares
3SLS	Three-Stage Least Squares
ANOVA	Analysis of Variance
APF	Airlines Procedure File
BADA	Base of Aircraft Data
BTS	Bureau of Transportation Statistics
CAS	Calibrated airspeed
CASM	Cost per available seat-mile
CCA	California Carbon Allowance
CCD	Climb-Cruise-Descent
CCX	Chicago Climate Exchange
CO	Carbon Monoxide
CO_2	Carbon dioxide
CORSIA	Carbon Offsetting and Reduction Scheme for International Aviation
DB1B	Airline Origin and Destination Survey
EDMS	Emission and the Dispersion Modeling System
EEX	European Energy Exchange
ETS	Emissions Trading Scheme
FAA	Federal Aviation Administration
FDA	Functional Data Analysis
GDP	Gross Domestic Product
GEV	Generalized Extreme-Value
GHG	Greenhouse Gas
GMBM	Global Market-Based Measure
GMM	Generalized Method of Moments
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
ICE	Intercontinental Exchange
IEA	International Energy Agency
IIA	Independence of Irrelevant Alternatives
iid	Independent Identically Distributed
ISA	International Standard Atmosphere
ITF	International Transport Forum
IV	Instrumental Variables
KETS	Korean Emissions Trading Scheme
LCC	Low Cost Carrier
LTO	Landing and Take-Off
MAPE	Mean Absolute Percentage Error
MBM	Market-Based Measures
MNL	Multinomial Logit
MSA	Metropolitan Statistical Area
NextGen	Next Generation Air Transportation System
NL	Nested Logit
NOx	Nitrogen Oxides
OAG	Official Airline Guide
O-D	Origin-Destination
OLS	Ordinary Least Squares
OPF	Operations Performance File
OTP	On Time Performance
PIANO	Project Interactive Analysis and Optimization
PTR	Pass Through Rate
RGGI	Regional Greenhouse Gas Initiative
RMSE	Root Mean Square Error
ROC(D)	Rate of Climb (Descent)
ROD	Rate of Descent
RPK	Revenue Passenger Kilometers

RTK	Revenue tonne kilometres
SHEA	Shanghai Emissions Allowance
TAS	True Airspeed
T-100	T-100 Domestic Segment for US carriers

The airline and airport abbreviations are given in Appendix B.

1 Introduction

1.1 Problem Statement

Years after the deregulation of the airline industry[2], the aviation environment has been affected by several changes: i) the formulation of airline mergers, which may lead to increased efficiency, reduced cost and increased airline revenues (Flores-Fillol, 2009; Merkert and Morrell, 2012), ii) the development of hub-and-spoke networks, which gives the passengers the opportunity to reach more destinations from a single origin and allows airlines to serve high traffic demand while reducing operating cost due to economies of scale (Berry et al., 2006; Nero, 1999; Ryerson and Kim, 2014), iii) the introduction of low-cost carriers (LCC), which has reportedly increased network competition which resulted in lower ticket prices and lower market power of full service carriers.

Over the last years, the aviation industry faces further challenges which come from the increased air traffic worldwide. In Europe, air traffic in terms of passenger kilometers increased by 26.8% between 2000 and 2013 (European Commission, 2015). In the United States, passengers miles increased by 17.9% between 2000 and 2014 (BTS, 2016a). Air traffic growth is expected to continue in the years to come. Boeing (2015) suggests that global passenger traffic will increase by an annual factor of 4.9% until 2034. The highest rates will be experienced in South and Southeast Asia where the annual growth rates will reach 9.9% and 8.9% respectively. Within Europe, the annual growth rate is estimated at 3.3% and within the North America at 2.4% (Boeing, 2015).

These levels of growth raise significant concern on the environmental impact of aviation. Currently, international aviation is responsible for around 1.3% of global carbon dioxide (CO_2) emissions, or approximately 450 million tons annually based on 2014 data (ITF, 2016). Recent statistics indicate that, if no mitigation action is taken, these rates may increase given the increasing trend of air traffic. Given the projections for air traffic growth in the coming decades, by 2040 fuel consumption and CO_2 emissions from international aviation are projected to increase 2.8 to 3.9 times the 2010 values (ICAO, 2016a).

Figure 1.1 presents the evolution of air traffic and aircraft CO_2 emissions since 1990 for Europe, the United States and worldwide. Air traffic has significantly increased in both

[2] Airline deregulation was first put in effect in the United States in 1978. In Europe, airline deregulation was the result of the Single European Act which the E.U. member states agreed to in 1986.

regions. In Europe, the passenger kilometers went up by 67.5% since 1995, while in the U.S. the corresponding increase is equal to 50.5% (since 1990). CO_2 emissions from international and domestic aviation in Europe increased by 79.2% between 1990 and 2012, while world CO_2 emissions from international aviation increased by 89.5 from 1990 to 2013.

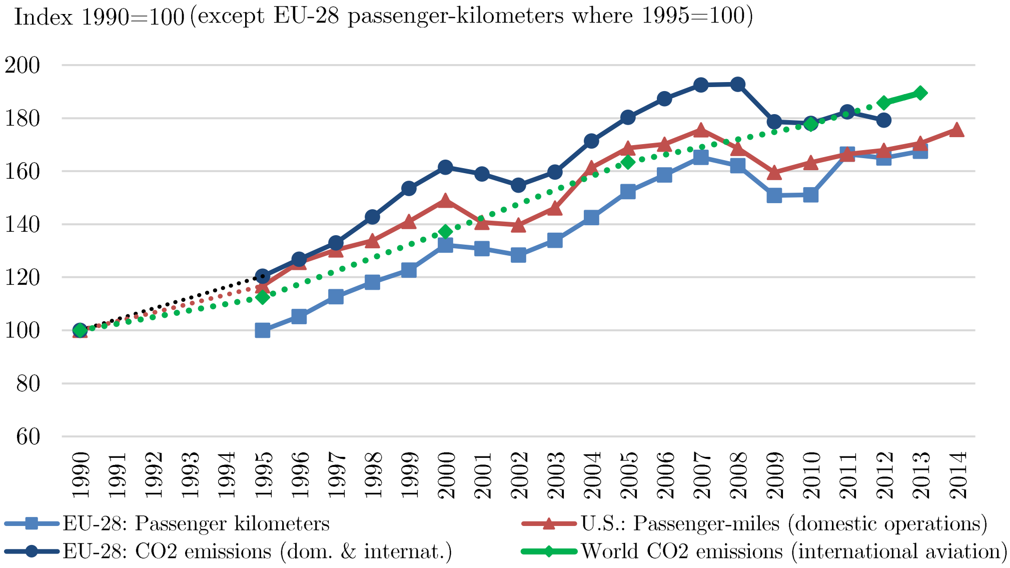


Figure 1.1. Evolution of air traffic and aviation CO_2 emissions (own elaboration with data from EC, 2015; BTS, 2016a and IEA, 2015)[3]

In recent years, in response to the increasing evolution of aviation greenhouse gas (GHG) emissions, market-based environmental policies have received significant attention around the world. Although at the last major United Nations Framework on Climate Change conference, in 2009 in Copenhagen, the EU Emissions Trading System (EU ETS) was the only major market-based measure in place, several carbon markets have been implemented the intervening years around the world. According to Kossoy et al. (2015), until 2015 about 40 national jurisdictions and over 20 cities, states, and regions had implemented a carbon pricing scheme. In aviation, the EU ETS was initially introduced in 2012. Then, due to strong objections from several countries and stakeholders, at the end of 2012, the EU ETS was suspended for one year and now it is applicable to all flights between airports in the European Economic Area region until 2016. Besides, in October 2016 the International Civil Aviation Organization (ICAO) Assembly decided to implement a global market-based measure (MBM) scheme in the form of the Carbon Offsetting and Reduction Scheme for International Aviation to come into force in 2020. In the meantime, two other ETS were introduced for domestic aviation: Shanghai's ETS was introduced in 2013, while the Korean Emissions Trading Scheme entered into force in 2015. Along with other carbon pricing initiatives (emissions charges in airports, voluntary carbon offset schemes etc), the above facts indicate that there is continuing trend towards the introduction of carbon pricing schemes in aviation on a global scale.

[3] Dotted lines are constructed by using linear interpolation as there were no available data.

The aviation sector is a complex and competitive system with several actors, e.g. airlines, passengers, airports, aircraft manufacturers, fuel suppliers etc. The introduction of a market-based measure is likely to affect the actors of the airline industry in different ways. First, airlines are impacted by the extra cost of carbon allowances or carbon charges/taxes/levies/fees in general (hereinafter referred to as carbon cost). Airlines' objective is to maximize profits. The introduction of the carbon cost will increase airline operating cost which, in the long run, may be passed on to passengers as higher fares (Forsyth, 2008). This, in turn, may affect passenger demand, as air travel is price elastic. Passengers may choose not to travel as a result of the price increase or may shift to other transport modes especially in short-haul markets (i.e., train, automobile, etc.) if comparative advantages are significant enough. Apart from ticket price, comparative advantages may include the difference in the level of service, reliability between the two modes etc. The extent to which an airline and its market share is affected by the implementation of a MBM may also depend on the market structure of competition. The air transport demand changes may, in turn, affect airports, aircraft manufacturers, fuel suppliers and other actors. However, these interactions are beyond the scope of this dissertation.

1.2 Research objectives

The main objective of this dissertation is **to develop a modeling framework that assesses the impact of environmental policies on aviation industry**, focusing on a market-based environmental measure that puts a price on airlines' carbon dioxide emissions. The assessment of the impact of such a policy necessitates the investigation of the interaction between the two main actors, passengers (demand side) and airlines (supply side). Therefore, the impact on airline ticket prices and market shares is assessed by integrating a game theoretic model with passenger's travel choice behavior as follows: we simultaneously model (i) the airline pricing decision in origin-destination city pairs with oligopolistic competition of airlines on ticket prices and (ii) the passengers' travel behavior changes after the policy implementation through a discrete choice analysis. Overall this dissertation uses empirical analysis to answer the following question: To what extent does the implementation of a market-based measure affect ticket prices, airline market shares and network-wide carbon emissions from air travel? Effects of the policy implementation on airlines' cost are additionally assessed, while a market- and airline-level analysis reveals the extent to which market structure and airline type affect the research outcomes.

To fulfil the above objective, five sub-objectives are defined and described as follows:

- O1. To develop an aggregate air travel demand model, which relies on discrete choice analysis of different airline connections in origin-destination markets.
- O2. To formulate and model the airlines' behavior in a competitive market, where a non-cooperative game between the competing airlines is developed.
- O3. To develop an appropriate equation system estimation approach so as to account for the interaction between demand and supply.

O4. To compute the amount of carbon dioxide of every airline connection in the study network in a relatively quick and accurate way.
O5. To apply the developed methodologies and simulate the ticket prices and market share changes under the scenario of a market-based measure implementation in a large airline network.

In order to achieve the above research objectives, a methodology is developed which consists of the following steps:

1. First, an extensive literature review covering the different domains of the overall research field is conducted.
2. Second, demand and supply econometric models, which explain air travel demand and the airlines' behavior respectively are specified, simultaneously estimated and validated. Air travel demand modelling is done by developing a discrete choice framework which models the airline connections' market share as a function of airline-route, market, airline and airport characteristics. The exploration of the factors that affect passengers' choice on airline connections is, thus, a significant part of this step. On the airlines' side, a game is assumed to be developed where airlines set their ticket prices with the aim to maximize profits. This setting enables to link passenger demand with the supply side and simultaneously estimate demand and supply models. The developed estimation procedure also accounts for the endogeneity issues caused by the correlation of some independent variables with the error terms. Validation of the two econometric models, by evaluating the estimated demand and supply model parameters and by conducting relevant statistical diagnostics is also conducted. The models are additionally validated by comparing the predicted passenger flows and ticket prices with the values actually observed.
3. The third step considers the development of an innovative methodology which is capable of calculating itinerary CO_2 emissions based on path profile estimation by clustering and registration methods. This step gives insight into understanding the key features that determine the aircraft altitude profile. This step additionally enables the computation of the carbon emissions cost per itinerary.
4. Step 2 and 3 are integrated so as to simulate a market-based environmental measure, by introducing the corresponding carbon emissions cost as a shifter in the airline's marginal cost function. In this way, resulting investigate effects on aviation industry are investigated.

The above steps are analyzed in the dissertation's chapters as described next.

1.3 Dissertation Organization

The dissertation is organized in nine chapters as shown in Figure 1.2.

Following the current chapter (Chapter 1), Chapter 2 constitutes the major part of the literature review and consists of several parts. In the first part, the current situation in the airline industry is presented, focusing on the evolution of air traffic and associated CO_2 emissions. Second, the environmental measures implemented on the aviation sector with a focus on the market-based measures are presented, along with their characteristics and geographic area of applicability. The next part reviews state-of-the-art studies which assess the impact of market-based environmental policies on aviation, focusing on their key parameters, assumptions and main findings. A state-of-the-art review on air travel demand models is then provided. The review examines the existing studies in terms of the nature of the approach, the factors chosen to explain air travel demand, the kind of data used and the methods of estimation. The final part of the review discusses state-of-the-art approaches to modelling landing/take-off and climb-cruise-descent fuel burn and carbon emissions. The above review findings are used to identify research needs and the chapter concludes with discussing how this dissertation builds on previous research.

Chapter 3 describes the development of a tool to compute aircraft fuel burn and carbon dioxide emissions for any given itinerary. The landing/take-off (airport-based) and climb-cruise-descent (route-based) phases are methodologically treated differently. The airport-based computations are built on the basis of the relevant review of Chapter 2. A route-based emissions model incorporates the consideration of actual flight performance of the aircraft between the origin and destination airports. Thus, additional review on the simulation of actual flight performance and construction of a typical altitude profile is carried out. Finally, modelling assumptions, main results and the evaluation of our emissions model are presented.

Chapter 4 concerns the air travel demand analysis. First a general formula for the air transport demand function is given. The developed demand model is based on discrete choice analysis. Thus, an introduction on discrete choice models is first provided, starting with an overview on random utility theory and focusing later on the developed aggregate model for air travel demand in an O-D city pair. The explanatory variables are grouped in four categories based on the airline-route characteristics, the airline, and the airports and the market served.

Chapter 5 describes the airline's behavior in the competitive O-D city pairs. First, the different market structures in terms of firm competition are described. Based on the characteristics of the airline industry, it is pointed out that airline markets are oligopolies and crucially rely on the strategic interactions between the competing players. Then, the oligopoly game developed by the airlines in each O-D market is described, along with the game's components and the associated mathematical expressions. Because the marginal costs that enter the airline's optimization functions are not observed, the chapter closes with the description of the marginal cost formulation and the associated cost explanatory variables.

In Chapter 6, the simultaneous econometric analysis of the demand model (Chapter 4) and the airline's behavior model (Chapter 5) is presented. The endogeneity issues raised by the correlation of some independent variables with the residuals are discussed, by identifying the sources of endogeneity and by specifying the instrumental variables used to address the problem. Then the Generalized Method of Moments (GMM), which is the selected method to cope with the endogeneity issues and the non-linearity of the equation system, is described. Finally, the assumed market-based environmental policy is specified, while the developed approach to simulate the assumed policy and examine its potential effects on airline ticket prices and market shares is presented.

Data sources used in this dissertation are provided in Chapter 7. First, the adopted filtering process is described while the resulting sample data is presented along with associated summary tables and statistics.

Chapter 8 presents the main results of the dissertation and is divided in two parts; the first part presents the results derived from the estimation of the air travel demand model and the airline's behavior model. Parameter estimates, validation of the models and estimates of the airlines' marginal cost are provided. In the second part, the findings obtained by the implementation of the market-based environmental policy are presented. Several elements such as the estimated post-policy equilibrium ticket prices and market shares, the network-wide environmental benefits and the estimated pass-through rates are discussed.

The major findings and overall conclusions are presented in Chapter 9. Recommendations for further research are also discussed.

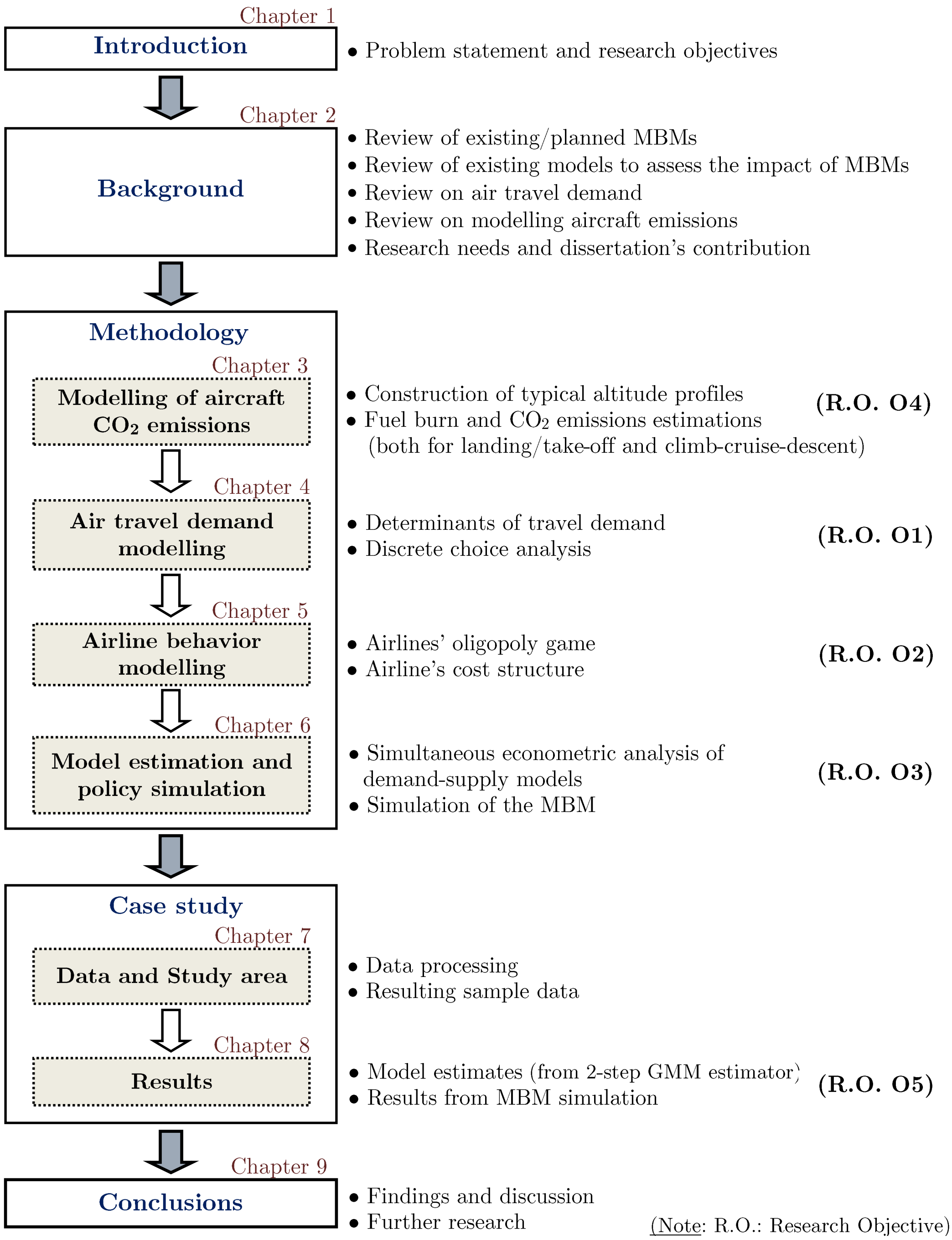


Figure 1.2. Flow diagram of the dissertation

2 Background

2.1 Current mitigation policy for aviation emissions

In response to the increasing evolution of aviation greenhouse gas emissions, attempts to reduce the aviation's greenhouse gases have followed a number of directions. These measures are related to technological improvements, operational efficiency improvements, use of alternative fuels and economic instruments and are further discussed below. This section provides an overall review of the environmental measures implemented on the aviation sector with a focus on the market-based measures for air transport, their characteristics and geographic area of applicability.

2.1.1 Four-pillar approach for sustainable aviation

Most aviation organizations, aiming to achieve aviation environmental goals, rely their initiatives on a four-pillar approach (FAA, 2015; IATA, 2013a; Sgouridis et al., 2011) that encompass technological improvements, operational efficiency improvements, use of alternative fuels and deployment of market-based instruments (see Figure 2.1).

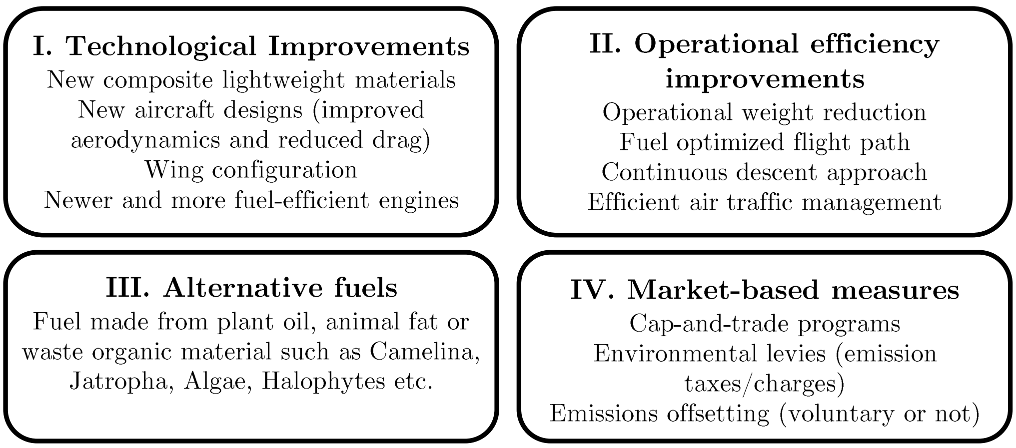


Figure 2.1. Four-pillar approach for sustainable aviation

Technological improvements: Technological improvements are expected to significantly contribute to fuel burn and emissions reduction. The initiatives for improving aircraft fuel efficiency focus on reducing aircraft weight, improving aircraft aerodynamics to reduce drag and improving engine efficiency, and on reducing fuel burn per unit thrust (Grote et al., 2014). The development of newer and more fuel-efficient airframes and engines, the use of new composite lightweight materials, the introduction of new aircraft designs are some of the future and emerging technologies considered by aircraft, engine and equipment manufacturers. According to IATA (2013b) the most promising airframe technology is the deployment of "Hybrid-Wing-Body aircraft" which may offer 10% to 25% fuel reduction benefits and is estimated to be market available after 2026. Among engine technologies, the introduction of "New engine core concepts" is estimated to provide the greatest emission reduction of around 25-30% (IATA, 2013b). However, the success of such technologies strongly depends on uncertain factors such as development status, benefits, risk and research and development costs. For example, some technologies, such as advanced airframes which are expected to have large potential on emissions reduction, may be years away from being available, and developing and adopting them is likely to face high development costs.

Operational efficiency improvements: Achieving more efficient aircraft operations is another pillar for reducing emissions from aviation. These improvements can be achieved through optimized airline operations, such as aircraft operational weight reductions by removing unnecessary onboard equipment, or optimized air traffic management operations, such as fuel optimized flight path, continuous descent approach and reduced flight delays. Both the United States and the European Union have taken important steps towards developing modernized air traffic management systems. In the United States, Federal Aviation Administration (FAA) is leading a multiagency effort to transform current U.S. air traffic control system to the Next Generation Air Transportation System (NextGen). NextGen is believed to increase the safety, capacity and efficiency of the U.S. airspace system (FAA, 2014). In Europe, the European Union launched the Single European Sky initiative which de-fragments the European airspace in order to provide air traffic conditions with lower delays, greater safety standards, lower aircraft emissions and lower costs related to service provision (Commission of the European Communities, 2008). According to IATA (2013b), CO_2 emissions from commercial flights could be reduced by 28 million tons in 2020 through airline operational measures.

Alternative fuels: Sustainable alternative fuels will play a critical role in the effort of achieving environmentally-friendly aircraft operations. Four drivers for the development of alternative jet fuel are recognized by Hileman and Stratton (2014): economic sustainability, environmental sustainability, energy supply diversity and competition for energy resources. Alternative fuels have lower lifecycle carbon dioxide (CO_2) emissions than conventional kerosene and thus offer the opportunity to reduce aviation's contribution to climate change and to air quality. However, the widespread production and development of alternative fuels may raise several concerns with the most important being the requirements on land and water usage (Hileman and Stratton, 2014; Rojo et al., 2015). Since the approval for commercial use of biofuels, various airlines have experimented with the use of biofuels on commercial flights demonstrating that alternative fuels can be safe and technically sound (IATA, 2014a).

Market-based instruments: Technology, operations and alternative fuel measures are the long-term solution for aviation's sustainable growth. However, due to the time required for their implementation, market-based measures are viewed as a short-term promising option for reducing aviation emissions. Lee et al. (2013) examined the mitigation potential of these measures and concluded that the non market-based measures will be important in the long-term, but they will not be sufficient to bridge the emission gap to achieve aviation's environmental goals. Instead, the extension of current market-based measures offers the greatest mitigation potential. Generally, market-based measures can achieve emissions reductions at less cost than other policies because they would give airlines the flexibility to decide when and how to reduce their emissions. For example, the development of low-emissions technologies (such as open rotor engines and blended wing-body aircraft) may be adopted by airlines (GAO, 2009). Market-based instruments may take the form of a cap-and-trade program with allowance auctions, an environmental levy (emissions tax or charge) or a voluntary emissions offsetting (Carlsson and Hammar, 2002; IMF, 2011; GAO, 2009). The aim of such policies is to establish a price per unit of emitted CO_2 and motivate airlines to adopt low-emissions technologies on their aircraft fleet in order to reduce their emissions.

Under a cap-and-trade program the amount of total emissions is capped to a predefined target and a market for carbon is established, allowing the participants to buy and sell emission permits. Cap-and-trade programs are also known as emissions trading schemes. The airlines are issued emission permits up to the established cap. If they exceed the cap, they are allowed to buy additional emission allowances to cover the excess between what they emit and the cap. If an airline emits less CO_2 than the cap, they sell the emission allowances. Under an open emissions trading system, aviation would be free to trade with other sectors that are included within the scheme. However, a closed trading system is limited to the aviation sector. Environmental levies aim to create an economic incentive to reduce emissions and can fall into one of two categories: taxes and charges. In general, a "tax" raises revenue from an activity and this revenue is then polled into general revenue, while a "charge" raises revenue from an activity for the purpose of paying the costs of providing services relating to the activity itself. Examples of such charges in the aviation context include airport charges and route charges. Under such a scheme in aviation, a fee for every amount of emission (such as carbon dioxide) emitted is levied to each polluter (airline). It can be implemented on any aircraft operation within a given airline network or an airport. Most known examples of emissions charges include the charges imposed by airports to airlines for their landing and take-off operations at the airports. En-route emissions charges are another option of environmental levy. According to the economic theory, an optimal emissions charge should be set at a level that represents the marginal damage cost of emissions (GAO, 2009). Carbon offset schemes are based on the concept of reducing emissions in another sector or location, rather than reducing an emitter's own emissions. In such a scheme, individuals or companies invest in environmental and carbon-offset projects around the world in order to compensate directly for their emissions. In the field of air transport, carbon offset programs are mainly voluntary. A carbon offset facility can either be run by the airline itself or by an independent service provider. If it is run by the airline, at the time of ticket purchase, passengers are encouraged to pay for the amount of CO_2 emissions resulting from their travel by making charitable contributions to several environmental projects such as forest conservation and renewable energy (IATA, 2008b). Since offsetting is basically a voluntary activity undertaken by passengers in a largely unregulated environment, its success is not guaranteed.

2.1.2 Existing or planned market-based measures for air transport

Market-based measures (MBM) encompass a range of policy tools that allow internalization of the environmental external costs in the context of the principle "the polluter pays" and create economic incentives for the sustainable development of the considered industry. To stabilize net aviation CO_2 emissions through carbon-neutral growth, several market-based instruments have been implemented or are planned for air transport.

There is continuing trend towards the introduction of carbon pricing schemes in several industries and on a global scale. According to Kossoy et al. (2015), until 2015 about 40 national jurisdictions and over 20 cities, states, and regions had implemented a carbon pricing scheme. It is interesting to note that current pricing schemes (as in 2016) cover more than 12% of global emissions, while in 2011 the coverage was less than 5%. These policy instruments are diverse incorporating carbon taxes, emissions trading schemes and carbon offset programs and are implemented in various industries.

European Emissions Trading Scheme (EU ETS)

The most known cap-and-trade policy is the European Union Emissions Trading Scheme (EU ETS). In the context of the Kyoto Protocol's requirements, EU implemented the EU ETS in 2005 which included several sectors, such as power and heat generation and mineral industries (EU, 2003). In 2008, the EU ETS was expanded so that, from 2012, it would include air traffic operations, by EU and non-EU airlines that depart from or arrive at European airports, i.e. both intra-EU flights and between EU and non-EU airports (EU, 2008). This meant that, for example, an American airline operating a flight from New York to London would still have to comply with the EU ETS. Within the EU ETS, a cap is set on the carbon dioxide emissions from all covered flights by aircraft operators and, then, allowances are allocated, bought or sold among the airlines though auctioning. For phase 3 (2013-2020) the provisional cap on aviation emissions[4] has been set at a constant level, which is equivalent to 95% of the historical aviation emissions (average aviation emissions over 2004-2006). The European Energy Exchange AG (EEX) is the transitional common auction platform for 25 Member States, while another auction platform includes ICE Futures Europe (ICE).

The inclusion of non-EU airlines in the EU ETS prompted strong objections from several countries and stakeholders in the United States, China, Russia, and India. In light of these disagreements, in 2014, the EU ETS directive was amended in order to apply to flights between airports in the European Economic Area (EU, 2014). Thus, from 2014 to 2016 flights to and from countries outside the EU would benefit from a general exemption. All CO_2 emissions from flights between airports in the EU would continue to be covered, while all overflights are exempt. The rationale behind this amendment was

[4] The aviation sector has a separate emissions cap within the EU ETS. This cap is different from the declining annual cap provided for other economic sectors in the EU ETS.

the fact that, by the end of 2016, the International Civil Aviation Organization would have a decision to implement a global Market-Based Mechanism (MBM).

According to the revised EU ETS Directive (EU, 2014), the auctioning revenues should be used by Member States for climate and energy related purposes and for funding research and development for mitigation and adaptation. Thus, from 2014 onwards, Member States are requested to report annually on the amounts and use of the revenues generated.

Korean Emissions Trading Scheme

The Korean Emissions Trading Scheme (KETS) is the second largest market after the EU ETS in terms of emissions covered among the different entities and it is expected to play a leading role in spreading emissions trading to developing countries. It entered into force in 2015 and it is the first nationwide cap-and-trade program in operation in East Asia. It covers domestic aviation and other 22 sectors, including steel, cement, power, buildings, waste etc (ICAP, 2016a). During its first phase (2015-2017), aviation is allocated free allowances based on previous activity data from the base year (2011-2013). In the next phases, a small percentage of the allowance will be auctioned.

A unique aspect of KETS is the ability of the government to increase the supply of allowances in order to stabilize prices around KRW 10,000 (around €7.9 or $9.0). However, this is believed to result in weakening the incentive for emission reductions for participating entities (Kim and Kim, 2015). Korean Allowance Units traded in 2015 at around €7.9 per ton (~$9.0), which was very close to the prevailing European Union Allowance price (Kossoy et al., 2015).

Shanghai Emissions Trading Scheme

Shanghai emissions trading scheme is one of the seven Chinese pilot ETS which were launched in different regions of China in order to mitigate greenhouse gases from several entities. These pilot programs are planned to be replaced by the China's national ETS which is scheduled for 2017.

Shanghai's ETS was introduced in 2013 and is the only program in China which covers GHG emissions from aviation (domestic only). Other covered sectors include shipping, railways, chemicals, electricity etc (ICAP, 2016b). Emission allowances are allocated according to the 2009-2011 emission levels, considering company growth and benchmarks.

One allowance in Shanghai's ETS is called Shanghai Emissions Allowance (SHEA), meaning to allow releasing 1 ton of CO_2. Trading takes place in the designated trading platform at the Shanghai Environment Energy Exchange. Similar to Korean ETS, price stabilization measures may take place if needed (in this ETS by the Shanghai Environment and Energy Exchange). SHEA prices show erratic behavior; SHEA average price between January '15 and April '15 was $4.85/ton, while SHEA average price was $3.25/ton between April and August 2015 (PMR, 2015).

Emission Charges

Emission charges represent any charge imposed to an airline for the amount of emissions generated either at an airport during the Landing and Take-Off (LTO) phase (emission airport charge) or during cruise (en-route charge). In other studies, emission charges are referred to as "emission fees" or "emission taxes". There are several examples of airport emission charges being applied in Europe, with Swiss and Swedish airports having the longest history. In 1997, Zurich airport became the first airport worldwide to introduce a nitrogen oxides (NO_X) emission-based charge in order to address air quality problems caused by air traffic. Later, Geneva airport followed this measure in 1998, Bern airport in 2001, Basel airport in 2003 and Lugano airport in 2007 (Zurich Airport, n.d.). Other airports in Germany and United Kingdom have already implemented such a policy by imposing extra landing charges on airlines, based on their amount of emissions generated at the vicinity of the airports. Emission charges have not been introduced at any airport in the United States. Boston Logan International Airport considered implementing such fees for NO_X emissions. Nevertheless, the airport operator conducted a study to assess the efficiency of the emission fees and concluded that, since these fees would be a small portion of airlines' operating expenses, the policy would be ineffective (GAO, 2003). Table 2.1 presents the emission charges applied to European airports.

Table 2.1. Airport emission charges in several European countries

Country	Airport	NO_X charge per landing or take-off (for 2015 or else as indicated)	Start year	Source
Switzerland	Zurich	2.50 CHF per kg NO_X	1997	FOCA (2016)
	Geneva	1.40 CHF per kg NO_X	1998	
	Berne	3.30 CHF per kg NO_X	2001	
	Lugano	3.40 CHF per kg NO_X	2007	
Sweden	Stockholm Arlanda, Bromma Stockholm, Göteborg Landvetter, Malmö, Luleå, Umeå, Kiruna, Åre Östersund, Visby, Ronneby	50 SEK per kg NO_X	1998	Swedavia (2015)
United Kingdom	Heathrow	£8.57 per kg NO_X	2004	Heathrow Airport Limited (2015)
	Gatwick	£2.80 per kg NO_X	2005	Gatwick Airport Ltd (2015)
Germany	Frankfurt	3.08€ per kg NO_X	2008	Fraport (2015)
	Munich	3.00€ per kg NO_X (year 2016)	2008	Munich Airport (2016)
	Cologne Bonn	3.00€ per kg NO_X (year 2016)	2008	Cologne Bonn (2016)
	Hamburg	3.00€ per kg NO_X	2010	Flughafen Hamburg GmbH (2015)
	Dusseldorf	3.00€ per kg NO_X	2011	Dusseldorf Airport (2015)
Denmark	Copenhagen	DKK 16.60 per kg NO_x	2010	Københavns Lufthavne (2015)

Airport emission charges reflect cost externalities and aim to compensate society for the consequences of relevant emissions. The charge at Zurich airport was introduced to encourage airlines to use less polluting aircraft when using the airport. At the same time, the weight-based landing fee was reduced to ensure that the charge remained revenue-neutral for the airport (Zurich Airport, n.d.).

An example of a CO_2 emission charge applied to the entire part of flight (and not only to the LTO phase at the vicinity of airports) is the Norwegian CO_2 tax on aviation fuel. It was implemented in 1999 for all domestic and international flights, although it later withdrew the tax relating to international flights due to violation of many bilateral aviation agreements which Norway had with other countries (OECD, 2005). Along with the introduction of ETS for aviation 1st of January 2012, the CO_2 tax has been reduced in Norway (ICAO, 2012b).

Voluntary Carbon Offset Programs by airlines

Carbon offset programs give the passengers the option to "neutralize" their proportion of aircraft emissions on a particular journey. Passengers willing to offset their emissions, pay an extra fee to the ticket price in order to be invested in environmental projects. These projects are usually based in developing countries and most commonly designed to reduce future emissions. Various airlines have already implemented voluntary carbon offset programs. Until 2014, over 35 airlines had launched their own voluntary carbon offset schemes (IATA, 2014b); some of them are:

- U.S. airlines: Delta, JetBlue, United, Virgin Atlantic
- Canadian airlines: Air Canada
- European airlines: Austrian Airlines, Air France, British Airways, Brussels Airlines, Easyjet, Lufthansa, SAS, Swiss, TAP Portugal
- Australian airlines: Cathay Pacific, Jetstar, Qantas Airways, Virgin Australia
- Asian airlines: Japan Airlines, Qatar Airlines, Thai Airways
- African airlines: Kenya Airways, South African Airways

Given that the above carbon offset schemes are not mandatory, their success, in terms of passengers participating, is uncertain. Reports by various airlines demonstrate a relatively satisfactory uptake of voluntary carbon offsets. For example, Jetstar and Virgin Australia indicate that 10% of their domestic aviation passengers choose to offset their flights (Australian Government, 2012).

ICAO global market-based measure

In October 2013, during its 38th session the International Civil Aviation Organization Assembly supported the development of a global market-based measure (GMBM) for international aviation as part of a broader package of measures including new technology, more efficient operations and better use of infrastructure (ICAO, 2013a). The aviation industry itself has expressed its interest for such a measure, stating that a global initiative is more preferable in comparison to a complex combination of different national or regional schemes (Kossoy et al., 2015).

The ICAO GMBM was scheduled to be adopted in 2016 and come into force in 2020. Initially three different options for a GMBM were discussed (ICAO, 2013b):

1. Global mandatory offsetting;
2. Global mandatory offsetting complemented by a revenue generation mechanism;
3. Global emissions trading using a cap and trade approach.

Since 2013, significant work was undertaken by ICAO and its Member States, in cooperation with the aviation industry and other stakeholders, in order to develop a global MBM for international aviation. Furthermore, both political and technical design elements were analyzed and discussed by representatives of governments, industry and civil society (Kossoy et al., 2015).

During its 39th session (October of 2016), the ICAO Assembly decided to implement a global MBM scheme in the form of the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) to address any annual increase in total CO_2 emissions from international civil aviation above the 2020 levels (ICAO, 2016b). CORSIA will be implemented in phases, starting with participation of States on a voluntary basis, followed by participation of all States except the exempted States, as follows:

- Pilot phase (2021-2023) and 1st phase (2024-2026) would apply to States that have volunteered to participate in the scheme; and
- Second phase (2027-2035) would apply to all covered[5] States

Concerning the coverage of the scheme, a route will be covered if both States connecting the route are participating in the scheme; similarly, a route will not be covered by the scheme if one or both of States connecting the route are not participating in the scheme. Through the ICAO's scheme, emissions from international aviation will be offset through the reduction of emissions elsewhere (outside of the international aviation sector), involving the concept of "emissions units". One "emissions unit" represents one tonne of CO_2.

The above stand for different approaches on emissions pricing (mainly carbon pricing) for aviation[6]. Figure 2.2 shows the geographical spread of existing market-based measures for air transport (excluding ICAO's GMBM).

In essence, the implementation of ETS or other emission pricing schemes raise airlines costs. The extent to which these costs may influence the airlines' strategies on ticket pricing, the air transport demand and the general framework of the aviation network has been examined by various studies in the past. The next section provides a review of the existing approaches to modelling the impact of emissions pricing schemes on air transport.

[5] Based on ICAO (2016b), covered States are those whose individual share of international aviation activities in Revenue tonne kilometres (RTKs) in year 2018 is above 0.5% of total RTKs or whose cumulative share in the list of States from the highest to the lowest amount of RTKs reaches 90% of total RTKs, except Least Developed Countries, Small Island Developing States and Landlocked Developing Countries unless they volunteer to participate in this phase.

[6] New Zealand's ETS is not mentioned as an aviation-related ETS. Transport and particularly domestic aviation has been indirectly covered by New Zealand's ETS by the coverage of liquid fossil fuels sector. Fuel used for international aviation is not included in the scheme, consistent with the Kyoto Protocol. Furthermore, in 2014 a per-passenger CO_2 levy was proposed in Portugal for domestic flights and for flights departing from Portugal to an airport outside of the European Economic Area (IATA, 2014c). However, the above proposal was not supported by the Portuguese Government and thus was not implemented.

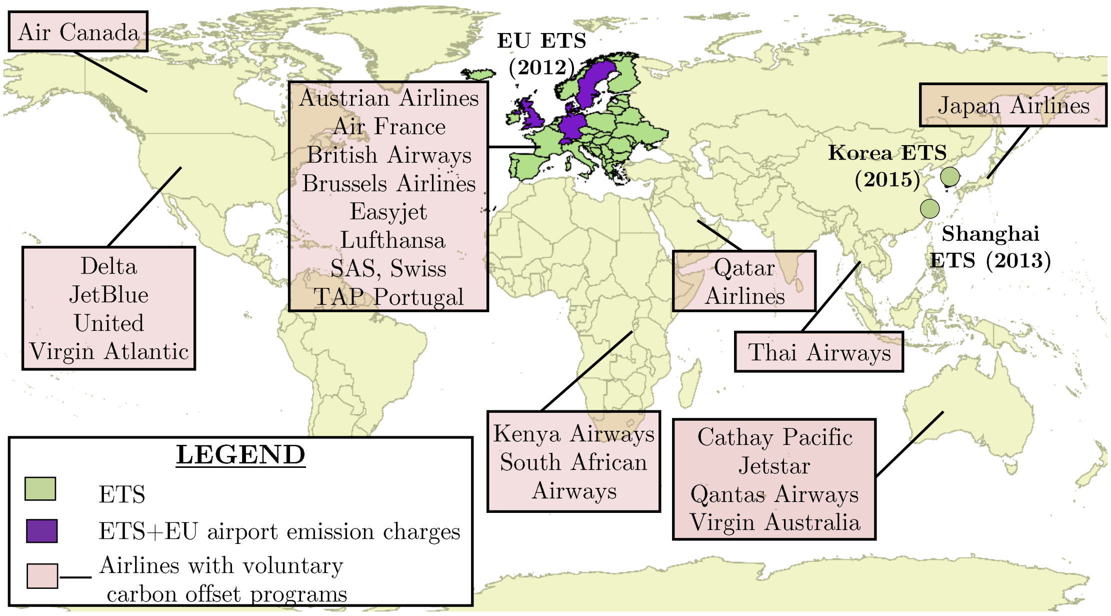


Figure 2.2. Overview of emissions pricing instruments for aviation

2.2 Existing assessment models of market-based environmental aviation policies

Existing studies that have analyzed the impact of market-based policies on air transport are based on various assumptions, different policy scenarios and modelling parameters.

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). Most of these studies concluded that until high carbon costs are implemented in a market-based policy, there will be limited impact on the tourism sector, airlines network reconfiguration and airline competition. Furthermore, the results of Brueckner and Zhang (2010) indicated that emission charges will raise fares, reduce flight frequency, increase load factors and raise aircraft fuel efficiency.

Other studies investigated the impact of market-based measures 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, weakening the competitive 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 may result 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. Mayor and Tol (2010) used the Hamburg Tourism Model to investigate the effect of three climate policy instruments in Europe on tourist arrivals and emissions for the countries concerned; the EU ETS, the Netherlands' flight tax[7] and the UK's boarding tax (in this case, the authors refer to the increase of the UK's air passenger duty in February 2007) were considered. Overall, the results indicated that the tourist flows decrease within Europe and grows elsewhere, as tourists substitute towards destinations is not affected by the price increase. In addition, a redistribution occurs within Europe, while emissions are only reduced by a very small amount. 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 for the route "London Heathrow to Johannesburg". The results demonstrated that the EU ETS could be an effective instrument except for very low carbon prices. Derigs and Illing (2013) explored the impact of EU ETS on air cargo network configuration, with specific focus on how airlines can optimize their profits by adapting their network and schedules. Their results show that EU ETS (as ruled for the next years) will result in no or only marginal impacts towards reducing CO_2 emissions. The reason is that cost increases are either negligible for airlines or can be limited by small changes in schedule. Only if cost per allowance is raised significantly will a reduction of CO_2 emissions be achieved. Meleo et al. (2016) estimated the direct costs linked to the implementation of the EU ETS in the Italian aviation sector. Three different hypotheses on emission permit price are used by the authors to forecast the EU ETS direct costs for the years 2015-2016. The results highlight that EU ETS costs and their impact on both companies and passengers are currently quite limited. However, the authors state that these costs are expected to slightly increase starting from 2016, due to the increase of carbon price.

The majority of the above-mentioned studies consider the EU ETS to show the impact of a market-based measure on ticket prices, demand change, networks and emissions reductions. A U.S. study by Malina et al. (2012) estimated the economic impact of EU ETS on U.S. 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. The authors 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. Finally, they showed that emission taxes may cause

[7] This tax was introduced on July 1st 2008 and abolished exactly one year later.

significant air-to-automobile diversion effects. Sgouridis et al. (2011) examined five emissions mitigation policies for commercial aviation. One of them included carbon pricing and it was used as a mechanism to increase the effective price of fuel and reduce demand through the price-demand elasticity relationship. The authors concluded that under a price of \$50 per ton CO_2 the impact on both global demand and emissions would be minimal (less than 3% in emissions reduction). They also suggested that carbon pricing schemes would need to maintain high price levels, while the combined use of carbon pricing and biofuels would provide a significant contribution to the overall goal of mitigating CO_2 emissions by 7–17% by 2024. Fukui and Miyoshi (2017) examined whether an increase in aviation fuel tax would decrease fuel burn and carbon emissions in the U.S. aviation. For this purpose, the authors used unbalanced annual panel data from 1995 to 2013. Their results suggested that an increase in aviation fuel tax of 4.3 cents may have negligible impact on CO_2 emissions. The reduction would be higher in the short run (1 year after the tax increase, CO_2 emissions may be reduced by 0.14-0.18%) in comparison to the long run (3 years later, the reduction would be about 0.008-0.01%). Gonzalez and Hosoda (2016) reviewed the effects of the Japanese Aviation Fuel Tax which has been levied in Japan since 1972 for domestic flights. In particular, they investigated the impact of the 30% reduction of the tax (implemented in April 2011) on aviation-related CO_2 emissions. The authors compared the amount of CO_2 emissions before and after the tax adjustment and found that, after the tax adjustment, CO_2 emissions were 8.89% higher in comparison with a "business as usual" scenario had the tax not been modified. Girardet and Spinler (2013) developed a dynamic optimization model which includes fluctuating prices for kerosene and CO_2 emissions. The authors assume a single airline network with no direct competition. Their analysis is conducted for multiple periods of time and for different routes, in terms of route length and trip purpose (business vs vacation). The results indicate that short-haul routes with low marginal costs and low pass through rates show quite stable demands, while for longer routes, demand reactions are more pronounced.

Table 2.2 provides a list of the reviewed studies focusing on those which considered the impact of market-based policies on ticket prices and air transport demand.

Table 2.2. Key parameters and assumptions used in the state of the art review (in chronological order)

Reference	Market-based scheme	Geographical area	Carbon price (per ton CO_2)	Cost pass-through rate	Other assumptions	Main findings
Scheelhaase and Grimme (2007)	EU ETS	EU ETS area for 3 European airlines	€15, €20 and €30	100%	Assumed price elasticity: -0.5 to -0.9 (business) -1.1 to -1.5 (leisure)	The financial impact of EU ETS will be significantly greater for low cost carriers and regional airlines than for network carriers.
Albers et al. (2009)	EU ETS	Individual flight routes	€20	35% and 100%	Assumed price elasticity: -1.13 for short-haul and -0.78 for long-haul flights	Ticket price increase: 0.94-3.79% (for 100% pass-through rate) and 0.33-1.33% (for 35% pass-through rate) Demand reduction: 1.18-2.96% (for 100% pass-through rate) and 0.41-1.03% (for 35% pass-through rate) No major route reconfigurations among European airlines.
Lu (2009)	LTO charge	6 intra-European short-haul routes in 2 city pairs	€20	100%	Average elasticity -1.52 (leisure) and -0.7 (business)	Demand reduction: 0.9% to 1.9 for business passengers and 4.5% to 7.8% for leisure passengers. Higher potential demand reduction (in %) for EasyJet's markets (due to lower fares).
Anger (2010)	EU ETS	EU ETS coverage area	€5, €20 and €40	100%	The author does not specify the assumed price elasticities.	EU ETS may lead to increased CO_2 emissions in the EU, if the auctioning revenues are used to increase government spending and thereby generate more economic activity. Annual change of CO_2 emissions: +0.09% (at €5/ton), +0.24% (at €20), -0.30% (at €40) in 2020 compared with no action scenarios.
Hofer et al. (2010)	Air travel CO_2 tax	U.S. domestic air travel	2% of the air fare	100%	Airfare elasticity: -1.15 Cross-elasticity: 0.041	Estimated demand decrease for U.S. domestic air travel: 2.3%. Short-haul markets: high air-to-auto substitution may result to the increase of total carbon emissions. Long-haul markets: substantial emissions reductions due to little to no air-to-auto substitution.
Mayor and Tol (2010)	EU ETS, Dutch and UK's tax	Europe, Netherlands, UK	€23 (EU ETS), fixed flight costs for Dutch and UK's tax	-	Various assumptions defined by the Hamburg Tourism Model	Tourist flows decrease in the EU and grows elsewhere, as tourists substitute towards destinations is not affected by the price increase. Emissions are only reduced by a very small amount
Sgouridis et al. (2011)	Carbon pricing	Global air travel	\$50 and \$200	100%	Input parameters used to calibrate the model based on historical time series data	CO_2 emissions reduction: 3% for the price of \$50 per ton and 8% for \$200 per ton
Malina et al. (2012)	EU ETS	U.S. carriers within the EU ETS area	€15 (2010)[(a)]	3 scenarios from 0 to 100%	Average elasticity -0.72 (passenger) and -0.99 (freight)	If cost pass-through rate=0%: no changes on CO_2 emissions under EU ETS. When some CO_2 costs are passed on to consumers, there are small reduction in emissions.
Derigs and Illing (2013)	EU ETS	EU ETS coverage region	€15 and €70	-	The study considers cargo airlines	ETS rules planned for the first years will have no or only marginal impacts towards reducing CO_2 emission.

Girardet and Spinler (2013)	Fuel and CO_2 emissions surcharge	8 routes (with different length and trip purpose)	€8	ranging	Different price elasticities used for different route length and trip purpose (business vs vacation)	In a single airline network with no direct competition, short-haul routes with low marginal costs and low pass through rates show quite stable demands, while for longer routes, demand reactions are more pronounced.
Miyoshi (2014)	EU ETS	London Heathrow to Johannesburg route	€7, €15 and €30	100%	A multinomial logit model for the route demand is constructed.	Route's ticket price increase: €3.9-5.5 (for €7/ton), €8.3-11.7 (for €15/ton) and €16.7-23.4 (for €30/ton). The results are different if airlines change aircraft type to more fuel-efficient aircraft.
Gonzalez and Hosoda (2016)	Japanese Aviation Fuel Tax	Japan	Adjustment from 26,000 to 18,000 ¥/lt fuel	-	A Bayesian structural time series model is used	Investigated the 30% reduction of the fuel tax on aviation-related CO_2 emissions. After the tax adjustment, CO_2 emissions were 8.89% higher in comparison with a "business as usual" scenario had the tax not been modified.
Meleo et al. (2016)	EU ETS	Italy	€7.1, €15 and €25	0%, 50% and 100%	Emissions data are obtained from an official authority in Italy	The impact on both companies and passengers are currently quite limited due to the vast surplus allowances and to a very low carbon price.
Fukui and Miyoshi (2017)	U.S. Aviation Fuel Tax	U.S. airlines	4.3 and 10-cent increase in aviation fuel tax	-	Regression model with dependent variable: the US carrier's annual jet fuel consumption	A 4.3-cent increase in aviation fuel tax may result in CO_2 emissions reduction by 0.14-0.18% in the short run and by about 0.008-0.01% in the long run.

Notes: [(a)] Increasing by 4% annually until 2020

2.3 A review on air travel demand

2.3.1 Classification of demand models

Demand models are classified into different types according to the level of aggregation (disaggregate or aggregate approaches) and the type of the model (linear regression or random utility models) (Hsiao and Hansen, 2011; Ortuzar and Willumsen, 2011; Postorino, 2010). Aggregate studies can be further classified into three main categories according to the type of the data analyzed: (i) cross sectional data (ii) time series data and (iii) panel data. Another classification (Carson et al., 2011) is based on the distinction between macroscopic and microscopic models and the choice of the dependent variable. Macroscopic models are used to estimate the development of air transportation in a certain country or region, while microscopic models estimate air transportation demand between two airports, cities or regions. Postorino (2010) also mention the distinction of demand models in multi-mode and uni-mode, which depends on whether they allow estimating market shares for alternative transport modes or for only one transport mode.

Disaggregate models in air transport demand analysis have attracted considerable interest over the recent years. Disaggregate models analyze air travel behavior at the level of the passenger using (i) stated and (ii) revealed preference data or (iii) a combination of both. An important proportion of studies on air travel choice behavior make use of revealed preference data, generally in the form of survey data collected from departing passengers or booking data (Carrier and Weatherford, 2014; Proussaloglou and Koppelman, 1995). Stated preference surveys allow for the analysis of hypothetical travel situations and have been used for airport and airline choice by De Luca (2012), De Luca and Di Pace (2012), Hensher et al. (2001), Hess et al. (2007), Hess (2008), Jung and Yoo (2014), Loo (2008). A combination of stated preference and revealed preference data were used by Ortuzar and Simonetti (2008) to model intercity choice between train, coach and air for medium distance trips.

Aggregate models aim at representing the behavior of more than one individual, i.e. a group of passengers travelling within a specific zone (route, airport, network etc). The distinction of aggregate models into cross-sectional, time series and panel data models is related to the scope of the study and data availability. To take account variations across countries, across cities or across routes, cross sectional data should be used. Time series analysis may accommodate the investigation of air transport demand variation over time. Panel data analysis can be conducted when both the time series and the cross sectional nature of the data are present. Time series analysis has been widely used for air travel demand forecasting by Carson et al. (2011), Kopsch (2012) and Marazzo et al. (2010). However, when the researcher needs to investigate the causal effect of an independent variable on the dependent variable, the use of econometric models on cross-sectional data is more appropriate.

Demand generation and assignment models have both been studied. Demand generation models consider the total demand at a specific unit of observation (such as airport, region, airline, city pairs, airport pairs, country pairs etc) and usually make use of regression models (either on cross sectional or time series data). These studies mainly use socioeconomic and supply-side characteristics as independent variables (Hsiao and Hansen, 2011). Demand assignment models explain the allocation of air traffic among alternative routes, airlines and other dimensions and estimate the market shares of routes serving the same O-D airport or city pair. Random utility models are employed for estimation, ranging from multinomial logit to nested logit and mixed multinomial logit models.

Disaggregate models can simulate with greater accuracy a transportation system, since the detailed information obtained from surveys can better explain passenger behavior. On the other hand, its disadvantages include the time and cost to construct and conduct the questionnaire survey and the limited generalizability. In addition, from an airline perspective, it would be computationally difficult to model the choice of every individual passenger (Garrow, 2010). Therefore, aggregate models play a significant role in air transport demand analysis.

One common problem for aggregate models in the airline industry is the absence of origin-destination data. Passenger traffic statistics typically made available provide the origin and destination airports of an individual flight, which are not identical with the "true" origin and destination of the passenger, because many passengers use connecting services. However, in the United States market-level itinerary traffic data are compiled by the U.S. Department of Transportation (BTS, n.d.) and cover the full itinerary of U.S. domestic passengers which means that one can determine the full composition of traffic in each route area. This kind of data are used in this dissertation for developing the aggregate air travel demand model; their usefulness and applicability are explicitly discussed in Chapter 7.

2.3.2 Existing approaches to modelling air travel demand

Numerous methodologies have been developed in the past to model air travel demand, which cannot be fully covered in this dissertation. Thus, the aim of this section is to review some studies linked to the pre-mentioned categories, focusing on the aggregate demand models and their most frequently used independent variables.

Gravity models are the earliest models developed for air travel demand modelling (Doganis, 2004; Grosche et al., 2007; ICAO, 2006). According to Doganis (2004), the first recorded use of gravity model on air transport was in 1951, when D'Arcy Harvey developed the gravity concept to evaluate the air traffic flow between two communities. In the field of transportation, gravity models have been used within the trip distribution analysis. Gravity models use Newton's law of universal gravity to explain the correlations between two regions. Various studies have used gravity models for air travel modelling (Bhadra and Kee, 2008; Evans and Schäfer, 2013; Grosche et al., 2007). In these studies, demand is a function of population and income (as measures of attractiveness) and distance or travel rime (as a measure of resistance). Gravity models have also been extended to include variables related to the offered level of service. Ticket price, flight delay and frequency have been used by Bhadra and Kee (2008) and Evans and Schäfer (2013) in their gravity models. A detailed review of gravity models for air passenger demand estimation can be found in Grosche et al. (2007). Gravity models are very useful when trying to model air travel on new routes, where no historical data are available or on routes where traffic records are inadequate or non-existent (Doganis, 2004).

For the estimation of air traffic demand at an aggregate level, the multiplicative (log-log) model is considered by other studies. Bhadra (2003) and Wei and Hansen (2006) developed demand generation models as functions of socioeconomic and supply characteristics and used cross-sectional data to estimate demand parameters. Common variables among these models included ticket prices and flight distance. Bhadra (2003) also included airlines' market power, hub presence and seasonal dummies as explanatory variables, while Wei and Hansen (2006) used flight frequency, aircraft size, income and other variables. More recently, Mumbower et al. (2014) predicted demand for JetBlue flights in four transcontinental markets and used a database of online prices and seat map displays to estimate parameters. Scotti and Dresner (2015) developed a demand model on carrier-route level in order to assess the impact of baggage fees on passenger demand and airline fares. The last two studies assumed that ticket price is endogenous and thus used instrumental variables methods to estimate their models. In Mumbower et al. (2014) demand model was estimated with two-stage least squares (2SLS), while in Scotti and Dresner (2015) three-stage least squares (3SLS) was used to address price endogeneity.

Panel data have been used by other studies. Valdes (2015) developed static and dynamic panel data models to calculate the effects of air travel demand determinants in Middle Income Countries. Both the dependent and independent variables were inserted in the model in logarithmic form. Abate (2016) developed a linear regression on panel data to empirically measure the economic effects of air transport liberalization. To account for ticket price and frequency endogeneity, the demand model was estimated using 2SLS random effects method. Finally, Rolim et al. (2016) performed an econometric analysis of pre-privatization and post-privatization patterns of demand developing a fixed effects model. Explanatory variables included GDP per capita, population, a proxy for ticket price, privatization stage and a dummy for the presence of low cost airlines. Price endogeneity was addressed by employing the two-step generalized method of moments estimator.

All the above models fall into at least one of the following categories: (i) demand generation models in the sense that they focus on the total demand at a specific level, i.e. city-pair, airport-pair, carrier-route level etc, and (ii) gravity models (demand assignment) which distribute trips among origins and destinations (based on their attractiveness and a measure of resistance). Most of these studies cannot deal with the competitive effects of alternatives within the analyzed market (i.e. city pair or airport pair). For example, within the same city pair, different routes are very likely to compete with each other. Furthermore, transport mode competition may also exist. To account for these issues, demand assignment models that explain the distribution of traffic among alternative airports, routes, airlines or other dimensions have been developed (Barnhart et al., 2014; Coldren et al. 2003; Coldren and Koppelman, 2005; Hsiao and Hansen, 2011; Wei and Hansen, 2005). These studies incorporate travelers' behavior through the use of discrete choice models. In general, discrete choice models are usually derived in a random utility model framework in which decision makers are assumed to be utility maximizers. Compared to public and land transportation, the use of discrete choice models to represent air passenger behavior is fairly limited. However, several papers developing discrete choice models to simulate air travel behavior have been published in the last years. Most of these studies frequently use data collected by surveys (stated or revealed preferences surveys). Due to the disadvantages of survey data some researchers have employed discrete choice models on aggregate data. These studies aim at estimating the share of passenger demand that will utilize each of a set of available itinerary choices within a market (i.e. from an origin to a destination city or airport). The explanatory variables include socio-economic aggregated data about the profile and behavior of the "average passenger", data on the level of service (frequency, connection quality, departure time etc) of the itinerary, itinerary fare data etc. The collected data are usually obtained from flight schedule databases (including the Official Airline Guide-OAG), computer reservation systems databases and other O-D itinerary datasets.

Potential application areas for discrete choice models are airport choice modelling and air itinerary choice modelling, or combinations of both. In consistency with the aim of this dissertation, the following review focuses on itinerary choice modelling. Itinerary share models can complement airlines' decision making process as they provide carriers with an understanding of the relative importance of different service factors. In the context of an airline hub competition model, Hansen (1990) developed a multinomial logit model and applied it to the United States air transportation system. The passenger utility for an itinerary was formed as a function of ticket prices, service frequency and a constant reflecting consumer preference for non-stop service. Passenger itinerary and fare data were obtained from the U.S. DOT and airline frequency data were derived from the Official Airline Guide. Coldren et al. (2003) developed aggregate itinerary share models for air transport estimated at city-pair level in the United States. For this purpose, multinomial logit models were employed. The independent variables include various itinerary service characteristics such as level-of-service, connection quality, carrier market presence, fares, aircraft size and type, and time of day. Later, Coldren and Koppelman (2005) assumed that the underlying competition among air-travel itineraries within the city-pair is not uniform. Thus, they re-estimated the aggregate itinerary share models by using generalized extreme value models in order to allow for the possibility of correlation between error terms for groups of alternatives. Both studies used computer reservation systems data from a commercial source. Wei and Hansen (2005) built a nested logit model to study the role of service related attributes in airlines' market share in non-stop duopoly markets. The variables considered were aircraft size, service frequency, seat availability and fare. Aggregate O-D data was used to estimate the demand model. Barnhart et al. (2014) developed a multinomial logit model for estimating passenger travel demand using aggregate data. Demand parameters concerned the time and day of departure, connection time, seating capacity and flight cancellation.

Table 2.3 summarizes the reviewed studies on aggregate air travel demand, along with their assumptions, model parameters and methods of estimation.

Table 2.3. Key parameters and assumptions used in the state of the art review on air transport demand (in chronological order)

Study	Region (Time period[a])	Dependent Variable	Independent variables	Model or Method of estimation[b]	Comments[c]
Hansen (1990)	Domestic U.S. (1985)	Itinerary passengers	Ticket price, Service frequency, Constant reflecting consumer preference for non-stop service.	Discrete choice models: Multinomial logit model	Passenger itinerary and fare data: U.S. DOT/BTS. Airline frequency data: Official Airline Guide
Bhadra (2003)	Domestic U.S. (1999-2000)	O-D passenger traffic	Ticket price, Population density, Intensity of economic activities, O-D distance, Market Power of dominant and non-dominant airlines, Dummies for presence of Southwest, for hub airport, Seasonal dummy	Semi-logarithmic regression model	Demand generation model O-D data from U.S. DOT/BTS
Coldren et al. (2003)	Domestic U.S. city-pair routes (January 2000)	Itinerary passengers	Level-of-service, Connection quality, Carrier, Carrier market presence, Fares, Aircraft size and Type, Time of day	Discrete choice models: Multinomial Logit	Data (market size and fare data) obtained from the 'Superset' data source (generated from O-D data by U.S. DOT/BTS)
Coldren and Koppelman (2005)	East West markets in U.S. and Canada (May 2001)	Itinerary passengers	Distance, Best connection time difference, Fare ratio Carrier, Departure time, Dummy variables for indicating 1) direct itineraries, 2) Code sharing, 3) That the itinerary is not the best connection, 4) Use of regional jet, 5) Use of propeller aircraft	Discrete choice models: Multinomial Logit and Nested Logit models	Official and comprehensive schedule and bookings data
Wei and Hansen (2005)	Domestic non-stop duopoly U.S. markets (1989-1998)	Itinerary passengers	Aircraft size, service frequency, seat availability and fare.	Discrete choice models: Nested Logit model	Obtained O-D data from U.S. DOT/BTS
Wei and Hansen (2006)	Domestic flights between U.S. hub airports (Q2 of 2000)	Airline-route specific passengers	Ticket price, Frequency, Aircraft size, Number of spokes served by the airline, Flight distance, Number of local passengers, Number of initiated passenger trips originating from spoke, Income, Aircraft arrival capacity	Log-linear regression model on cross-sectional data	Demand generation model in a hub-and-spoke network O-D data from U.S. DOT/BTS
Grosche et al. (2007)	German airports (Jan.-Aug. 2004)	City-pair passenger volume	Population, Buying power index, Gross domestic product, Distance, Travel time	Gravity model	Booking data of flights between Germany and 28 European countries

(Table 2.3 continued)

Bhadra and Kee (2008)	Domestic U.S. (1995-2006)	O-D passenger traffic	Ticket price, Income, Population, O-D distance	Regression analysis of panel data	Demand generation model (using a gravity model framework). O-D data from U.S. DOT/BTS
Evans and Schäfer (2013)	Domestic flights between 22 busiest U.S. airports (2005)	O–D city pair passengers	Income, Population, Fare, Travel time, Flight delay, Flight frequency	Gravity-type model estimated by OLS and 2SLS (due to frequency endogeneity)	Airline behavior model included. O-D data from U.S. DOT/BTS
Barnhart et al. (2014)	Domestic U.S. (2007)	Itinerary passengers	Time of departure, Day of week, Connection time, Flight cancellations, Seating capacities.	Discrete choice models: Multinomial Logit	Publicly available aggregate data derived from the U.S. DOT/BTS
Mumbower et al. (2014)	JetBlue flights in 4 transcontinental markets (21 days in Sep. 2010)	Number of bookings	Ticket price, Date of promotional sales, Departure time, Number of days prior to departure, Departure day, Booking day, Market dummy	Regression model estimated by OLS and 2SLS (due to price endogeneity)	Booking data (flight, fare, and seat map information) were collected by automated web client robots
Scotti and Dresner (2015	Domestic airport-to-airport routes (Q1 of 2007-2010)	Number of passengers on carrier-route level	Fare, Baggage fee, Population, Income, Distance, Dummies for tourist origin/destination and for multiple airports, Airline dummy	Semi logarithmic regression demand model estimated by 3SLS method	Demand model estimated simultaneously with the fare model (system equations)
Valdes (2015)	32 Middle Income Countries (2002-2008)	Country's total passengers carried	GDP per capita, Net flows of foreign direct investment (proxy of the income), Consumer price Index (proxy for airfare), Jet fuel price, Total number of seats offered by LCCs	Static model (fixed effect model) and Dynamic models (Arellano Bond estimator with the GMM)	Aggregate data from World Bank, the countries' official websites and the Official Airline Guide.
Abate (2016)	20 African city-pair routes (2000–2005)	Round-trip route passengers carried	Roundtrip economy fare, Departure frequency, Income, Population, Distance of the route	Log-linear regression on panel data estimated by 2SLS random effects	Fare and frequency variables are endogenous
Rolim et al. (2016)	Domestic routes in Brazil (2003-2013)	Airport-pair revenue passengers	Yield (proxy for ticket price), Population, GDP per capita, Distance, Flight time, Intermodal competition, Presence of LCC competition Privatization stage	Semi logarithmic regression model on panel data (fixed effects); estimated by 2-step GMM	Used publicly available aggregate data Considered price endogeneity

Notes: [(a)] Q1=1st Quarter, Q2=2nd Quarter, ... of the year

[(b)] 2SLS: Two-stage Least Squares, 3SLS: Three-stage Least Squares, OLS: Ordinary least squares, GMM: Generalized Method of Moments

[(c)] U.S. DOT/BTS is the abbreviation of the U.S. Department of Transportation/Bureau of Transportation Statistics

2.4 Existing approaches to modelling aircraft emissions

Aviation, being an energy intensive sector, is an emitter of Greenhouse Gases which contribute to climate change and of air pollutants that affect the local air quality in the vicinity of airports. The main GHG emissions of aircraft include carbon dioxide (CO_2) and water vapor (H_2O), which can cause global warming, with CO_2 being the most important anthropogenic GHG (IPCC, 2007). Air pollutants include hydrocarbons (HC), carbon monoxide (CO) and nitrogen oxides (NO_X) that affect air quality around airports.

Emissions modelling has attracted a wide interest internationally. In the middle 1990s, emission inventories were developed by the National Aeronautics and Space Administration (NASA) (Baughcum et al., 1996) and the Abatement of Nuisance Caused by Air Traffic/European Commission working group (Gardner et al., 1997). These studies collected and analyzed data of global fuel burned and emissions of NO_X from aircraft. In addition, the NASA inventory provided distributions of CO and HC emissions. Since then, further studies have been published which estimate fuel burn and emissions on a global, national, route, airport or airline level. When estimating aircraft emissions, researchers typically distinguish flight into the Landing and Take-off (LTO) phase and the Climb-Cruise-Descent (CCD) phase, since LTO and CCD phases feature different operational conditions and call for different modeling assumptions and approaches.

The computation of emissions generated during the LTO cycle is mainly based on the use of the ICAO Engine Emissions Databank. This databank is developed and maintained by the International Civil Aviation Organization and gives fuel flow rate and emissions data on specific engine types. Although this databank has been used by studies focusing on the computation of air pollutants (HC, CO, NO_X etc) that affect air quality around airports (Kesgin, 2006; Mazaheri et al., 2011; Yılmaz, 2017), there are a number of studies incorporating LTO CO_2 emissions in their computations. Turgut and Rosen (2010) estimated LTO CO_2 emissions and other pollutants at eight busy international airports. The results indicated that Chicago, Los Angeles, Frankfurt and Tokyo were relatively clean airports compared with London and Beijing. Nikoleris et al. (2011) presented a method of detailed estimation of fuel consumption and emissions during taxi operations using aircraft position data from actual operations at Dallas/Fort Worth International Airport. As part of a study which assessed the carbon emission costs for air cargo, Chao (2014) computed LTO and CCD[8] CO_2 emissions for six routes and six types of aircraft. The author pointed out that when CO_2 emissions are allocated to ton-kilometers, the emissions by aircraft type and by flight are greater for small aircrafts than for their larger counterparts. Cokorilo (2016), initiated by the rapid increase of Serbia's flag carrier aircraft operations, compared the distribution of five pollutants (including CO_2) by aircraft type at the airport "Nikola Tesla" Belgrade. The results indicated that A319 aircraft were the largest source of CO_2 emissions, due to high level of LTO emission factor for CO_2 and due to large number of LTO cycles. Other databases used for LTO emissions computations include the EMEP CORINAIR published by the European Environment Agency and the Emission and the Dispersion Modeling System (EDMS) developed by the Federal Aviation Administration (EDMS has been replaced by the Aviation Environmental Design Tool as

[8] CCD CO_2 emissions in Chao (2014) were computed with the use of BADA database.

of May 2015). The latter uses the latest aircraft engine emission factors from the ICAO engine Emissions Databank and EUROCONTROL Base of Aircraft Data for aircraft performance modeling. EDMS was used by Song and Shon (2012) to calculate the emissions of GHGs and air pollutants at four major international airports in Korea. LTO CO_2 emissions have been computed by the use of EMEP CORINAIR in Alonso et al. (2014), Miyoshi and Mason (2009), Symeonidis et al. (2004), Tsilingiridis (2009). A comparison of methodologies estimating emissions of aircraft pollutants around airports is presented in Kurniawan and Khardi (2011).

Regarding the CCD emissions[9], the most widely used tool is the Base of Aircraft Data (BADA), developed and maintained by the Eurocontrol Experimental Centre (Nuic, 2013). Kim et al. (2007), Wasiuk et al. (2015), Schaefer (2012) and Simone et al. (2013) have used BADA database to assess global aviation fuel burn and emissions. The respective results of these studies were compared with other literature findings and showed noticeable variations in the overall results, despite similar trends. Furthermore, some of them presented the distribution of fuel burn and emissions by region and by altitude. Other researchers have used BADA to compute fuel burn and emissions in specific regions, airlines or routes. Pham et al. (2010) estimated fuel flow and aircraft emissions for Australian airspace, while Turgut et al. (2014) developed empirical equations for the cruise phase fuel flow for domestic flights of the national flag carrier airline of Turkey, Turkish Airlines. Sheng et al. (2015) analyzed stratospheric fuel burn by civil commercial flights to, from, or within the United States. Finally, other studies used BADA's fuel flow rates in the context of projects that assess the impact of operational mitigations or market-based environmental policies on aircraft-related fuel burn and emissions. Williams et al. (2002) examined the impact of restricting cruise altitude on fuel burn, while Malwitz et al. (2007) investigated the impact of reduced vertical separation on aircraft-related fuel burn and emissions for the domestic United States. Scheelhaase et al. (2010) estimated the impact of EU ETS on the competition between European and non-European airlines, while Albers et al. (2009) examined the effect of the same environmental policy on airfares and passenger demand at individual route level.

A common feature of some of the above studies is the collection of flight profile data in order to use the BADA performance model. Past flight track data or cruise altitude data as a function of aircraft type and distance have been used by Kim et al. (2007), Scheelhaase et al. (2010), Wasiuk et al. (2015) and Schaefer (2012), while the rest studies either do not use past profile data or do not clarify this information in their research papers. For example, Sheng et al. (2015) assigned notional cruise altitudes to each flight without considering altitude deviations among different aircraft types and distances. Albers et al. (2009) assumed that the assignment of flight cycle pattern and flight altitude depends on flight distance, ignoring aircraft type's potential deviations. Apart from BADA model, other tools previously employed for the CCD fuel burn and emissions include the EMEP CORINAIR database (Alonso et al., 2014; Park and O'Kelly, 2014) and the

[9] Most of the studies mentioned in this paragraph have used the ICAO Engine Emissions Databank to compute LTO emissions. Then these emissions are summed up with CCD emissions to derive emissions of the entire flight.

PIANO (Project Interactive Analysis and Optimization) performance model (Eyers et al., 2004; Lee et al., 2005).

Based on the above literature, this dissertation obtains fuel flow rates from the ICAO engine Emissions Databank for LTO emissions modelling and from the BADA performance model for the CCD phase. In few cases where these databases cannot be applied, the fuel burn data derived from the EMEP CORINAIR database are used. The methodology for the LTO CO_2 emissions is developed with reference to two of my journal papers: Pagoni and Psaraki (2014) and Loo et al. (2014). For the CCD CO_2 emissions modelling, our methodology is divided in two parts: the first considers the estimation of typical altitude profiles based on historical data and then emissions are computed by the use of BADA's fuel flow coefficients.

2.5 Research needs and dissertation's contribution

The above literature review enabled the identification of the research needs and potential open research questions in the research domain of this dissertation.

With regard to the assessment models of the market-based environmental policies for aviation, the state-of-the-art review indicates that there are numerous efforts that have investigated the effects of such policies on aviation. However, most of these studies rely on some simplifying overly restrictive assumptions listed below.

- First of all, a wide range of the existing studies (as revealed by the column "Other assumptions" of Table 2.2) rely on existing price elasticities of demand. These studies do not consider the development of air travel demand models. Instead, the impact of the studied policy is approached via: computing the resulting CO_2 emissions by route or airline, computing ticket price increase, assuming a price elasticity of demand and deriving the demand decrease due to airfare increase.
- Second, a set of fixed percentages of cost pass-through rate is often assumed to estimate the level of price increase after the implementation of the market-based policy (see column "Other assumptions" of Table 2.2).
- Third, some studies do not incorporate CO_2 emissions calculations but instead derive average values of CO_2 emissions by route/airline.
- Finally, some studies are limited to specific routes or small networks. However, there are some efforts that examine the impact of environmental policies on large-scale networks, most of which focus on the European ETS (as it is the largest cap-and-trade policy implemented on aviation). There is limited research on the impact of aviation emissions pricing in other regions: in the United States these include Hofer et al. (2010), Sgouridis et al. (2011) Malina et al. (2012) and Fukui and Miyoshi (2017), while Gonzales and Hosoda (2016) focused on the Japanese aviation fuel tax and Sgouridis et al. (2011) considered global air travel.

For policy analysis, the knowledge of the demand and supply structure and the mechanism of their interaction are necessitated. The review identifies a gap in the literature in the domain of simulating airline pricing strategies and assessing travel demand changes due to the implementation of environmental measures, through the use of demand and supply models. In general, the demand models work reasonably well provided the supply-side factors remain stable. But in the air transport environment, complex interaction may occur between supply and demand. To represent simultaneous causality, researchers have developed supply and demand equations models. Some of them are comprised of a discrete choice model to simulate air demand model and a profit maximization model which simulates airlines' behavior (Pels et al., 2000; Adler, 2005), while other studies use different approaches to model air travel demand (for example in Hsu and Wen (2003) route market shares are determined by the minimization of passengers' generalized travel cost). This dissertation builds on the work of Berry (1994), which is based on using market level data and estimate discrete choice models on the demand side while running a profit maximization problem on the supply side. This approach has been widely used in the industrial organization economics literature, while some efforts have been noted in the air transport industry considering the effects of (i) hub networks (Aguirregabiria and Ho, 2012; Berry et al., 2006; Israel et al., 2013), (ii) airlines' merger (Chen and Gayle, 2013; Doi and Ohashi, 2015; Lee, 2013a), (iii) airline code sharing (Shen, 2012) and (iv) airline alliances (Gayle and Brown, 2014) on ticket prices and passenger demand, while no study was found on the implementation of an emissions pricing scheme on aviation network. The use of this approach has several advantages which have been incorporated in the current dissertation. First, in most existing air travel demand studies, demand generation and demand assignment are considered separately. In real circumstances, the sequential method may not be consistent with the passenger's decision-making process, since decisions of whether to make a trip, the destination, and the travel mode are seldom undertaken by the passenger in stages. Thus, some studies have adopted the simultaneous estimation of two or more stages of the overall transportation process (Ortúzar and Willumsen, 2011). This dissertation simultaneously models the demand generated within a city pair and distributes it into routes. For this purpose, discrete choice models are employed for the representation of passenger behavior. Within an origin-destination city pair, the choice set includes the alternative of travelling by an airline connection or the non-air alternative. By the inclusion of the non-air alternative, potential passengers are not forced to choose an airline connection (if it has become less attractive). To avoid the independence assumption within the Multinomial Logit model, a Nested Logit model, with mode choice as the upper level and the connection choice as the lower level is developed. Moreover, aggregate data are used for the estimation. The model accounts for the fact that not all connections' characteristics are observed by the researcher and, thus, a single term capturing unobserved (to the analyst) characteristics is included. Instrumental variables methods are used to address the potential endogeneity of some independent variables in the demand and the supply functions. Finally, airline's behavior is modelled by assuming the airline is participating in an oligopoly game within the origin-destination city pair, where the objective is to maximize profits. This facilitates the demand and supply interaction by including the market share function in the first order condition of each airline's profit.

Overall, in this dissertation, a model of the U.S. airline industry is presented, representing passenger travel behavior and airlines' pricing decisions for the full line of airline connections operated in a year (study year=2012). The proposed methodology integrating the simulation of a market-based environmental policy with the combination of a methodology for carbon emissions modelling and econometric analyses of demand and supply produces five major contributions. **First**, the integrated model allows for policy analysis of the large-scale airline industry of the United States considering potential interaction between the demand and the supply and facilitates ticket price and travel demand changes in the presence of a market-based environmental policy. This is achieved by altering the airline's cost function so as to introduce a new cost shifter which corresponds to the carbon emissions cost resulting from the environmental policy. **Second**, contrary to existing studies, the impact of the market-based policy on ticket prices and air travel demand is not based on given values of cost pass-through rate and price elasticity of demand. Posterior policy ticket prices are determined from the computation of the new equilibrium in demand and supply. Carbon cost pass-through rate is determined by the demand and supply model and, thus, depends on a number of factors, including prevailing ticket prices, carbon costs, airline type etc. **Third**, this research extends earlier work by explicitly introducing additional air travel demand attributes not formerly used in aggregate models. These include the presence of alternative airport, which may explain passenger's preference on an airport nearby his origin or destination city, and departure time, which is regarded to play a significant role during the air traveler's decision process. **Fourth**, a CO_2 emissions model is developed which enables the estimation of the amount of carbon dioxide of every airline connection in a given network in a relatively quick and accurate way. **Last**, the above models are applied to the large-scale airline network of the United States, contributing to the very limited research on the field for this specific region.

To summarize, the proposed methodology significantly improves on existing approaches to simulate airline pricing responses and air passenger choices under an environmental policy. On the one hand, it extends a sound methodology so as to accommodate a market-based environmental measure, while, on the other hand, it corresponds to an integrated research which internally computes all the required research components, without relying on existing values from past studies (e.g. existing elasticities, average emission values etc).

3 Fuel Burn and Carbon Emissions Model

3.1 Introduction

The aim of this chapter is to develop a tool capable to compute aircraft fuel burn and carbon dioxide (CO_2) emissions for any given itinerary within a given airspace. Then, CO_2 estimates are used as input in Chapter 6, where the impact of a market-based environmental policy on air transport industry is assessed. Aircraft fuel consumption is related to various factors including the actual aircraft type, the flight distance and time, the flight mode, the time consumed in each mode, the flight level etc. Given the aircraft fuel consumption, CO_2 emissions can be calculated by using the appropriate emission index. In this chapter, a tool is developed to calculate fuel burn and CO_2 emissions for the entire flight. The Landing and Take-off (LTO) phase is separated from the Climb-Cruise-Descent (CCD) phase since different operational conditions result in significant deviations in terms of fuel burn and CO_2 emissions and different modeling assumptions and approaches should be adopted. A description of flight phases and their characteristics is given in Section 3.2.

The overall structure of this chapter and the underlying computational models and databases are depicted in Figure 3.1. The tool combines data from external databases with a number of sub-models in order to determine fuel burn and CO_2 emissions separately for the LTO and the CCD cycles. Fuel and emissions computations during the LTO cycle are based on the ICAO Engine Exhaust Emissions Databank (ICAO, 2016c) and the EMEP CORINAIR database (EEA, 2013) and are described in Section 3.3. Data on aircraft and engine types and time spent in each LTO sub-phase (approach, taxi-in, taxi-out, take-off and climb-out) are required to derive fuel burn and CO_2 emissions during LTO. The computation of fuel burn and CO_2 emissions during the CCD cycle is strongly related to the actual flight performance of the aircraft between the origin and destination airports. Variation in the aircraft performance (route, altitude, speed) may result in substantial differences in flight distance and time, air traffic flow, imbalances between demand and capacity and fuel burn. Accurate estimation of the aircraft altitude profile is important in order to obtain accurate estimations of aircraft fuel burn and CO_2 emissions during the CCD cycle. The construction of aircraft altitude profile, also referred to as vertical flight profile, represents a popular indicator of the relationship between flight distance or time and altitude and constitutes a significant part of this chapter. Typical flight paths are computed using a rich set of historical flight profile data and by employing a combination of clustering and landmark registration techniques. This method exploits the flight track information of the entire trajectory of historical flights. The paths estimated by the above method are compared to those obtained by the point mass Base of Aircraft Data (BADA) model. Noticeable deviations in the resulting estimates of the operational characteristics are found. The typical altitude profiles obtained by the two methods are then used to determine fuel burn and CO_2 emissions by applying aircraft-specific fuel flow coefficients derived by BADA tables. The difference in the resulting CO_2 emissions estimates are less stark.

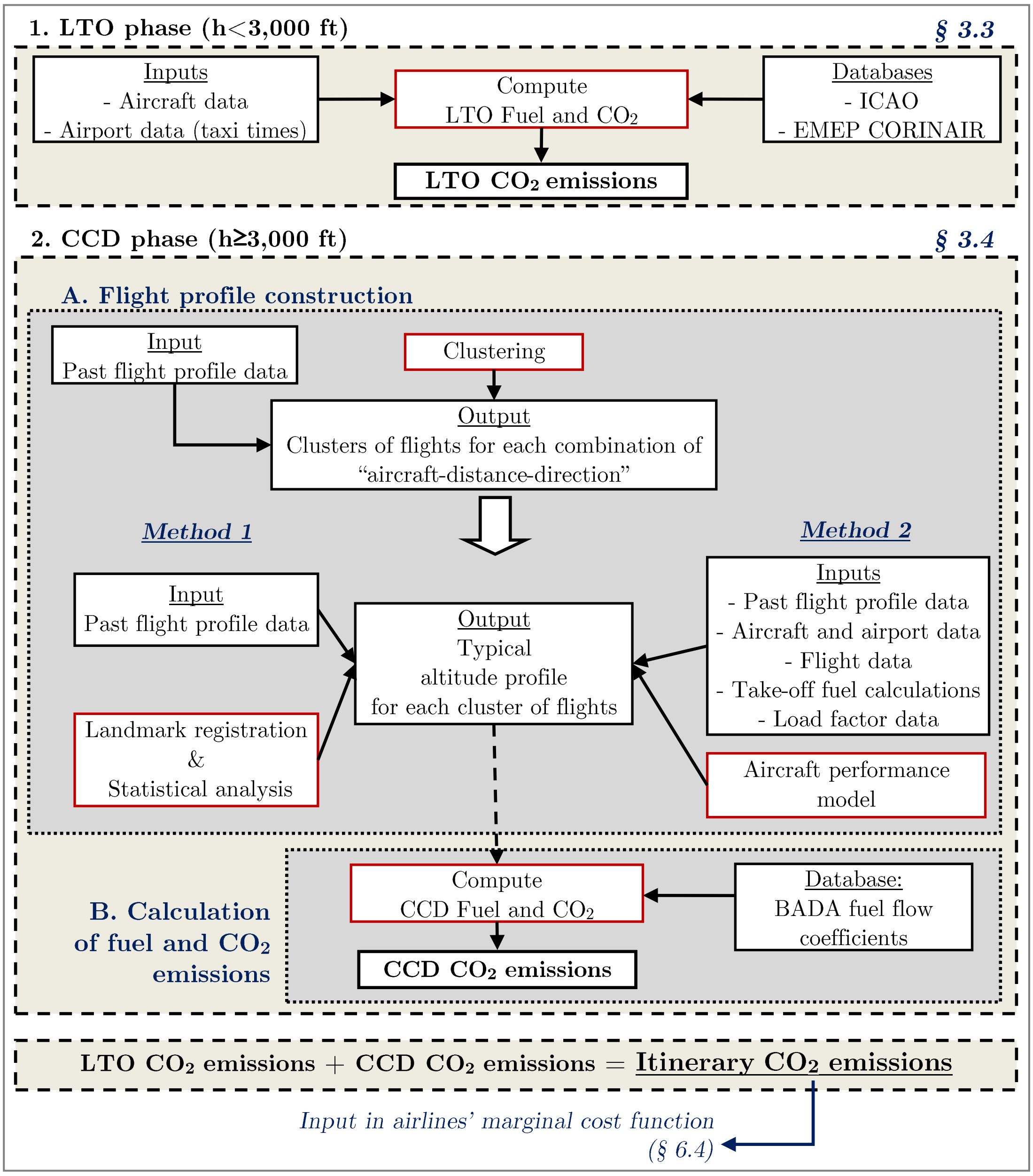


Figure 3.1. Illustration of the fuel burn and CO_2 emissions model

The final output of this chapter is the determination of CO_2 emissions for every itinerary in the study airspace. Thus, this chapter is strongly interlinked with Section 6.4 since CO_2 emissions cost is introduced in airlines' marginal cost function after the implementation of the market-based environmental policy. In this dissertation, the proposed tool and resulting outputs are illustrated in the case of domestic commercial aviation in the United

States and the results are validated by comparing our emissions values with existing studies (see Section 3.7).

3.2 Flight description

Operations of aircraft are usually divided into two main parts: the Landing/Take-off (LTO) and the Climb-Cruise-Descent (CCD) cycles. The LTO cycle includes all activities near the airport that take place below 3,000 feet and include taxi-in and out, take-off, climb-out, and approach. CCD phase is defined as all activities that take place at altitudes above 3,000 feet. No upper limit of altitude is given. CCD includes climb from the end of climb-out to cruise altitude, cruise, and descent from cruise altitudes to the start of LTO operations. Figure 3.2 shows the sequence of the flight phases and the databases employed in this work to compute fuel burn and emissions in each cycle.

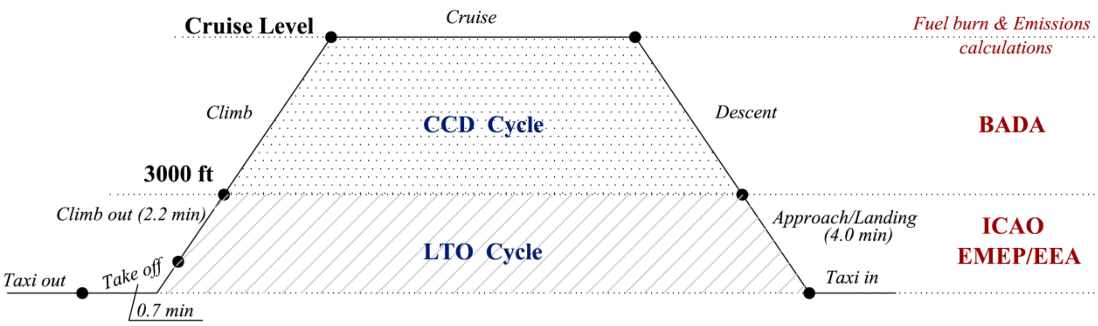


Figure 3.2. Illustration of flight phases

This chapter adopts a three-level approach to estimate CO_2 emissions: airport-based, route-based and itinerary-based. Airport-based CO_2 emissions include those generated during the LTO cycle. Route-based CO_2 emissions include those generated at altitudes above 3,000 feet during the CCD cycle. Then these airport- and route-based emissions are summed to generate itinerary-based emissions.

3.3 Airport-based CO_2 emissions

Airport-based fuel burn and CO_2 emissions include those generated at the vicinity of airports, i.e. at altitudes lower than 3,000 feet. The actual trajectory of the aircraft may not be available at altitudes below 3,000 feet and, thus, we use the typical LTO cycle defined by ICAO (1993) and its five sub-phases: taxi-out, take-off, climb-out, approach and taxi-in. Each of these is associated with a specific engine thrust setting; the take-off phase requires full engine thrust (100%), and thus more fuel (EEA, 2013). For climb-out thrust setting is 85%, for approach it is 30% and for idle phases (taxi-in and out) it is 7%. As the aircraft ascends to higher altitudes, the rate of fuel burn decreases. Each LTO sub-phase is also associated with a specific time-in mode as depicted in Figure 3.2.

Fuel flow for each LTO phase is obtained from the ICAO Engine Exhaust Emissions databank (ICAO, 2016c). The input variables include the engine type, the number of engines per aircraft and the time spent in each LTO segment. The ICAO databank does not provide fuel flow data for turboprop aircraft. Fuel flow data for turboprops are obtained from the EMEP CORINAIR database (EEA, 2013). The input variables include the aircraft type, the flight distance and the time spent in each LTO phase. As mentioned in Chapter 2, both databases have been widely used for emissions modeling. It is noted that this work does not consider emissions from startup of engines because there is currently little information available for estimation. On the basis of the above, the formula for the calculation of LTO CO_2 emissions ($E_{CO2,LTO}$) [in tn] is given in Eq. 3.1:

$$E_{CO_2,LTO} = \begin{cases} 10^{-3} \cdot EI_{CO_2} \cdot n_{e,a} \cdot \sum_{p=1}^{5} ff_{LTO,e,p} \cdot t_p & for\ jets \\ 10^{-3} \cdot EI_{CO_2} \cdot \sum_{p=1}^{5} fc_{LTO,d,a,p} & for\ turboprops \end{cases} \qquad \textbf{Eq. 3.1}$$

where EI_{CO2} is the emission index of CO_2 (which is equal to 3.157 kg CO_2/kg fuel), $n_{e,a}$ denotes the number of engines for aircraft type a, $ff_{LTO,e,p}$ is the fuel flow [kg/min] of engine type e for sub-phase p ($p=1,...5$ for taxi-out, take-off, climb-out, approach and taxi-in) of the LTO, t_p is the time spent in sub-phase p of the LTO [in minutes] and $fc_{LTO,d,a,p}$ is the fuel consumption [in kg] of aircraft type a for flight distance d during p LTO sub-phase.

Time spent in each LTO sub-phase (t_p) is treated in the following way: taxi times (taxi-in and taxi-out times) are defined as airport-specific parameters, while times for climb-out, approach landing and take-off are specified using the typical LTO cycle defined by ICAO (ICAO, 1993). Thus, take-off lasts 0.7 min, climb-out 2.2 min and approach landing 4 min. Airport-specific taxi in/out times are based on our analysis of the Airline On-Time Performance Data (hereinafter referred to as OTP) available by the U.S. Department of Transportation (BTS, n.d.). This database provides taxi-in and taxi-out times for non-stop domestic flights by major U.S. air carriers. Data for the study year (2012) are collected and are aggregated so as to represent taxi-in and taxi-out times for the considered airports aggregated by quarter (of 2012). The quantity $ff_{LTO,e,p}$ is derived by the ICAO Engine Exhaust Emissions databank, while $fc_{LTO,d,a,p}$ is obtained by the EMEP CORINAIR database. The EMEP CORINAIR's $fc_{LTO,d,a,p}$ for the idle modes are given under the assumption of typical taxi time (equal to 26 minutes for both taxi in and out). In this work, this value is properly adjusted so as to account for the airport-specific taxi in/out times, by using linear interpolation methods.

Eq. 3.1 requires the operating aircraft and engine type. Both databanks provide fuel burn rates for a specific list of aircraft and engine types. In case, the operating aircraft or engine type is not included in this list, the tool combines the input data with two external databases (aircraft and engine databases) and maps the actual aircraft type to a representative aircraft type and engine type. This level of computation essentially entails clustering techniques whereby the set of all potential engines and types are represented by a smaller yet appropriate set of representatives. Representative aircraft and engine types are built upon the analysis of their technical specifications obtained from aircraft manufacturers and other sources (EEA, 2013; ICAO, 2016c). In a few cases where information on equivalent aircraft types is not available, the aircraft is substituted with an aircraft type of similar characteristics, that is, maximum take-off weight, size, cruise speed and range. A detailed table with the actual aircraft and engine operating type and their equivalent type is given in Appendix B-4.

3.3.1 Network-wide application and validation analysis

Network-wide CO_2 emissions correspond to those generated in a given aviation network for the entire flight cycle, i.e. both the LTO and CCD phases. Following Section 3.3, LTO CO_2 emissions are computed by the ICAO Engine Exhaust Emissions Databank. Regarding the CCD cycle, once CO_2 emissions for the typical profiles are calculated, the associated emission values for every flight in a given aviation network can be obtained by applying linear interpolation. For example, the CCD fuel burn and CO_2 emissions of a 850 sm flight operated by a Boeing 737-700 are obtained by using the CCD fuel and emissions known values of the distance clusters 750 sm and 1000 sm and applying linear interpolation. The methods are applied to the U.S. domestic aviation network for 2012 using air traffic data from the T-100 Domestic Segment database for U.S. Carriers. Aggregated CO_2 emissions results by distance cluster for the U.S. domestic aviation network are given in Table 3.1.

Table 3.1. Network-wide CO_2 emissions by distance cluster

Distance cluster	Annual (2012) departures (million)	Annual CO_2 emissions for BADA-based profiles (million tn)	Annual CO_2 emissions for Registration-based profiles (million tn)
400 sm	0.35	2.3	2.5
500 sm	0.99	7.9	8.9
750 sm	1.00	11.1	12.1
1000 sm	0.85	14.9	15.9
1500 sm	0.43	11.4	11.8
2000 sm	0.19	6.6	6.9
2500 sm	0.19	9.5	9.7
>2500 sm	0.01	0.6	0.5
Total	4.01	64.1	68.4

Note: The above CO_2 values correspond to the entire flight, i.e. both LTO and CCD phases.

The above table indicates that the CO_2 emissions are under estimated by BADA-based typical profiles across all aircraft types and flight distances in comparison to registration-based profiles. On network-wide level, BADA-based typical profiles are estimated to consume 6.3% less fuel in comparison to registration-based profiles. In particular, the total CO_2 emissions of the flights in the sample are 64.1 tn and 68.4 tn for the BADA-based and registration-based profiles respectively.

The validity and reliability of our methods and results at CCD- and network- wide level can be assessed by the above findings. First, a different fuel consumption database is employed in order to derive CCD CO_2 emissions. Comparisons are presented in Figure 3.20 and Figure 3.3. In particular, the fuel consumption database EMEP CORINAIR (EEA, 2013) is used, which provides aircraft fuel consumption as a function of flight distance per aircraft type and flight phase. The data are given for a generic aircraft type and for a number of standard flight distances. Interpolation methods are used to obtain fuel burn data for flight distances other than standard. The EMEP CORINAIR database has been used by several researchers and several European Member States in their official reporting of national emission inventories. In its previous versions (EMEP/EEA air pollutant emission inventory guidebook 2009), EMEP CORINAIR used modelled data derived from the aircraft performance model PIANO. In its current version (EMEP/EEA air pollutant emission inventory guidebook 2013), fuel burn data are based on real 4D trajectories and EUROCONTROL's BADA database (EEA, 2013). Figure 3.20 depicts the CO_2 emissions computations for different distance clusters and four aircraft types for both EMEP CORINAIR versions. It can be seen that the calculations for the BADA- and registration-based typical profiles are closer to the 2013 EMEP CORINAIR results for the majority of aircraft. We note that EMEP CORINAIR does not distinguish eastbound and westbound flights. A more detailed look at our data indicates that A321's and B738's registration-based typical profiles produce on average the same amount of CO_2 emissions with those documented in the 2013 EMEP CORINAIR database. For B737 and B752 the deviations are on average 7% and 9% respectively, where the 2013 EMEP CORINAIR database reports higher emissions than our estimates. CO_2 emissions results based on 2009 EMEP CORINAIR are for most cases lower than our estimates for the registration-based typical profiles and higher than our estimates for the BADA-based typical profiles. Although these differences are explained by the underlying modeling process of the EMEP CORINAIR database, no general conclusion can be drawn from the comparison of our methods with the 2009 version of the database.

Figure 3.3 provides for a comparison of CO_2 emissions for the entire set of studied "aircraft-distance-direction" combinations. We use three approaches: (i) registration-based typical profiles, (ii) BADA-based typical profiles and (iii) 2013 EMEP CORINAIR database. The x-axis corresponds to the estimated CO_2 emissions for the registration-based typical profiles. These values are compared to the CO_2 emissions of the y-axis: the BADA-based typical profiles (blue dots) and those derived from the 2013 EMEP CORINAIR database (green dots). Despite the large discrepancy of flight characteristics between BADA-based and registration-based approaches, the CO_2 emissions estimates are close to each other. This result is consistent with the findings of Table 3.1. Figure 3.3 shows that our estimates for the registration-based typical profiles are also close to the emission values derived by the 2013 EMEP CORINAIR database. Averaged on the analyzed flight profiles, the estimates of CO_2 emissions differ by 2.5%, where the 2013 EMEP CORINAIR database reports higher emissions than our estimates.

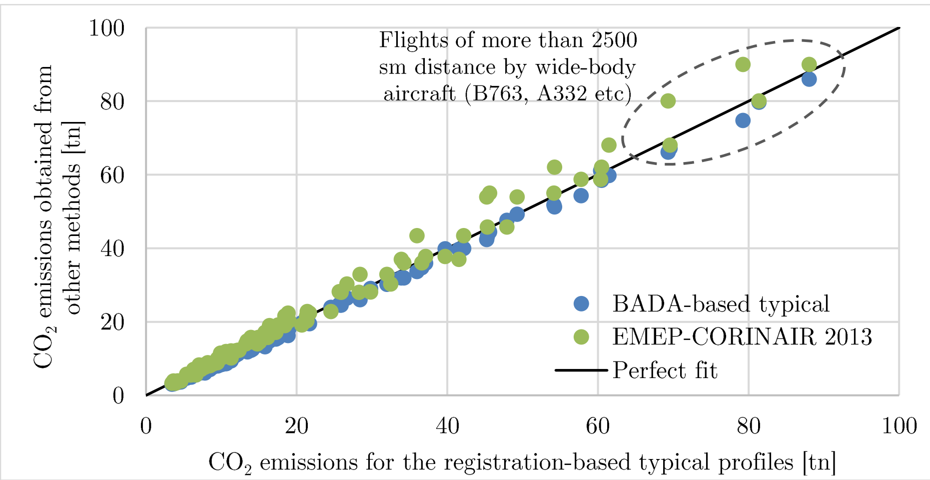


Figure 3.3. Validation of CO_2 emissions results

Next, our estimates are compared to existing fuel and emissions statistics for the U.S. airspace. The sample considered in this chapter includes 4.01 million departures. Given the aggregate figures of CO_2 emissions in Table 3.1, we infer that each departure consumes

5.07 tn fuel and 16 tn CO_2, if BADA-based estimation is used and 5.41 tn fuel and 17.1 tn CO_2, if registration-based typical profiles are considered. Wilkerson et al. (2010) report 31.3 million departures and 188.2 million tons of fuel, or 6.01 tn fuel per departure. Similarly the estimate given in Wasiuk et al. (2015) amounts to 5.27 tn fuel per departure for the study year 2006, while Wasiuk et al. (2016) reported a value of 5.44 tn fuel per departure for 2011. Finally, the emission inventory of Pham et al. (2010) in Australia estimated a value of 5.14 fuel tn per departure for 2008. Overall, it is concluded that our estimates generally agree with other published estimates. Differences may stem from the different mix of air traffic considered in these studies (other aircraft types and flight distance), the assumptions made about aircraft weight estimation etc. Table 3.2 compares the fuel burn estimates of previous studies with our estimates. Despite the small differences, the proximity of estimates provides a good indication of the validity and reliability of our methods and results at network wide level.

Table 3.2. Comparison with other studies

Study	Departures (millions)	Fuel (million tn)	Fuel per departure (tn)	Study year	Region
Kim et al. (2007)	32.4	203	6.27	2005	Global
Wilkerson et al. (2010)	31.3	188.2	6.01	2006	Global
Wasiuk et al. (2015)	28.9	152.2	5.27	2006	Global
Pham et al. (2010)	0.49	2.52	5.14	2008*	Australia
Wasiuk et al. (2016)	31.8	173.2	5.44	2011	Global
This dissertation**	4.01	21.7	5.41	2012	U.S.

Note: * *for a six month period*
** *based on the registration-based typical profiles*

3.4 Route-based CO_2 emissions

Route-based CO_2 emissions include those generated during the Climb-Cruise-Descent (CCD) cycle. Similar to the LTO phase, CO_2 emissions are computed as a function of aircraft fuel burn. CCD fuel consumption is strongly related to the actual flight performance of the aircraft between the origin and destination airports. Variation in the aircraft performance (route, altitude, speed) may result in substantial differences in flight distance and time, air traffic flow, imbalances between demand and capacity and, thus, fuel consumption. Thus, accurate estimation of the aircraft altitude profile is important in order to obtain accurate estimations of aircraft fuel burn and CO_2 emissions during the CCD cycle.

3.4.1 Motivation for the computation of typical altitude profiles

The aircraft altitude profile, also referred to as vertical flight profile, represents a popular indicator of the relationship between flight distance or time and altitude. The aircraft altitude profile during the CCD cycle consists of three stages: climb, cruise and descent. The aircraft performance in each flight stage depends on a number of flight characteristics including aircraft type, flight distance and direction of flight (for instance Eastbound or Westbound). Furthermore the altitude profile exhibits random fluctuations caused by atmospheric conditions, airline or pilot planning and operational or traffic control random events. For example, bad weather conditions may force pilots to fly on lower or higher altitude or reroute aircraft for safety and comfort reasons. Due to these random variations, altitude profiles cannot be identical even for the same flight on a different day. Figure 3.4

presents the vertical profiles of nine flights between the JFK and TPA airports operated by Boeing 717-200 (B712) for a distance of 1,007 sm. The illustrated flights were operated between 9 and 20 October 2016. It is observed that the flight profiles are differentiated in terms of their cruise level, duration and rate of climb and descent.

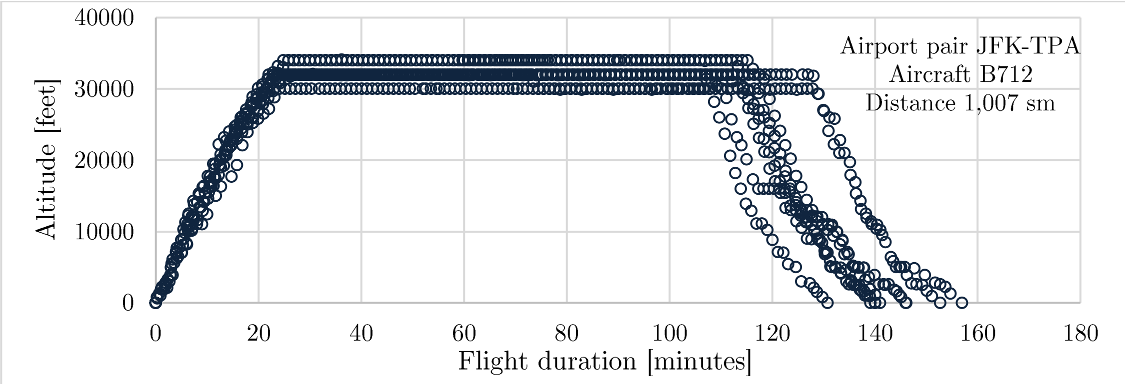


Figure 3.4. Different vertical profiles for the airport pair JFK-TPA

To achieve the ultimate goal of this chapter, which is to compute CO_2 emissions for any given itinerary within our study flight network, vertical flight profiles of each itinerary are required. Considering the profile deviations shown in Figure 3.4 and the large number of flights in our traffic sample (thousands of itineraries which consist of tens of thousands of non-stop flights during the entire year of 2012), the construction of vertical profiles for each itinerary would require high computational effort with uncertain representation of reality. In this work, this issue is addressed by developing a method to compute typical[10] flight profiles for groups of flights with similar characteristics by using a repository of prior flight profile information. Given the generated typical flight profiles, fuel flow rate is calculated as a function of calibrated and true airspeed, flight altitude, engine thrust, aerodynamic drag, aircraft weight etc. Then, flight fuel burn and CO_2 emissions can be computed for every itinerary in our traffic sample by applying interpolation methods.

In our work, preliminary data analysis and clustering arguments are employed to extract flight characteristics and organize altitude profiles. The key features found are the flight distance, the aircraft type and the flight direction. These are of mixed type, numeric (flight distance) and categorical (aircraft type, flight direction). Thus the flight distance is represented by a finite set of values which are determined by the distribution of the flight distance. This distribution in turn is estimated from flight data. Flight altitude profiles are then estimated within each cluster possessing the same features.

3.4.2 Clustering

Extraction of flight profile characteristics and clustering of path profiles are considered in this section. Our focus is on the Climb-Cruise-Descent (CCD) cycle where the aircraft is located at altitudes above 3,000 ft. In this context, profiles are regarded as trajectories composed of one Cruise stage connected by the Climb and Descent stages. An example of flight altitude profile is given in Figure 3.5. As shown, the key elements that shape the CCD path and explain its variation are the duration of the three stages (climb, cruise, descent) and the cruise altitude. Other important features such as the rate of climb and

[10] Typical flight profiles may be sometimes referred to as representative profiles.

descent can be derived from the above. Hence we focus on cruise altitude and duration of phases. The characteristics affecting altitude and duration are split into those related to the aircraft and those related to the route. The first group of characteristics is adequately represented by a single factor, the aircraft type. The second group is described by the flight direction and the flight distance. We demonstrate that the above are genuine shifters of altitude and duration by considering a rich sample from the T-100 Domestic Segment for US carriers (hereinafter referred to as T-100) (BTS, n.d.).

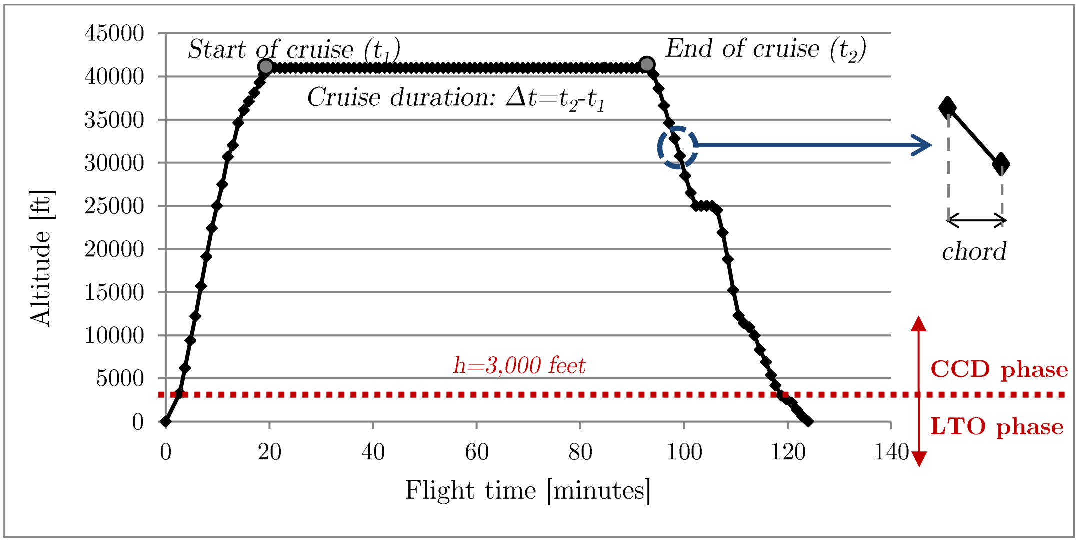


Figure 3.5. An example of flight altitude profile

To reveal the differentiation of flight altitude profile with respect to aircraft type, flight distance and direction, a preliminary data analysis follows. Actual flight track data are used for the following analysis. More details on the data sources are given in Section 3.4.3.

Flight distance

The impact of flight distance on altitude and duration are depicted in Figure 3.6 and Figure 3.7. The altitude variability is evident; shorter flights fly in lower altitudes, while most of the flights longer than 400-500 statute miles generally fly above 25,000 feet. Cruise altitude has an increasing slope for flight distances up to 750 sm, while for the majority of flights longer than 750 sm, it falls within the range of 30,000 and 40,000 ft. We also observe that cruise duration is linearly related with flight distance.

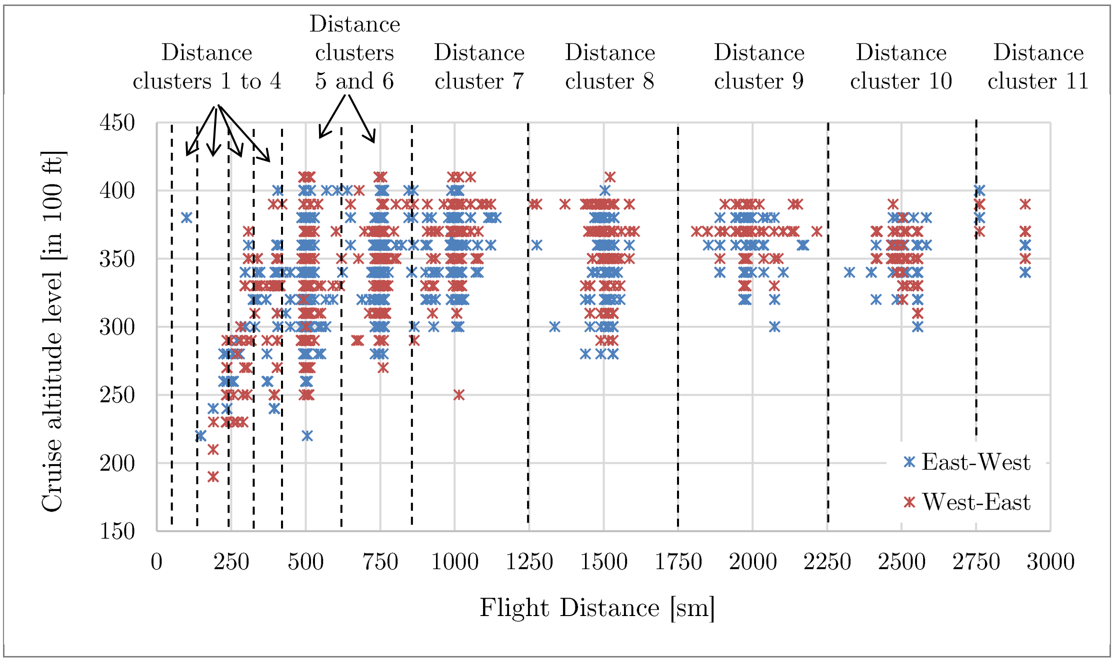


Figure 3.6. Flight altitude in relationship with flight distance

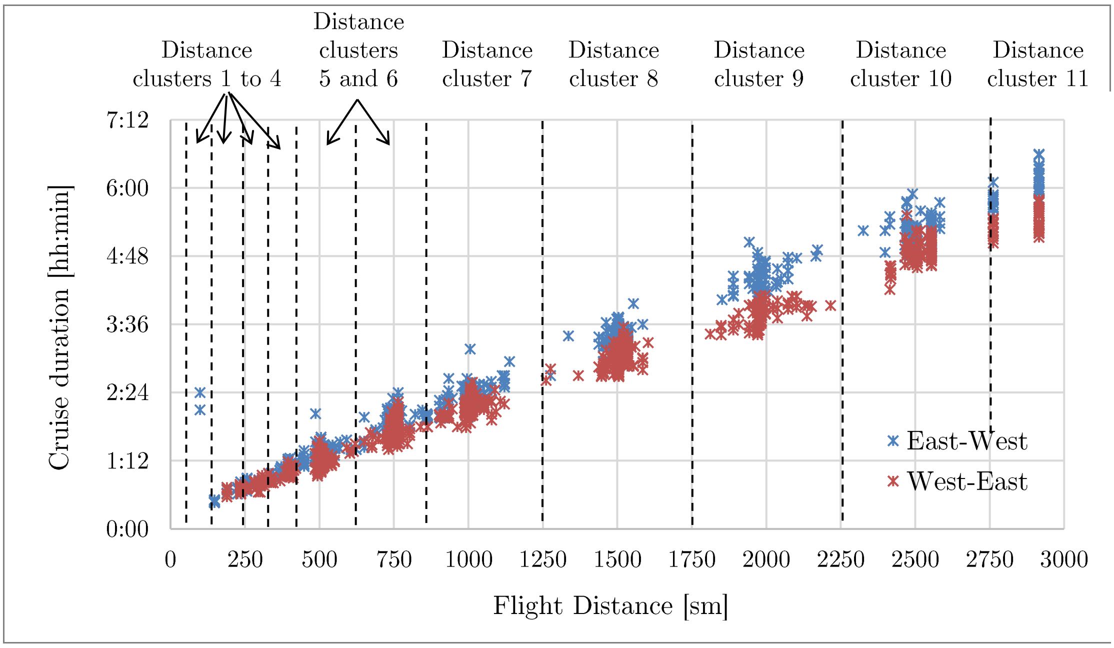


Figure 3.7. Cruise time in relationship with flight distance

To allow for a harmonized treatment of the impact factors, flight distance is represented by a finite set of values. These values are not evenly spaced; instead they are chosen to provide sufficient group separation and manageable complexity. A small distance resolution creates a large number of typical flight profiles of limited variability and increased computational load. In contrast, a large distance resolution results in within-combination deviations which could give rise to abnormal typical profiles. Lee et al. (2005) divided their sample in distance increments of 500 km (≈310 sm) to derive average cruise altitudes, while other studies used longer distance bands of 500 nm (about 575 sm) (Kim et al. 2007; Rustenburg et al., 2008).

In our work, we employ clustering arguments for the construction of typical profiles. Based on the literature review, we adopt a 250sm distance increments for flight distances between 450 and 825 miles. For longer flights we adopt a higher distance increment of 500 sm. The resulting clusters of the flight distances based on the above assumptions are shown in Figure 3.6 and Figure 3.7. It is noted that the initial selection of these clusters do not rely on the employment of a clustering method. However, the hierarchical clustering method was used to check whether the number of clusters were reasonable based on the data collected. In particular, it was important to check if the number of the initially adopted clusters should be higher. For every pair of aircraft type and flight direction, hierarchical clustering was applied and the Elbow criterion was used to check the number of clusters. The elbow criterion involves observing (in x-y plot) the set of possible numbers of clusters relative to how they minimize the within-cluster sum of squares. The number of clusters is equal to the largest K that has positive marginal gain. In few pairs of aircraft type and flight direction, less clusters were indicated by the hierarchical clustering in comparison with the number of clusters initially defined. However, to maintain a constant set of clusters among the different pairs, the number of clusters set by the initial analysis were finally chosen. Flights shorter than (or equal to) 300 sm are treated in a different way in order to compute their fuel consumption and CO_2 emissions during the CCD cycle, as explained in Section 3.5, because our analysis showed that the altitude estimation methods presented in Section 3.4.4 failed to construct reliable typical profiles for flights. Thus, in the following text, clusters of flights longer than 300 sm are only considered (distance clusters 4 to 11).

<u>Flight direction</u>

Data plots in Figure 3.6 and Figure 3.7 are separately given for eastbound (West→East) and westbound (East→West) flights. To improve separation during the cruising phase, flight levels are assigned according to the aircraft's magnetic cruising track. The standard rule is that westbound flights fly on even flight levels and eastbound traffic follow the odd flight levels. In this way, the risk of head-on collisions is avoided. Figure 3.7 shows that eastbound flights are faster than westbound (red points are below blue points). This is due to the prevailing jet-stream winds which cause eastbound flights to be significantly shorter than westbound flights even for the same flight distance. We conclude that the direction of flight affects flight performance and the two directions are analyzed separately.

<u>Aircraft type</u>

The differences in cruise altitude or duration that appear in Figure 3.6 and Figure 3.7 for the same distance clusters are largely due to the different aircraft types. For example, at the distance cluster of 750 sm, the higher altitudes from 36,000 to 40,000 ft correspond to the B737-700 while the low altitudes of 29,000-33,000 ft correspond to the regional jet CRJ200. In addition, within our sample profiles, flying with different aircraft types result, in some cases, in different cruise duration even for the same flight distance. To assess if there is an overall effect of the aircraft type on cruise altitude and cruise duration, we performed a one-way analysis of variance (ANOVA). The one-way ANOVA is a parametric test that compares the means of two or more independent groups in order to determine whether there is statistical evidence that the associated population means are significantly different. In this work, ANOVA is used to determine whether there are significant differences between the means of cruise altitude and duration of independent groups of aircraft types and is run for the studied distance clusters (4 to 11). First we checked for normality and tested equal variance assumptions statistically. Both cruise altitude and duration were found normally distributed based on their normal Q-Q plots. The test results indicated that there are statistical differences in cruise altitudes and cruise duration across the different aircraft types, since for all distance clusters and directions the significance levels were $p<0.05$. Table 3.3 suggests that the aircraft type affects the resulting flight performance and each aircraft type should be analyzed separately.

Table 3.3. One-way ANOVA analysis

		Cruise altitude		Cruise duration	
Distance cluster [sm]	Direction	$F_{statistic}$	p-value	$F_{statistic}$	p-value
400	E-W	23.56	0.00	3.69	0.01
	W-E	65.41	0.00	7.48	0.00
500	E-W	22.63	0.00	5.36	0.00
	W-E	36.14	0.00	4.52	0.00
750	E-W	17.01	0.00	19.35	0.00
	W-E	38.17	0.00	20.45	0.00
1000	E-W	38.97	0.00	5.71	0.00
	W-E	49.01	0.00	16.54	0.00
1500	E-W	95.32	0.00	16.81	0.00
	W-E	45.59	0.00	14.45	0.00
2000	E-W	17.74	0.00	14.75	0.00
	W-E	25.55	0.00	34.08	0.00
2500	E-W	16.99	0.00	9.55	0.00
	W-E	30.50	0.00	24.15	0.00
>2500	E-W	55.56	0.00	14.46	0.00
	W-E	77.63	0.00	17.93	0.00

Overall the above analysis demonstrates that flight distance, aircraft type and flight direction are key features which affect aircraft flight performance and, thus, aircraft altitude profile. Typical altitude profiles are constructed for each unique combination of "aircraft type, flight distance and direction", which is hereinafter referred to "aircraft-distance-direction" combination. For example, the combination "A321-1500-EW" refers to flights within the distance cluster of 1500 sm, directed from East to West and operated by the aircraft type A321. This combination may include flights longer than 1250 sm and shorter (or equal to) 1750 sm operated by A321 from East to West.

3.4.3 Data sources and Pre-processing

The estimation procedure developed in this chapter relies on the combination of two datasets: (i) commercial air traffic data within the U.S. airspace for the year 2012 and (ii) flight track data. These datasets are combined to obtain a multi-dimensional database that stands for an accumulated knowledge on how aircraft perform in realistic circumstances and is used to (i) conduct the clustering analysis and define the relationship between the different combinations of "aircraft-distance-direction" and flight performance and (ii) derive representative aircraft altitude profiles for the combinations under consideration.

Air traffic data are obtained from three databases: the Airline Origin and Destination Survey (DB1B), the T-100 Domestic Segment for U.S. Carriers (T-100) and the On-Time Performance (OTP) database[11]. These databases are available from the U.S. Department of Transportation and published in the website of the Bureau of Transportation Statistics (BTS, n.d.). DB1B is used to extract the different airport pairs of our analysis, i.e. for which carbon emissions estimates need to be obtained for the simulation of the market-based environmental measure considered in this dissertation. T-100 is used to derive the representative aircraft types by airport pair. As already explained, aircraft type is an input in the estimation method of LTO and CCD carbon emissions. OTP is used to obtain the taxi-in and taxi-out times by airport (useful input for the LTO estimations). Based on these, the different combinations of "aircraft-distance-direction" are defined.

The original flight data are supplemented by historical fight track information obtained from the FlightAware website (FlightAware, n.d.). FlightAware provides flight track data for flights within several countries around the world and has been used by several researchers in the past (Alcabin et al., 2009; Felix patron et al., 2014; O'Kelly, 2014; Serafino et al., 2012; Sheng et al. 2015). Each record includes date, time, aircraft location, orientation (course, direction), ground speed and altitude, given at approximately one minute intervals from takeoff "wheels up" to landing "wheels down". FlightAware compiles, aggregates and processes data from various sources including airlines, commercial data providers, its own Automatic Dependent Surveillance-Broadcast flight tracking network and the FAA Aircraft Situation Display to Industry real time data feed. Flight track information is collected for a variety of aircraft types, routes and days of operations. Flights are randomly selected with respect to day of the week, time of day, airline, and weather conditions. Then these datasets are collectively employed to carry out the clustering tasks and to obtain the representative aircraft altitude profiles.

During the flight track data collection process, several altitude data issues were encountered and dealt with the following filtering process.

- Flights with missing profile data were disregarded.
- Some flight profiles were found with large gaps of data. If these data gaps occurred during cruise flight (where the altitude level before and after the gap is the same), the solution was to substitute the missing values with the constant cruise level, as shown in Figure 3.8. The dot points represent the original profile while the red line represents the correction of the data gaps. In circumstances where the data gaps could not be corrected, the flight profile was omitted from the analysis.

[11] See Appendix C-1 for more information on the databases.

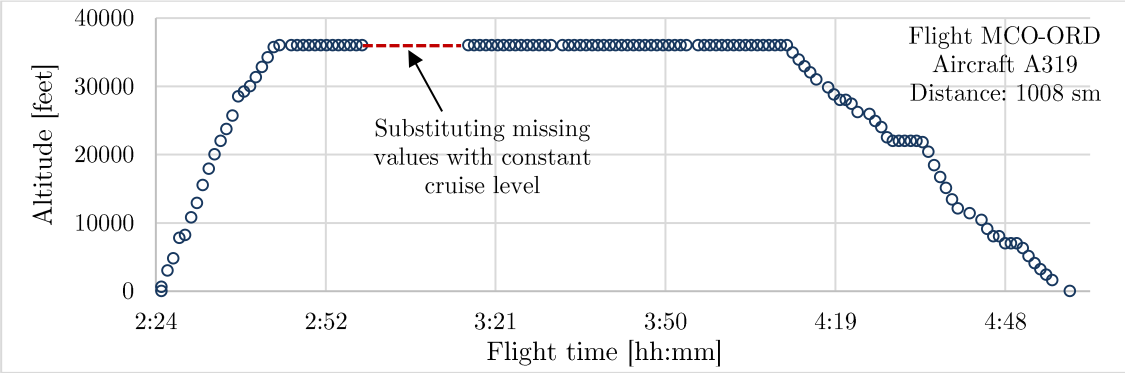


Figure 3.8. Altitude profile with large gaps of altitude data

- In some profiles, the altitude had a "wrong" value, e.g. a sharp fall was observed during the climb or cruise phases, the altitude became zero etc. In these cases the "wrong" points were viewed as "missing values" and a similar approach to the previous one was followed, as shown in Figure 3.9.

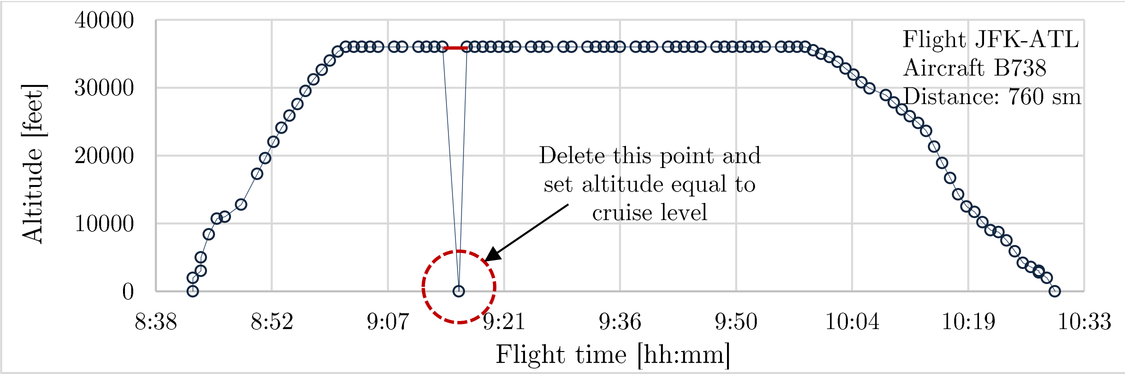


Figure 3.9. Altitude profile with "wrong" altitude value

- Abnormal flight profiles were excluded from the analysis. An example is shown in Figure 3.10, where the profile of a diverted flight is illustrated. A diverted flight is one that has been routed from its scheduled destination to a new temporary destination. Based on the track information the flight of Figure 3.10 travelling from DCA airport was diverted to PHL airport at 8:53. The flown distance was 716 sm, which amounts to 604% of the planned distance (119 sm). Another poorly predictable flight is shown in Figure 3.11. This profile corresponds to a flight of 405 miles operated by Boeing 737-700. Based on Section 3.4.2, this flight belongs to the cluster "B737-400-WE". In this cluster most flights flew on 33,000-35,000 feet for about 18 minutes. However, this flight had a different altitude pattern, climbing on 40,000 feet for a short time and then descending for a long time. Such flights cannot be viewed as regular and are not considered in the construction of representative flight profiles.

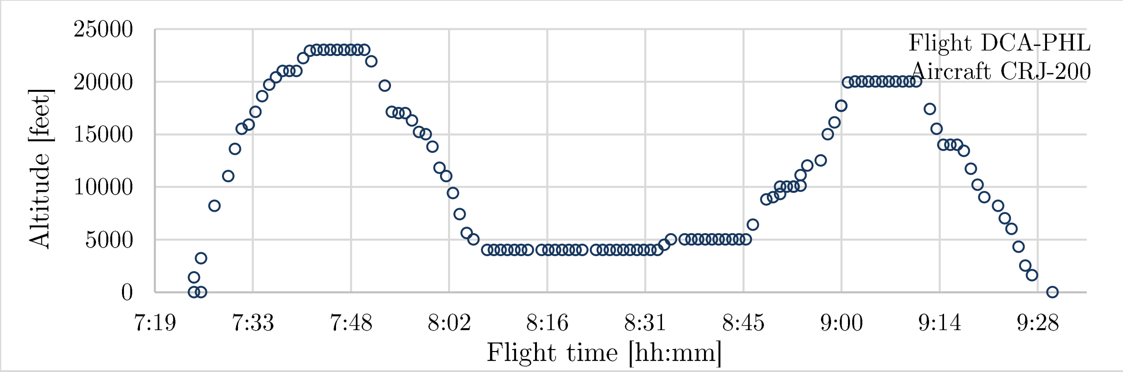


Figure 3.10. Altitude profile of a diverted flight

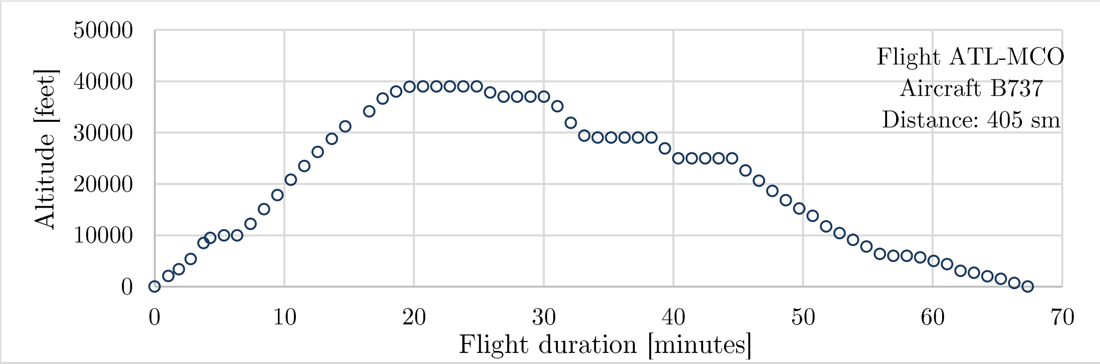


Figure 3.11. Altitude profile for a poorly predictable flight

- Finally, two data checks were applied following FAA (2005). First, track points were checked so that their altitude is not less than 0 feet and greater than 45,000 feet. If these checks fail, the profile is not included in the final profile database. The second check is related to the Rate of Climb (ROC) and Descent (ROD). Based on experience from analyzing trajectory data, FAA (2005) adopted a limit of 18 m/s for ROC and -18m/s for ROD to check the profile data (18m/s=3,543 feet/min). If two consecutive points result in higher ROC than 18m/s (and lower ROD than 18m/s accordingly), the spike is smoothed by replacing the “wrong” point’s altitude by the value calculated from the ROC of the previous chord.

3.4.4 Estimation of typical flight profiles

In the literature, the estimation of the flight altitude profile has been approached by two main ways, point mass models and machine learning methods. The EUROCONTROL’s Base of Aircraft Data (BADA) is an aircraft performance model which is based on the total energy model of the aircraft and can be considered as a reduced point-mass model (Nuic, 2013). Wasiuk et al. (2015) used the BADA model along with a database of global commercial aircraft movements to calculate global aviation fuel burn and NO_X emissions during the time period 2005-2011. BADA was also used by Schaefer (2012) to simulate flight trajectories and predict the corresponding aircraft fuel consumption and emissions. In his work, typical aircraft- and distance-specific cruise altitudes were derived by a statistical analysis of historical radar data in the Aero2k inventory of global aviation (Lee et al., 2005). Simone et al. (2013) developed a BADA based methodology for the calculation of aircraft performance and resulting emissions on a global scale. This study did not use radar track information and thus made simplifying assumptions for aircraft takeoff weight and cruise altitude. In particular, a fixed factor of 60.9% of maximum payload capacity was used for all flights and cruise altitude was set to 7,000 feet below the maximum cruise altitude of the aircraft, as specified by BADA. Scheelhaase et al. (2010) used the BADA model to derive average CO_2 emissions for different mission types (regional, short-haul, medium-haul and long-haul) and estimate the impact of EU-ETS on the competition between European and non-European airlines. BADA has been also used to model en-route aircraft performance in the context of projects that assessed the impact of operational mitigations on aircraft-related fuel burn and emissions (Lovegren and Hansman, 2011; Malwitz et al., 2007; Williams et al., 2002). Finally, BADA has been widely used to compute aircraft fuel burn when actual flight data records are available or a flight profile has been specified otherwise (Kim et al., 2007; Pham et al., 2010; Sheng et al., 2015; Turgut et al., 2014; Williams and Noland, 2005).

The BADA modeling framework is based on aircraft-specific parameters which are used to define standard airline procedures. Thus, it does not incorporate actual aircraft operations in real circumstances. Furthermore, to simulate the real local conditions under which an aircraft operates, more detailed information on atmospheric conditions and winds are required which are not readily available. For these reasons, attention was recently turned into regression and machine learning methods for the estimation of the flight altitude profile. Nicol (2013) applied functional principal component analysis to analyze aircraft trajectories. The author used a set of track data and estimated the registered profiles for flights between two specific airports. Tastambekov et al. (2014) developed an approach for short to mid-term aircraft trajectory prediction based on local linear functional regression. Their method considered past radar tracks for a given airport pair and estimated the aircraft position over a 10–30 min time horizon. Hamed et al. (2013) used a combination of a point-mass model and regression to predict the altitude of the aircraft during climb phase. They studied flights departing from two airports using a single aircraft type and they concluded that regression models were more predictive than the point-mass model. Hrastovec and Solina (2014) used the nearest neighbor's algorithm to simulate aircraft flight performance. Their machine learning model searched for similar flights in a database and predicted aircraft performances based on similar flights performed in the past. Their results suggest that machine learning provided lower prediction errors than the BADA performance model.

In this section, typical flight paths are computed using a rich set of historic data and two estimation approaches. The first approach employs a combination of clustering and landmark registration techniques and exploits the flight track information of the entire trajectory of historical flights. The paths estimated by the above method are compared to those obtained by the point mass Base of Aircraft Data (BADA) model, in terms of the extracted flight operational characteristics. Noticeable deviations in the resulting estimates are found. On a fleet-wide level, the prediction errors produced by BADA-based estimation are much higher than those obtained by clustering and landmark registration.

3.4.4.1 Landmark registration

This estimation approach uses real altitude data from a large flight dataset so as to construct representative altitude profiles. The recording of past vertical profile data results in a sample of numerous functional observations (curves) of aircraft altitude $h(t)$ with respect to time t. Aircraft profile data can be regarded as functional data, with the basic unit of information being the entire observed function (curve) rather than a vector of numbers. The statistical techniques for analyzing curves or functional data are included in the field of Functional data analysis (FDA) (Ramsay and Silverman, 2005). The main steps of the landmark registration method are illustrated in Figure 3.12 and are summarized below:

- Step 1: Conversion from discrete to functional data
- Step 2: Landmark registration
    - Define landmarks
    - Obtain warping functions
    - Compute registered altitude profiles
- Step 3: Statistical Analysis of the registered profiles

Following the collection of raw data (indicated in colored lines in the upper left panel of Figure 3.12), which includes altitude data recorded at short discrete time intervals (Step 0), the aim of the Step 1 is to represent data recorded at discrete times as a continuous function x_i with values $x_i(t)$ for any desired time value t. Based on Ramsay and Silverman (2005), we use interpolation methods for the discrete to functional data conversion process as the discrete values in our dataset are closely spaced. In case there was evidence of observational errors so that the initial discrete values would need removing, the conversion from discrete data to functions could involve smoothing. Step 2 deals with eliminating a common problem of functional data which is called phase variation. In general, altitude curves present common shape features, as they consist of three distinct flight stages, those of climb, cruise and descent. However, the timings of these stages vary from curve to curve. The FDA literature refers to these lateral displacements in curve features as phase variation. This implies that different functions should not be compared at the same time t because the occurrence of similar features is not synchronized. An important tool for analyzing phase variation is curve registration. There are several types of curve registration including shift registration, landmark registration and continuous registration (Ramsay and Silverman, 2005). In this dissertation, we apply landmark registration, which involves transforming the domain of each curve so that points specifying the locations of shape features are aligned across curves. The other methods, shift and continuous registration, are mainly applied in cases where landmarks are not clearly identifiable in all curves (Kneip and Ramsay, 2008). A landmark of a curve is a characteristic that one can associate with a specific argument value t. In flight profiles, landmarks may include the transition points from one stage to another and can be identified by the change of the curve's slope. In our work, three landmarks are defined: two points that match the maximum flight level (top of climb and top of descent) and one point that matches the end of flight.

Suppose that after the conversion process (from discrete to functional data), we have a sample of K functions $x_i(t)$, where $i=1,2,\ldots,K$ and $t \in [0,T_i]$. Each curve is defined over an interval $[0, T_i]$ where T_i can be different from curve to curve. The aim of the registration is to estimate a transformation of time for each curve so that qualitative shape features become better aligned. To start the registration step, in each curve we define f (where $f=1,\ldots,F$) landmark time points $t_1, t_2, \ldots, t_f$ where $t_1<t_2<\ldots<t_f$ as explained in the previous

paragraph. Then we construct time warping functions $w_i(t)$ for each curve i based on the following properties:

- Boundary conditions are defined by: $w_i(0)=0$ and $w_i(T_i)=T_i$
- Landmarks have the form: $w_i(t_{0f})=t_{if}$ for all $f=1,..,F$. The target point t_{0f} is constructed from the data as the sample mean of the landmarks.
- Monotonicity requires that each $w_i(t)$ is strictly increasing: if $t_1<t_2$ then $w_i(t_1)<w_i(t_2)$. This strict monotonicity condition ensures that the function w_i is invertible, so that for each y in the interval $[0, T_i]$ there is a unique t for which $w(t)=y$.

We first estimate the inverse warping function $w_i^{-1}(t)$ such that $w_i^{-1}(w_i(t)) = t$ and get the values of this inverse function at equally spaced values of t. The inverse function $w_i^{-1}(t)$ is computed by interpolating the relationship between $w_i(t)$ and t plotted on x-y axis. We then use simple interpolation to get the values of this inverse function at an equally spaced set of values of t. The registered curves $\tilde{x}_i(t)$ are computed as $\tilde{x}_i(t) = x_i(w_i(t))$. We first interpolate the relationship between $w_i^{-1}(t)$ plotted on the x-axis and $x(t)$ plotted on the y-axis and by re-inverting we obtain the values of the registered function $\tilde{x}_i(t)$ at a set of values of t. After the registration process we obtain the registered flight profiles and estimate the desired statistics (average and standard deviation) for each "aircraft-distance-direction" combination.

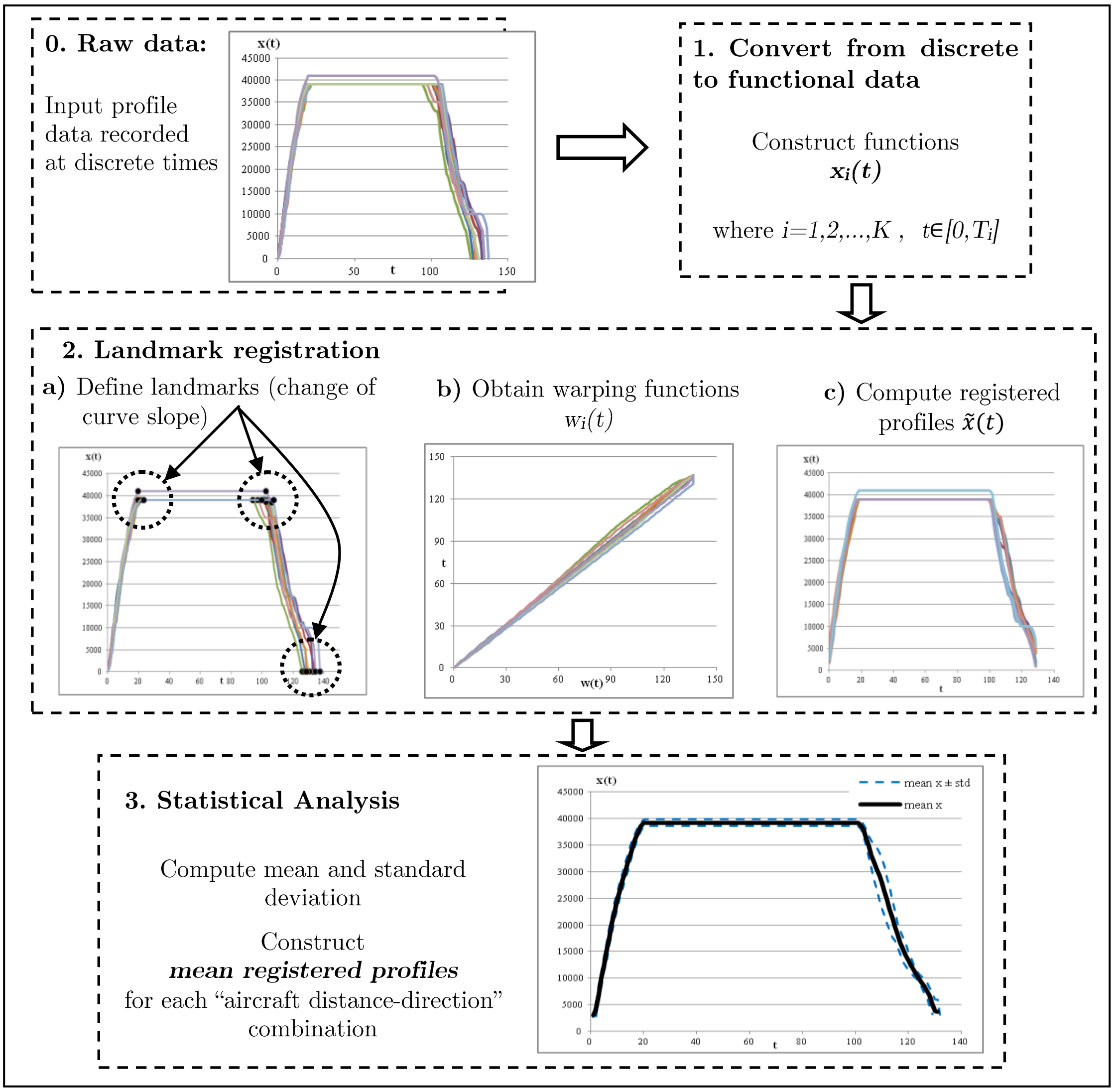


Figure 3.12. Steps of the Registration-based estimation on flight profile

Figure 3.13 displays the registered and unregistered flight profiles for the "B737-1000-WE" combination. The left figure includes the unregistered flight profiles in black while the unregistered mean curve is depicted in red. The figure shows that the pattern of the unregistered mean curve is distorted due to the phase variation, especially on the two regions indicated by the blue circles (end of cruise and last minutes of the flight). On the contrary, aggregating the registered curves (illustrated in black on the right side of the figure) provides a more reliable mean curve (depicted in light blue on the right side of the figure).

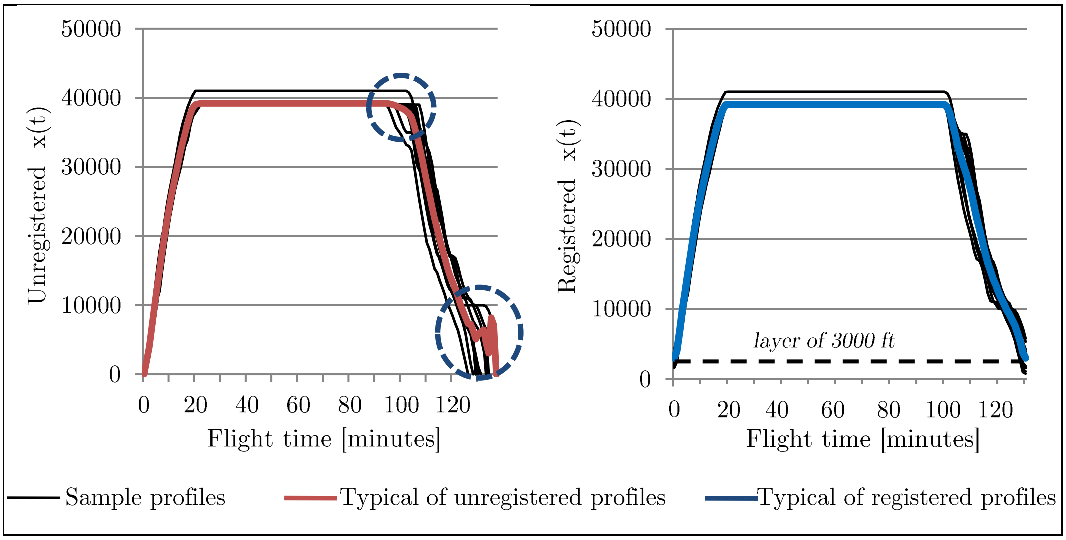


Figure 3.13. Typical profile for registered and unregistered sample profiles

3.4.4.2 Point mass BADA model

The Base of Aircraft Data (BADA) is an aircraft performance database maintained by EUROCONTROL (Nuic, 2013). It includes a mathematical model for the aircraft performance and the associated databases of the operating parameters for a wide range of aircraft and can be considered as a reduced point-mass model. The BADA performance model is based on the Total-Energy Model (Nuic, 2013) which describes the relationship between three performance-related parameters: thrust (Thr), true airspeed (V_{TAS}) and rate of climb/descent (dh/dt) as given in Eq. 3.2.

$$(Thr - D) \cdot V_{TAS} = m \cdot g_0 \cdot \frac{dh}{dt} + m \cdot V_{TAS} \cdot \frac{dV_{TAS}}{dt} \qquad \textbf{Eq. 3.2}$$

Given two of these variables, the third one can be obtained. Rearranging Eq. 3.2, we can get the rate of climb/descent by Eq. 3.3 if thrust and speed are known.

$$\frac{dh}{dt} = \frac{(Thr - D) \cdot V_{TAS}}{m \cdot g_0} \cdot \underbrace{\left[1 + \left(\frac{V_{TAS}}{g_0}\right) \cdot \left(\frac{dV_{TAS}}{dh}\right)\right]^{-1}}_{f\{M\}} \qquad \textbf{Eq. 3.3}$$

where D is the aerodynamic drag [Nt], m is the aircraft mass [kg], h is the altitude [m], and g_0 is the gravitational acceleration (9.80665 m/sec^2). The last part of Eq. 3.3 is defined as an energy share factor $f\{M\}$ which specifies how much of the available power is allocated to the vertical evolution as opposed to acceleration while following a selected speed profile during climb or descent. In real operations, the choice of $f\{M\}$ during speed changes can be handled by either the flight management system or the pilot.

In this estimation procedure we divide the CCD phase in small discrete steps which are referred to as chords. Figure 3.5 illustrates the flight chords in an example of recorded flight. Within each chord, a number of performance equations derived by the BADA model are employed in order to calculate aircraft speed, altitude, engine thrust and aerodynamic drag. Then Eq. 3.3 is used to compute the Rate of Climb or Descent (ROCD). To create more realistic profiles, the reduced climb power rather than the maximum climb power is adopted during the climb phase, where aircraft use a reduced setting during climb in order to extend engine life and save cost (Nuic, 2013). For the cruise phase, ROCD is set equal to zero. Figure 3.14 illustrates the procedure and the variables computed in each chord in order to simulate a flight profile and calculate the resulting fuel consumption. Based on historical flight profile data, the average cruise level and the average cruise duration are calculated for each "aircraft-distance-direction" combination. The initial conditions which include the initial aircraft altitude and mass are set next. Since flight profiles are created only for the CCD cycle, the initial flight level is set equal to 3,000 feet and the initial aircraft mass corresponds to the aircraft mass at the beginning of the CCD phase (after completing the take-off cycle). Finally BADA coefficients are obtained from the BADA database for each aircraft type.

Next an iterative approach is applied to compute the required performance variables at every flight chord. The variables computed at different flight levels are shown in Figure 3.14, while the parameters used in each computation are presented in Table 3.4. Atmospheric variables are determined as a function of aircraft altitude assuming International Standard Atmosphere (ISA) conditions, due to lack of real atmospheric data. As fuel is burnt during the flight, aircraft mass is recalculated at every iteration, by subtracting the fuel consumed in the current chord from the aircraft mass of the previous flight chord (fuel flow over each flight chord is calculated based on the model presented in Section 3.4.5). Based on these information and the current aircraft altitude, aircraft speeds are calculated (calibrated airspeed-CAS, true airspeed-TAS and Mach number). The desired output of each iteration is the ROCD (computed according to Eq. 3.3) which is used to determine the flight level of the next iteration. Starting from the end of the take-off cycle, the aircraft altitude raises until reaching the average cruise flight level (estimated from the historical flight profiles). When aircraft reaches cruise flight level, the ROCD is set equal to zero. Then, the duration of the cruise phase (of the typical profile) is set equal to the average cruise duration (estimated from the historical flight profiles). When the construction of the flight profile has been completed, the fuel burnt during the CCD cycle is computed as the sum of the fuel flow over the flight chords.

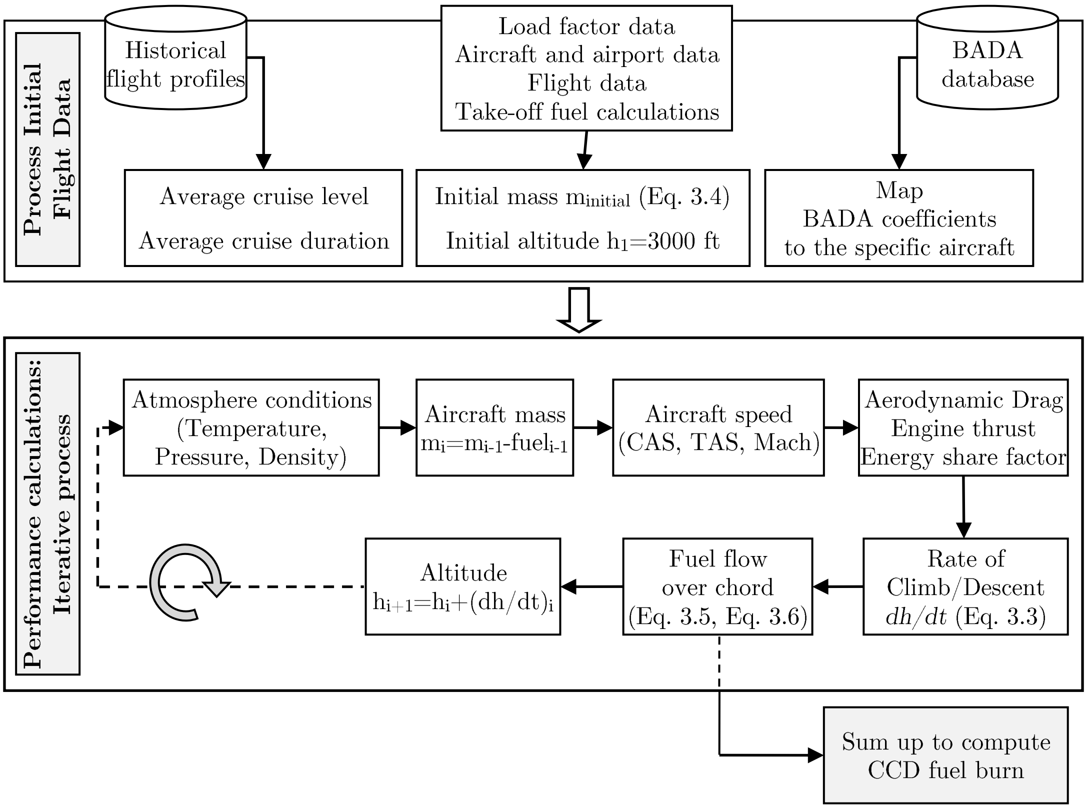


Figure 3.14. BADA-based estimation steps on flight profile and fuel burn

Two BADA data files are used to calculate the performance coefficients of the supported aircraft types: (i) the Airlines Procedure File (APF) which includes recommended speed procedures for climb, cruise and descent conditions (i.e. speed $V_{cl,1}$, $V_{cl,2}$, $V_{cr,1}$ etc and mach number M_{cl}, M_{cr}, M_{des}) and (ii) the Operations Performance File (OPF), which specifies the operations performance parameters for each aircraft type (i.e. stall speed V_{stall}, drag coefficients CD_0 and CD_2, parameters for thrust specific fuel consumption C_{f1}, C_{f2}, C_{f3} etc). Our computations are cross-checked with another BADA file, the Performance Table File which specifies cruise, climb and descent performance at different flight levels assuming three aircraft mass levels (low, nominal and high). Table 3.4 presents the parameters derived by BADA data files to conduct the aircraft performance computations.

Table 3.4. Aircraft performance parameters derived by BADA data files

	Variable	Symbol	Input variables: BADA coefficients [BADA file]	Input variables: Inputs from previous steps	Equation in BADA user manual (Nuic, 2013)
	Atmosphere Conditions				
1	Temperature	T	-	h	3.1-13 to 3.1-16
2	Air Pressure	p	-	T, h	3.1-18 to 3.1-20
3	Air Density	ρ	-	p, T	3.1-21
4	Speed of Sound	a	-	T	3.1-22
	Aircraft Performance Variables				
5	Transition altitude	$H_{p,\ trans}$	$V_{cl,2}$, $V_{cr,2}$, $V_{des,2}$ [APF] M_{cl}, M_{cr}, M_{des} [APF]	-	3.1-27 to 3.1-29
6	Aircraft speed	V_{TAS} V_{CAS} M	$V_{stall,TO}$ [OPF] $V_{cl,1}$, $V_{cr,1}$, $V_{des,1}$ [APF] $V_{cl,2}$, $V_{cr,2}$, $V_{des,2}$ [APF] M_{cl}, M_{cr}, M_{des} [APF]	ρ, T, rho, a	4.1-1 to 4.1-8 3.1-23 to 3.1-26
7	Aerodynamic Drag	D	$CD_{0,LDG}$, $CD_{0,\Delta LDG}$, $CD_{2,LDG}$ [OPF] $CD_{0,AP}$, $CD_{2,AP}$ [OPF] $CD_{0,CR}$, $CD_{2,CR}$ [OPF], S [OPF]	ρ, V_{TAS}, m	3.6-1 to 3.6-5
8	Engine Thrust	Thr			
	- Climb *(maximum climb thrust)*	$Thr_{max\ climb}$	$C_{Tc,1}$, $C_{Tc,2}$, $C_{Tc,3}$ [OPF]	H, V_{TAS}	3.7-1 to 3.7-3
	- Cruise	Thr_{cruise}	*equals to drag (use drag equations for cruise)*		
	- Descent	Thr_{des}	$C_{Tdes,high}$, $C_{Tdes,low}$, $C_{Tdes,app}$, $C_{Tdes,ld}$ [OPF]	$Thr_{max\ climb}$	3.7-9 to 3.7-12
9	Energy share factor	$f\{M\}$	-	M, T	3.2-8 to 3.2-11
10	Rate of Climb or Descent (ROCD)	dh/dt	Based on the Total-Energy Model (inputs: Thr, D, V_{TAS}, m, $f\{M\}$) See Eq. 3.3 above		
	Fuel Consumption				
11	Fuel flow	ff	C_{fcr} , C_{f1} , C_{f2} , C_{f3} , C_{f4} [OPF]	Thr, V_{TAS}	3.9-1 to 3.9-9

Abbreviations: h: altitude, CD: drag coefficient, C: general coefficient, S: reference wing surface area, m: aircraft mass, V_{TAS}: True airspeed, V_{CAS} : Calibrated airspeed, M: Mach number

The average cruise duration and altitude and the initial aircraft mass are two essential determinants of aircraft performance. They are determined at the initial step of processing initial flight data (upper panel of Figure 3.14).

Average cruise duration and altitude: The recorded flight profiles are initially decomposed into different flight phases: LTO, climb, cruise and descent. The start and end points of the cruise segment are identified manually, by observing each flight profile. An example is given in Figure 3.5, where the cruise phase extends between the indicated start (t_1) and end (t_2) points. For each "aircraft-distance-direction" combination, cruise durations and altitudes of the individual flights are averaged to derive the average cruise duration and altitude.

Initial aircraft mass: The initial aircraft mass is an essential determinant of aircraft performance which affects climb and descent rates, as well as fuel burn. It depends on a number of factors; operating empty weight, fuel required for the trip, reserve fuel and passenger/cargo payload and requires load factor data, aircraft, airport and flight data and take-off fuel. Most of these factors are not available and need to be estimated. Eyers et al. (2004) assumed a global average figure of 60.9% in order to estimate take-off aircraft mass as a function of maximum payload capacity. In other studies (Zou, 2012; Félix Patrón et al., 2014) the reference aircraft mass given by aircraft performance models was used to derive the initial mass, while Ansberry (2015) assumed that initial aircraft mass is equal to the maximum take-off mass. Lee et al. (2007) used aircraft take-off weight data based on their stage length in order to account for the increased fuel requirement for longer flights.

The determination of aircraft mass factors for every individual flight requires an iterative approach which increases the computational effort and thus has been adopted by few researchers (Wasiuk et al., 2015; Schaefer, 2012; Sherry and Neyshabouri, 2014). Eq. 3.4 expresses the aircraft initial mass ($m_{initial}$) as the sum of the operating empty weight (m_{OE}), the passenger and cargo payload ($m_{payload}$) and a sufficient amount of fuel (m_{fuel}) based on the fuel requirements explained below

$$m_{initial} = m_{OE} + m_{payload} + m_{fuel} \qquad \textbf{Eq. 3.4}$$

The operating empty weight (m_{OE}) is an aircraft-specific parameter which is derived from BADA OPF files, where it is referred to as the minimum mass.

Aircraft payload ($m_{payload}$) is a product of passengers carried and passenger weight. Passengers carried are given by the aircraft seat capacity times the aircraft load factor. Based on the aircraft type, seat capacity is determined by aircraft manufacturer tables. Appendix B-4 presents the seating capacity of the studied aircraft types. Load factors are averaged by airline and distance combination for each quarter in 2012 based on the T-100 database. The passenger weight may vary by airline, mission distance and type of passenger (business and leisure). An average passenger weight of 90 kg (including cabin luggage) is assumed based on ICAO (2009).

The pre-flight calculation of usable fuel required (m_{fuel}) may include: trip fuel, contingency fuel, destination alternate fuel and final reserve fuel (ICAO, 2012a). Trip fuel (f_{trip}) includes the fuel burnt during the CCD phase and the landing and taxi-in fuel at the destination airport. Landing and taxi-in fuel calculations are based on ICAO Engine Exhaust Emissions databank (ICAO, 2016c) as explained in Section 3.3. Contingency fuel (f_{cont}) is the amount of fuel required to compensate for unexpected factors, such as meteorological conditions, extended holding procedures, deviation from planned horizontal or vertical profile and it is set 5% of the planned trip fuel (ICAO, 2012a). Destination alternate fuel (f_{alt}) is the amount of fuel required to fly from the original to the alternate destination, while final reserve fuel (f_{res}) is the amount of fuel required to fly above the alternate airport under standard conditions. Based on Wasiuk et al. (2015) and ICAO (2012a), destination alternate and final reserve fuel are in total equal to the amount of fuel used cruising for 60 min (jet) or 45 min (turboprop) at the cruise altitude. The estimation uses the cruise fuel burn rate for the aircraft weight at the end of cruise.

Based on the aircraft type, m_{OE} is directly obtained from BADA tables, while $m_{payload}$ can be calculated by combining seat capacity data and load factor data. On the contrary, m_{fuel} cannot be directly computed and an iterative algorithm is applied. In the first iteration, $j=1$, the initial aircraft mass is assumed to be equal to the nominal aircraft mass (m_{ref}) minus the fuel burnt during departure (taxi and take-off) at the origin airport (f_{dep}), i.e. $m^1_{initial}=m_{ref}-f_{dep}$. Taxi and take-off fuel burn rates are obtained from the ICAO Engine Exhaust Emissions databank (ICAO, 2016c). Based on $m^1_{initial}$, flight profile is generated and the trip fuel consumption f^1_{trip} is calculated. Contingency f^1_{con}, destination alternate f^1_{alt} and reserve fuel f^1_{res} are then calculated as described in the previous paragraph. The total fuel load is calculated as $m^{1}_{fuel}=f^{1}_{trip}+f^{1}_{con}+f^{1}_{alt}+f^{1}_{res}$. In the second iteration, $j=2$, the initial aircraft mass is calculated based on Eq. 3.4, where $m_{fuel} \equiv m^{1}_{fuel}$. Then the first iteration is repeated (re-calculate the trip fuel consumption, re-calculate contingency, destination alternate and final reserve fuel etc). The iterative algorithm stops when the updated initial mass converges to that of the last iteration, such that $\left|m^{j+1}_{initial} - m^{j}_{initial}\right| \leq 0.001$. Initial aircraft mass is shown as a function of iterations in Figure 3.15 for four aircraft types operating a flight of 1000 sm distance. It is observed that in most profiles, convergence occurs after 4 to 5 iterations. The iteration of convergence is indicated with the black arrow. To start the iterations, the initial aircraft mass is set equal to the nominal aircraft mass minus the fuel burnt during departure at the origin airport.

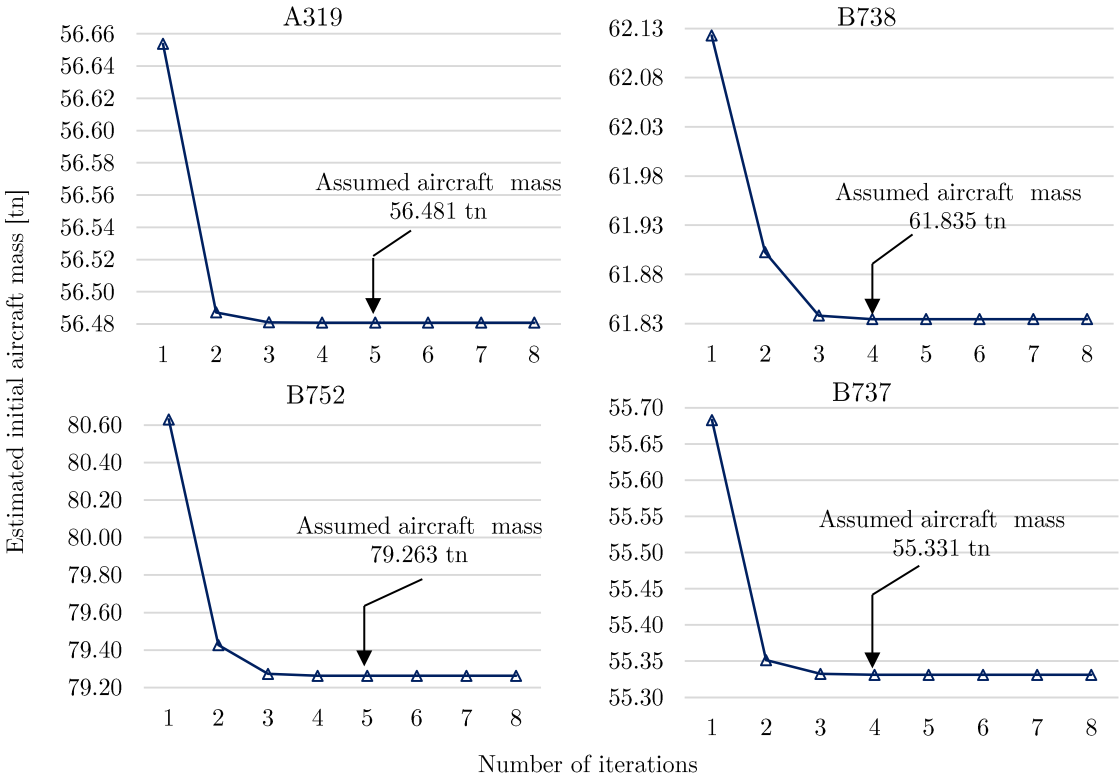


Figure 3.15. Convergence of initial aircraft mass estimates

3.4.5 CCD fuel burn and CO_2 emissions model

Aircraft fuel burn and CO_2 emissions are influenced by various factors including aircraft type, flight distance, flight mode, time consumed in each mode and aircraft performance. Given the generated typical flight profiles, instantaneous fuel flow of an aircraft can be calculated at any point of the typical profile. Each chord's fuel burn is determined by multiplying fuel flow (ff_s) and time spent within the chord (dt_s), while CCD fuel and resulting CO_2 emissions $E_{CO2,CCD}$ [in tn] are subsequently calculated by summing up the corresponding fuel and emission values of all flight chords as expressed in Eq. 3.5.

$$E_{CO_2,CCD} = 10^{-3} \cdot EI_{CO_2} \cdot \sum_{s=1}^{S} dt_s \cdot ff_s =$$

$$= 10^{-3} \cdot EI_{CO_2} \cdot \begin{cases} \sum_{s=1}^{S} dt_s \cdot \eta_s \cdot Thr_s \cdot C_{fcr} & for\ Cruise \\ \sum_{s=1}^{S} dt_s \cdot \eta_s \cdot Thr_s & for\ Climb/Descent \end{cases}$$ **Eq. 3.5**

where EI_{CO2} is the emission index of CO_2 (equal to 3.157 kg CO_2/kg fuel (ICAO, 2014), η_s [in kg/(min·kN)] is the thrust specific fuel consumption of segment s, Thr_s [in kN] is the engine thrust within segment s and C_{fcr} is a cruise fuel flow factor derived by OPF BADA tables based on the aircraft type. The thrust specific fuel consumption is calculated based on Eq. 3.6 depending on the engine type (jet or turboprop).

$$\eta = \begin{cases} C_{f1} \cdot \left(1 + \frac{V_{TAS}}{C_{f2}}\right) & for\ jet \\ C_{f1} \cdot \left(1 - \frac{V_{TAS}}{C_{f2}}\right) \cdot \left(\frac{V_{TAS}}{1000}\right) & for\ turboprop \end{cases}$$ **Eq. 3.6**

where V_{TAS} [in kt] is the true airspeed and C_{f1} and C_{f2} are aircraft-specific fuel flow coefficients derived by OPF BADA tables. When the aircraft switches to the approach and landing configuration (during descent phase) the calculation of fuel flow is based on the second expression of Eq. 3.5 but should be limited by a minimum fuel flow given in Nuic (2013).

The resulting output consists of two $n \times m \times p$ matrices where n is the number of aircraft types, m is the distance clusters and $p=2$ gives the number of different directions (west-east/WE or east-west/EW). These matrices contain the fuel burnt and the carbon dioxide emitted for each combination of "aircraft-distance-direction". Once the fuel burn and CO_2 emissions for all typical flight profiles are known, the corresponding fuel and emission values for every itinerary of our traffic sample can be obtained by applying linear interpolation.

3.5 Modeling assumptions

The methodology for calculating aircraft fuel burn and CO_2 emissions during LTO and CCD phases presented in this chapter rely on a number of simplifying assumptions that are common among studies modeling fuel burn and emissions for large geographical regions (Eyers et al., 2004; Kim et al., 2007; Schaefer, 2012; Wasiuk et al., 2015).

- Use of representative aircraft or engine types: CCD CO_2 emissions are computed using aircraft-specific coefficients derived by BADA tables, while LTO CO_2 emissions depend on engine-specific fuel flow rates derived by ICAO Engine Exhaust Emissions databank for jet aircraft and aircraft-specific fuel flow obtained from EMEP/EEA database for turboprops. When the actual aircraft is not included in the above databases, a proper proxy is used instead (see Appendix B-4 for the equivalent aircraft and engine types used in this dissertation). The use of representative aircraft and engine types is a standard approach when computing aircraft CO_2 emissions of large-scale networks, while the mapping is based on the review of reliable sources (EEA, 2013; ICAO, 2016c).

- No consideration of wind and actual atmospheric conditions: In BADA-based profile estimation, the International Standard Atmosphere (ISA) conditions and no winds are assumed, since this kind of data is not available on the desired level of analysis. This information is indirectly considered in the estimation through their impact on flights' cruise level and cruise duration. Flying into a headwind decreases aircraft ground speed and thus increases flight time and fuel burn. On the contrary, flying with a tailwind will have a positive effect on fuel consumption. Zou (2012) reported an A320 flying in tailwind consumes around 3.9% less fuel compared to the no wind condition for a 1280 nm trip. Baughcum et al. (1996) concluded that headwinds may have a +1.1% effect in fuel burn for North-Atlantic round-trip flights and a +0.4% effect for North-south round trips, based on analyses for a Boeing 747-400. This difference is due to the difference in wind speed between the two regions.
- Use of standardized flight trajectories: The profiles are simulated under the assumptions of continuous climb out to cruise altitude, constant cruise altitude during the entire cruise phase and a continuous descent. Non constant trajectories along the entire cruise phase can be dealt with additional carefully chosen landmarks and suitable warping functions.
- No consideration of local conditions: Typical profiles are estimated for combinations of distances, aircraft types and direction of flight; thus, special air traffic conditions or differences in the air traffic management that are related to a specific airport pair are not considered. The analysis could be augmented to incorporate local conditions at the origin and destination airports. However, the additional burden to collect and analyze flight profile data for every airport pair of our traffic sample, is not believed to contribute more to our current approach.
- Aircraft mass assumptions: Aircraft mass assumptions are based on pre-flight assumptions with respect to average load factor, average passenger weight and fuel required. Although the estimated initial aircraft mass may deviate from the actual one, it is believed that the proposed weight calculation is satisfactory.
- Typical LTO times: Typical LTO times based on ICAO are used to derive time consumed during take-off, climb-out and approach landing, since such data are not available. For the idle phases (taxi-in/out), airport-specific times are used.
- Altitude profiles for short flights: Very short flights (shorter than 200 sm) often lack significant cruise leg or do not reach cruise level. In these cases, CCD stages (climb, cruise and descent) could not be distinguished and, thus, the proposed profile estimation methods could not applied. Furthermore, in the clusters of distance less than 300 sm, the flights followed different altitude patterns and thus both registration- and BADA-based estimation failed to construct a reliable typical profile. Therefore, for flights shorter than 300 sm, CCD CO_2 emissions were computed by the use of the EMEP CORINAIR database based on the following formula.

$$E_{CO_2,CCD} = 10^{-3} \cdot EI_{CO_2} \cdot fc_{CCD,d,a} \quad \textbf{Eq. 3.7}$$

where EI_{CO2} is the emission index of CO_2 (equal to 3.157 kg CO_2/kg fuel) and $fc_{CCD,d,a}$ is the fuel consumption [in kg] of aircraft type a for flight distance d during CCD phase obtained by the EMEP CORINAIR database (version 2013). This database provides fuel consumption data for a number of standard flight distances. Interpolation methods are used to obtain fuel burn data for flight distances other than standard.

- Other assumptions: Delays, cancellations, or reroutings are not modeled.

3.6 Evaluation of the CCD profile estimation approaches

The paths estimated by the registration-based estimation approach are compared to those obtained by the BADA-based approach in terms of flight characteristics. In particular, the time consumed in each stage of the CCD cycle and the rate of climb and descent of the actual profiles are compared with the corresponding values of the typical profiles. Two metrics are used to evaluate the predictability power of the methods: the Mean Absolute Percentage Error (MAPE) and the Root Mean Square Error (RMSE).

Let n stand for the number of analyzed profiles of each "aircraft-distance-direction" combination and $X_{obs,i}$ and $X_{model,i}$ be the observed and modeled values of a given characteristic. Then MAPE and RMSE are computed by Eq. 3.8 and Eq. 3.9.

$$MAPE[\%] = \frac{100\%}{n} \cdot \sum_{i=1}^{n} \left| \frac{X_{obs,i} - X_{model,i}}{X_{obs,i}} \right| \quad \textbf{Eq. 3.8}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (X_{obs,i} - X_{model,i})}{n}} \quad \textbf{Eq. 3.9}$$

We use X for the climb, cruise and descent duration or the rate of climb or descent. The MAPE and RMSE metrics are computed for every "aircraft-distance-direction" combination and all evaluated flight characteristics. The results can be further aggregated by aircraft type or distance group or flight direction. As stated in Section 3.5, altitude profiles were disregarded for flights shorter than 300 sm. Thus, the evaluation process has been conducted for every combination of "aircraft-distance-direction", with distance longer than 300 sm.

Each distance cluster may be served by several aircraft types. Figure 3.16 presents the most frequent aircraft types by distance cluster, along with passengers' share in 2012, based on the T-100 Domestic Segment for US carriers for 2012. Airbus 321 (A321), Boeing 737-700 (B737), 737-800 (B738) and 757-200 (B752) demonstrate high percentages in almost every distance cluster. Regional jets such as the Canadair Regional Jet 900 (CRJ9) and 200 (CRJ2) and the Embraer 145 (E145) mainly serve short- to medium-haul flights (400 to 1000 miles). Larger aircraft, such as Airbus 330-200 (A332) and Boeing 767-300 (B763), 767-400 (B764), 777-200 (B772) mainly serve longer flights (longer than 2500 miles). For clarity reasons, small percentages are not given in Figure 3.16 for some aircraft types.

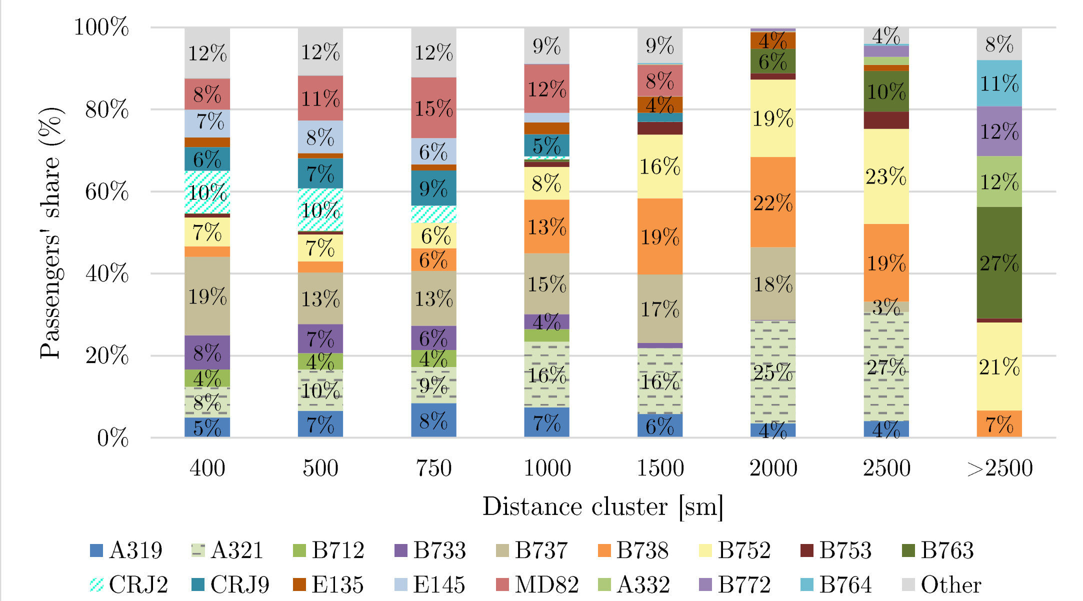


Figure 3.16. Share of passengers carried in 2012 by aircraft type

The predictive performance of the two methods in terms of climb, cruise, descent duration and the duration of the entire CCD is evaluated by the Mean Absolute Percentage Error and is aggregated by distance cluster in Table 3.5. Flights longer than 2500 sm are grouped in one category, since they only share the 2.3% of 2012 total passenger miles.

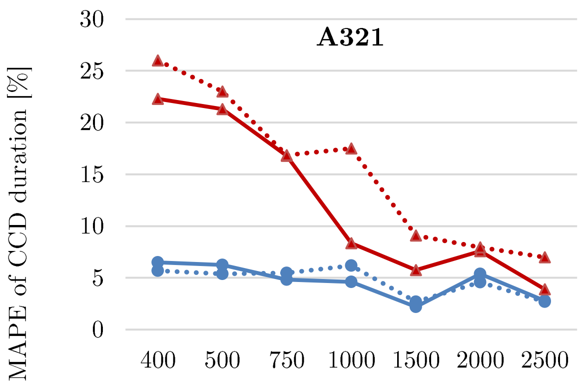
Table 3.5. Mean Absolute Percentage Error by distance group

	Mean Absolute Percentage Error [%]							
	BADA-based estimation				Registration-based estimation			
Distance cluster	Climb duration	Cruise duration	Descent duration	CCD duration	Climb duration	Cruise duration	Descent duration	CCD duration
400 sm	25.5	10.0	33.4	17.8	13.7	16.4	17.6	5.2
500 sm	27.1	12.1	39.3	19.5	13.2	14.7	19.9	6.3
750 sm	26.3	8.8	41.3	15.4	12.2	9.3	18.6	5.0
1000 sm	23.4	7.7	41.7	12.4	11.2	8.2	19.0	4.8
1500 sm	19.5	4.2	38.8	7.4	10.2	4.6	18.3	3.4
2000 sm	22.2	4.3	44.8	6.8	13.0	4.5	21.2	3.8
2500 sm	24.0	3.3	38.9	5.3	9.4	4.3	18.1	3.9
> 2500 sm	28.1	2.4	38.3	4.9	10.1	2.8	12.1	2.4

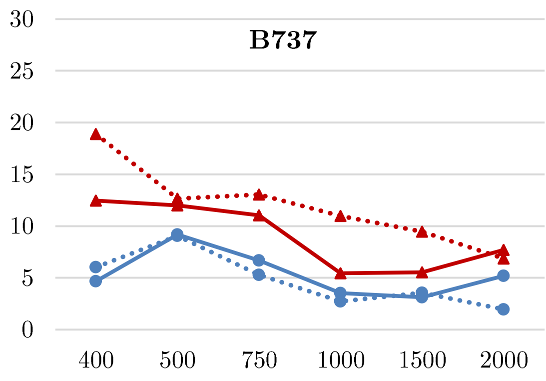
As expected, the above results indicate that the registration-based estimation performs significantly better than the BADA-based model in the prediction of all flight characteristics under consideration. Climb phase is predicted by the registration-based method with average errors of 9.4-13.7%, while BADA estimation errors range from 19.5 to 28.1%. The accuracy of BADA falls notably in the case of descent. For example, in the case of shorter flights (400 sm), the simulated descent duration computed by the BADA model differs, on average, from the actual values by 33.4%. In contrast, registration-based estimation fails to predict descent duration by a percentage of 17.6% in these flights. Regarding CCD duration, the BADA based MAPE decreases with distance. For long flights (longer than 2500 sm), $MAPE_{CCD}$ is equal to 4.9%. Our results suggest that

BADA's accuracy on descent duration deteriorates due to a higher rate of descent (ROD) than the actual. BADA typical profiles have an average ROD equal to 2230 feet/minute, while the corresponding value is equal to 1283 feet/minute for the registration-based typical profile estimation. Analogous deviations appear in the case of the rate of climb (ROC), where BADA-based typical value is 2157 feet/minute and registration-based is equal to 1588 feet/minute. The actual climb and descent rates vary in practice due to air traffic control constraints, variations in the wind profile and other local conditions. However, BADA parameters are global and cannot take into account the particular factors which influence aircraft operation characteristics. To account for the local aircraft operation characteristics and improve the modelling accuracy of the BADA-based flight profile, BADA enables the users to modify the BADA default values. This requires more detailed information on aircraft performance and local conditions which are usually not widely available. Finally, Table 3.5 indicates that although cruise and CCD prediction errors decrease with distance, this is not true for climb and descent prediction errors. This behavior is explained by the share of the cruise part within the climb-cruise-descent phase. Analysis of the data shows that the cruise phase holds 38-51% of the CCD cycle for short flights (500 sm) depending on the aircraft type and the profile estimation method, while this proportion increases to 84-89% for longer flights (2500 sm). Thus, although descent and climb prediction errors are still high for long flights, they are eliminated when the CCD prediction error is considered.

The prediction accuracy of the two methods is further clarified in the following figures. Figure 3.17 plots the MAPE prediction errors of the CCD duration and Figure 3.18 illustrates the RMSE of the rate of descent by aircraft type. Based on Figure 3.16 a variety of frequently employed aircraft types in the different distance clusters are considered: Airbus 321 (A321), Boeing 737-700 (B737), Boeing 737-800 (B738) and Boeing 757-200 (B752). Both figures show that BADA errors are generally higher than those of the registration-based estimation for all aircraft types and distance clusters. B738 is more accurately predicted in terms of CCD duration and rate of descent by both methods in comparison to the other aircraft types. Figure 3.17 also indicates that the percentage errors have a decreasing trend in relationship with flight distance in approximately all circumstances. In contrast, the RMSE of the rate of descent does not decrease with distance, while in some cases the error increases with distance.



(a)



(b)

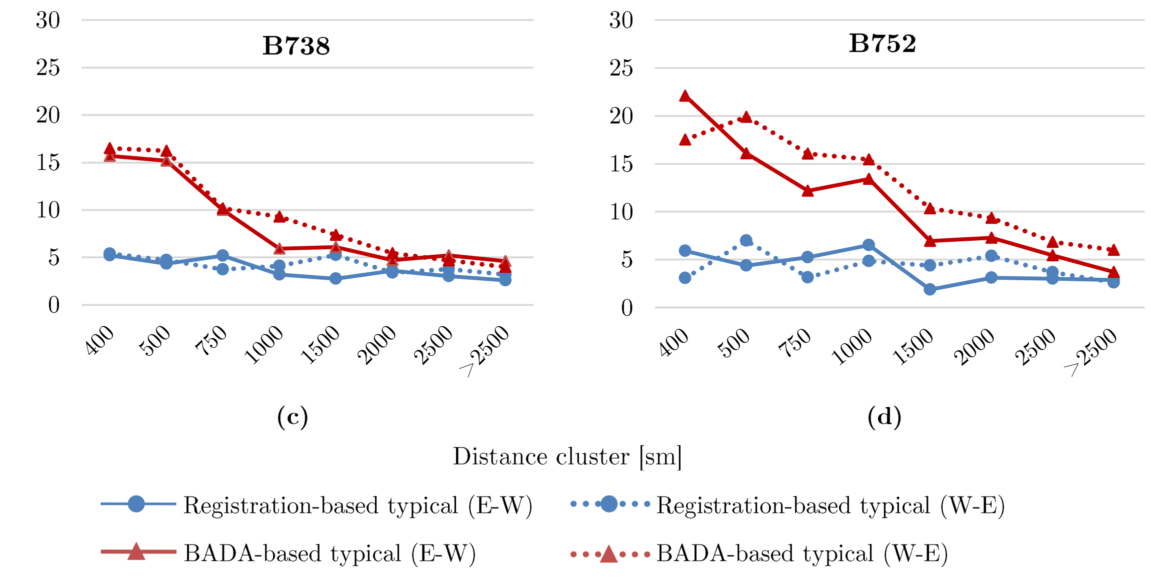


Figure 3.17. Mean Absolute Percentage Errors of CCD duration by aircraft type

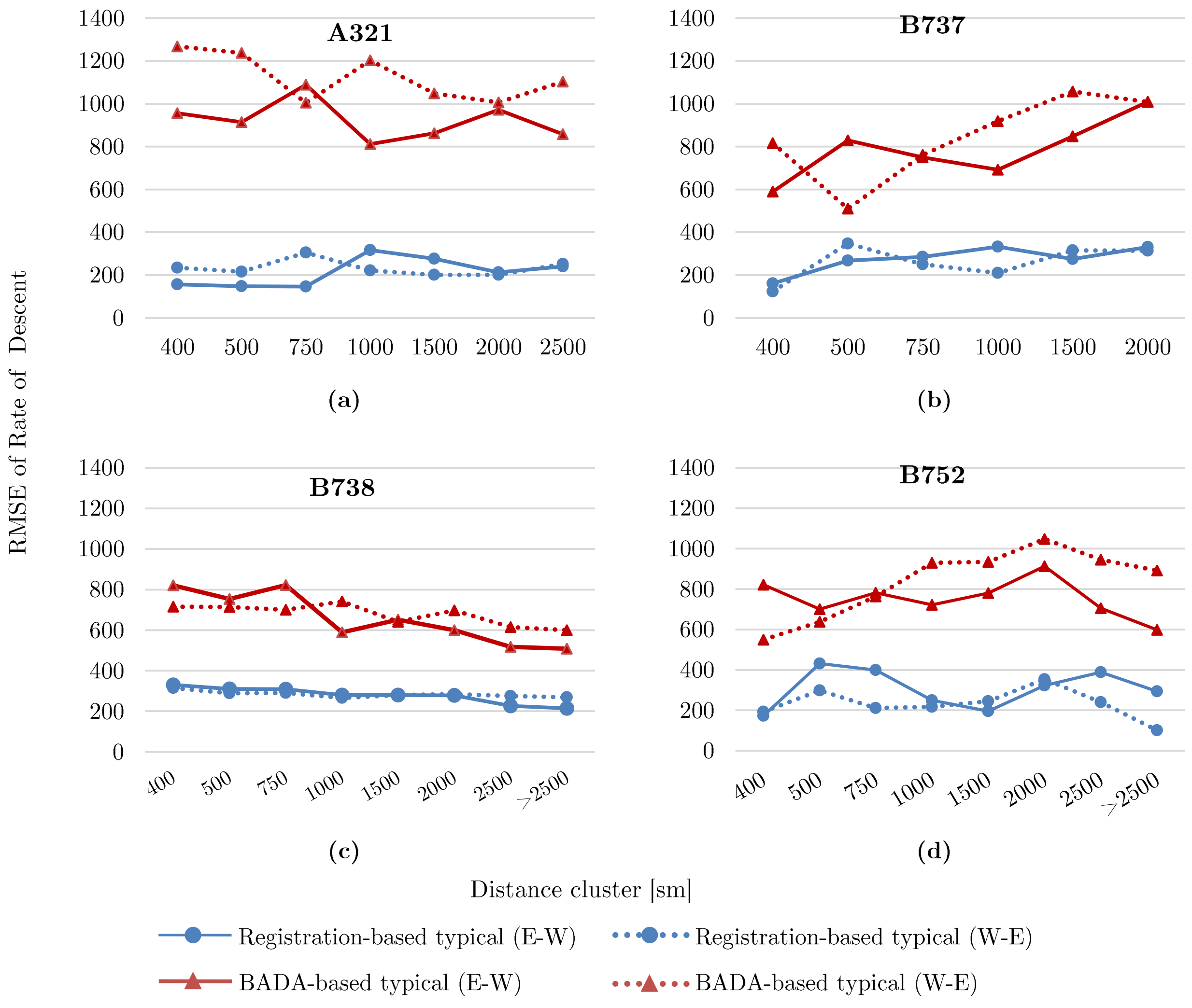


Figure 3.18. Root Mean Square Errors of the rate of descent by aircraft type

Figure 3.19 presents the climb and descent rates averaged by aircraft type. These values correspond to average values for all distance clusters. As already stated, it can be seen that BADA-based estimation result in higher rates of climb and descent than the actual. However, the actual climb and descent rates are lower and vary due to air traffic control constraints, variations in the wind profile and other local conditions. BADA parameters are global and cannot take into account the particular factors which influence aircraft operation characteristics.

The results demonstrate that there is a large discrepancy of flight characteristics between BADA-based and registration-based approaches. Similar results are reported in Hrastovec and Solina (2014), who compare the BADA performance model with a machine learning model. Based on their results, on average BADA failed to predict descent by 40.75% and climb by 27.31%. These values are close to our results presented in Table 3.5. The extent to which these deviations in flight characteristics affect CCD fuel consumption is addressed in the next section.

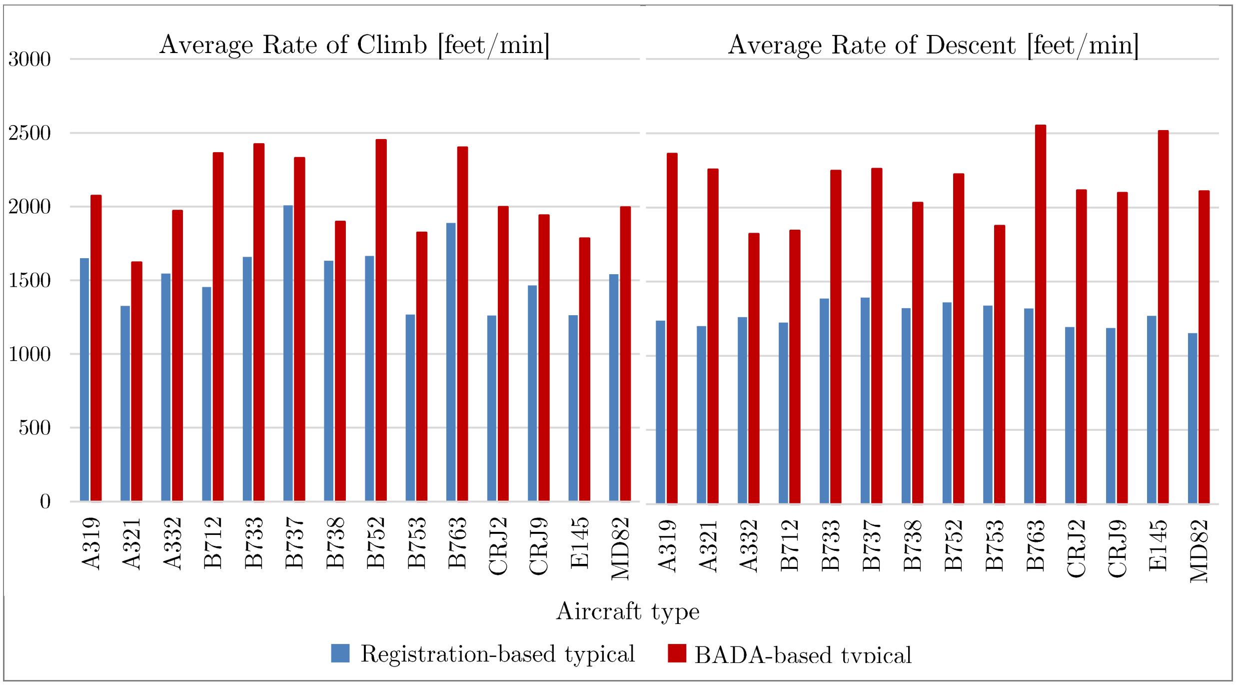


Figure 3.19. Average Rates of Climb and Descent by aircraft type

3.7 Carbon emissions results

3.7.1 CCD-level CO_2 emissions results

Regarding the CCD cycle, the fuel burn and CO_2 emissions for all combinations of "aircraft-distance-direction" is calculated by the methods described in Section 3.3.1. The results are grouped by the studied distance clusters in Table 3.6.

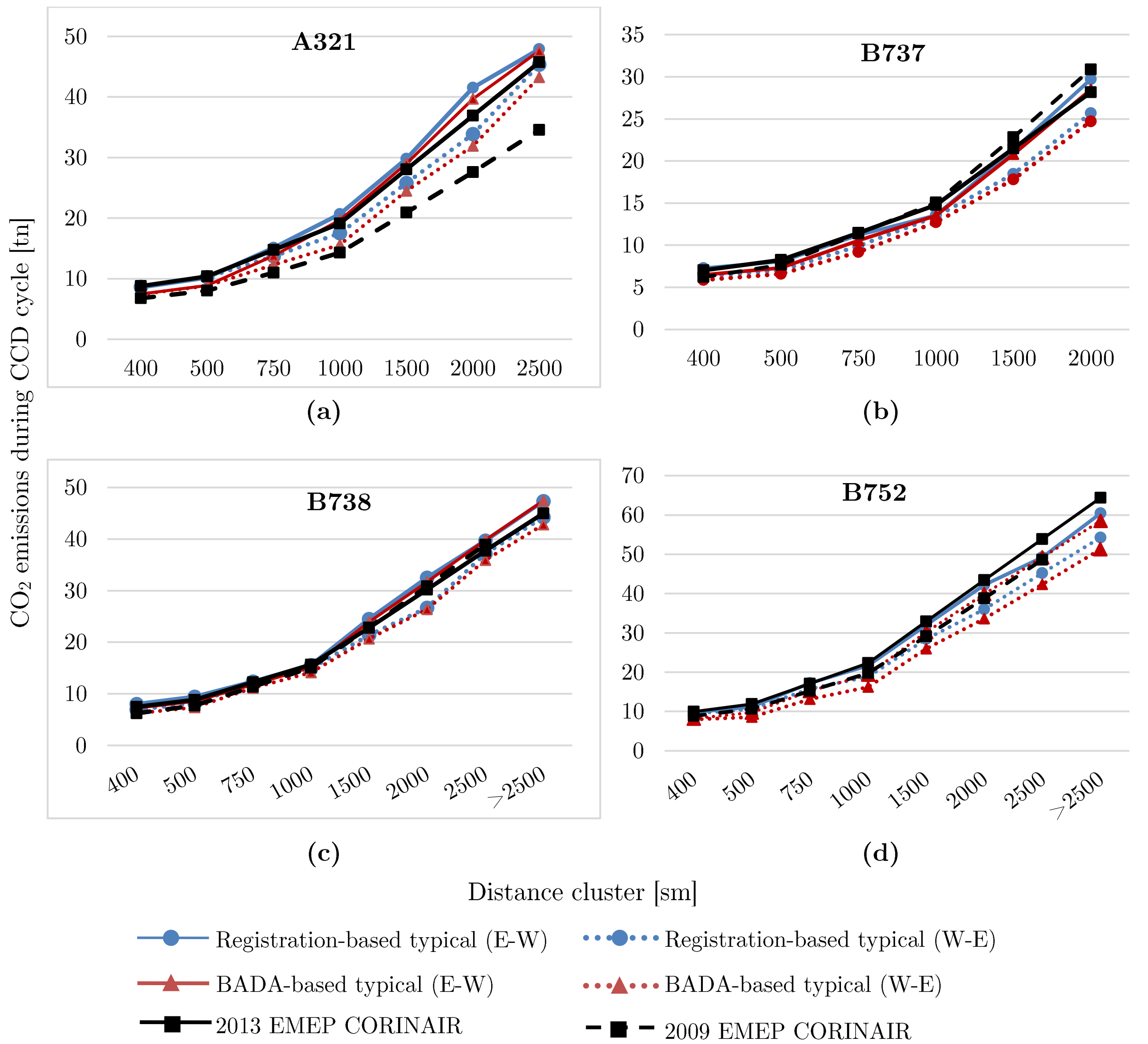
Table 3.6. CCD CO_2 emissions aggregated by distance cluster

Distance cluster	BADA-based estimation Average CCD CO_2 emissions [tn]	BADA-based estimation Average cruise CO_2 emissions rate [kg/min]	Registration-based estimation Average CCD CO_2 emissions [tn]	Registration-based estimation Average cruise CO_2 emissions rate [kg/min]	Δ_{CO2} CCD [%] (BADA/registration)
400 sm	5.90	115.9	6.72	116.2	-12.2%
500 sm	6.76	108.3	7.89	108.5	-14.4 %
750 sm	9.79	105.9	11.02	106.0	-11.2 %
1000 sm	14.08	117.0	15.41	117.1	-8.6 %
1500 sm	24.94	138.1	26.20	138.2	-4.8 %
2000 sm	35.26	151.2	36.78	151.3	-4.1 %
2500 sm	50.04	171.9	51.36	171.9	-2.6 %
>2500 sm	69.36	207.6	71.14	207.7	-2.5%

It is observed that CO_2 emission calculations do not vary significantly between the two altitude estimation methods, especially for longer flights. The last column indicates that the difference in CO_2 values between the two typical profiles decreases with distance while the BADA-based estimates are lower than the registration-based results. For example, the CO_2 emissions computed for long-haul flights (longer than 2500 sm) by the two methods differs by 2.5%. For shorter flights, the difference is sharper, 14.4% and 11.2% for distances of 500 sm and 1000 sm respectively. Overall, the typical profiles calculated by BADA underestimate fuel burns and CO_2 emissions in comparison to registration-based profiles, while the discrepancies are attenuated with distance. A closer look at Table 3.5 reveals that the share of climb and descent phases in the overall flight explains the above observed pattern. Climb and descent phases are responsible for the large differences in the two estimation procedures as shown in Table 3.5. In long flights, the climb and descent phases form a relatively small part of the entire CCD cycle and the cruise phase plays the most important role on fuel and CO_2 emissions computations. As indicated in Table 3.6, the cruise CO_2 emissions rate difference resulting from the two methods ranges from 0.25% for short flights (400 sm) to 0.05% for longer flights (>2500 sm). Therefore the CCD fuel burn and CO_2 emissions estimates of the two typical profiles are close and practically identical over long flights.

For specific aircraft types, the above deviations of fuel estimates may significantly differ from average values. Figure 3.20 illustrates the amount of CO_2 emitted during the CCD cycle by distance group for four aircraft types. Calculations are based on the typical profiles extracted by the two methods and on the use of the BADA fuel flow coefficients for the determination of fuel flow rates. The carbon emissions of the registration-based typical profiles are illustrated in blue. In red, we depict the emissions of the BADA-based typical profiles. In all cases, registration-based typical profiles lead to slightly higher carbon emissions than the BADA-based profiles. In some cases emission levels are almost indistinguishable. B752 exhibits the most notable difference in emission estimates. The impact of orientation is also considered; different plots are given for westbound (continuous line) and eastbound (dotted line) flights. CO_2 emissions are higher for westbound flights due to their higher flight duration (see Figure 3.7). Figure 3.20 indicates the difference in emissions levels between various aircraft types. Heavier aircraft such as

B752 produce approximately 1.5-2 times more CO_2 emissions compared to the lighter aircraft B737.



Notes: 2009 EMEP CORINAIR calculations are based on mapping actual aircraft to the equivalent aircraft types: (a) A320, (b) and (c) B734, (d) B757.

Figure 3.20. CO_2 emissions calculations by aircraft type

3.7.2 Uncertainty on the initial aircraft mass estimation

The construction of BADA-based typical profiles depends on estimates of the aircraft weight at the start of the CCD cycle. Any uncertainty in the computation of the initial aircraft weight is translated into uncertainty in the fuel burn and emissions estimates. To explore the effect of this aircraft weight uncertainty on our estimates, we conduct sensitivity analysis. Figure 3.21 shows the sensitivity results for six aircraft types (A319, A321, B737, B738, B752 and MD82). The x-axis represents the percentage change in the estimated aircraft mass (where aircraft mass is estimated based on Section 0). The upper and lower values of the aircraft mass used in the analysis are bounded by the minimum and maximum weight respectively for each aircraft type. The lower bound refers to operating empty weight while the upper bound is the maximum aircraft payload. Both values are available from BADA performance tables. The y-axis represents the percentage change in the CCD aircraft fuel.

The slope of the curves suggest that one percent increase in the initial aircraft mass has a larger impact on CCD fuel than an equivalent decrease in aircraft mass. In particular we observe that an increase of 10% in aircraft mass results in 7-9% increase in CCD fuel burn, while a similar decrease in aircraft mass may lead to a 5.8-8% decrease in CCD fuel burn depending on the aircraft type. The sensitivity analysis shows that the fuel burn and CO_2 emissions estimates of BADA-based typical profiles are sensitive to the initial aircraft mass estimation.

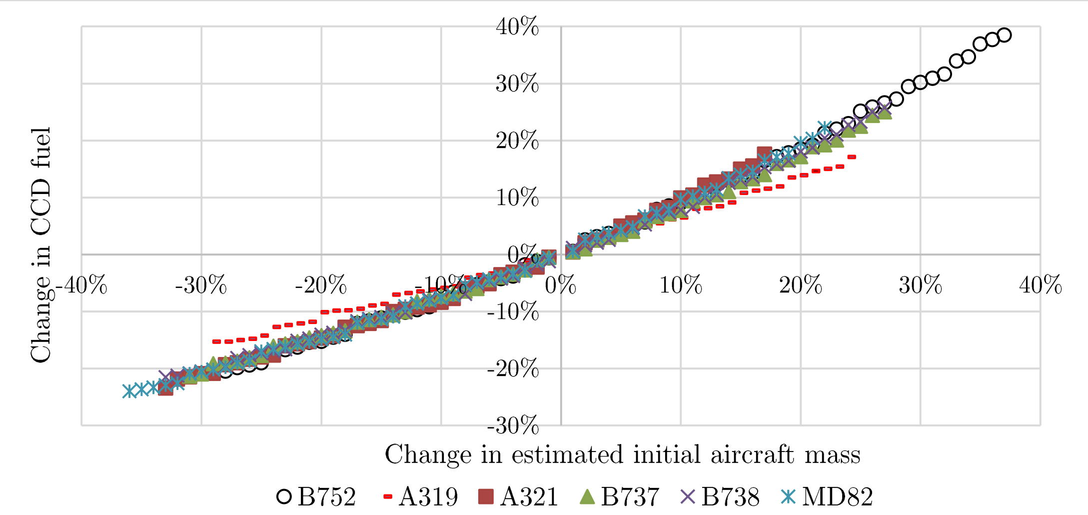


Figure 3.21. Sensitivity analysis of CCD fuel with respect to aircraft mass

3.8 Conclusions

In this chapter a tool is developed to compute aircraft fuel burn and carbon dioxide (CO_2) emissions for any given itinerary within the U.S. airspace. For the CCD cycle, typical altitude profiles are estimated using two estimation approaches and a wide range of flight distances and aircraft types.

The first estimation method uses a novel combination of clustering and landmark registration techniques. This method exploits the information of the entire trajectory of historic flights. The second estimation method relies on the point mass BADA model, which has been used by several researchers in the past. With this method, the aircraft altitude profile is constructed based on standard airline procedures described by aircraft-specific operating parameters.

The operational characteristics of the typical altitude profiles obtained by the above methods are compared. The registration-based method performs significantly better than the BADA-based estimation. This is explained by the fact that the registration-based method fundamentally relies on operational data and can capture actual flight performance more reliably. Subsequently, the aircraft profiles were used to compute fuel consumption and CO_2 emissions across three hierarchical layers: aircraft-specific, distance-specific and network-wide. Big datasets of air traffic and flight track information over a wide range of U.S. domestic flights were employed in the above analysis.

It was found that despite the substantial difference in the calculation of the flight characteristics among the two profile estimation methods, the difference in the estimates of fuel consumed over the CCD phase is less pronounced. In a nutshell, BADA typical profiles burn less fuel than registration-based profiles, while the discrepancies fade with flight distance. The two latest versions of EMEP CORINAIR, an aircraft fuel consumption database, were also used for comparison and it was found that its last version (EMEP CORINAIR 2013) gives similar results with our methods, especially for the registration-based profiles.

Overall, our comparisons with past emission studies and the widely-used EMEP CORINAIR database suggest that our method, which combines (i) the use of ICAO Engine Exhaust Emissions databank for the LTO CO_2 emissions and (ii) the implementation of BADA fuel flow coefficients on the registration-based typical profiles, provides reliable CO_2 emission estimates for large scale networks, similar to our study U.S. airline network. The estimated CO_2 emissions act as input in Chapter 6, where the market-based environmental policy on air transport industry is simulated.

4 Passenger demand for air transport

Travel demand analysis constitutes an important part of airport planning. Demand analysis is also a necessary condition for efficient decision making when pricing policies or other regulatory measures are under consideration, since it can demonstrate how the change of certain key factors after the implementation of a policy, may affect travel demand. Aggregate data (either time-series or cross-sectional) are publicly available and form a rich resource for demand analysis. In this dissertation, aggregate market-level data is assumed to be observed by the researcher. This chapter presents the passenger demand model for air transport. First a general formula for the air transport demand function is presented and, then, the air travel demand model based on discrete choice analysis is described.

4.1 Air travel demand function

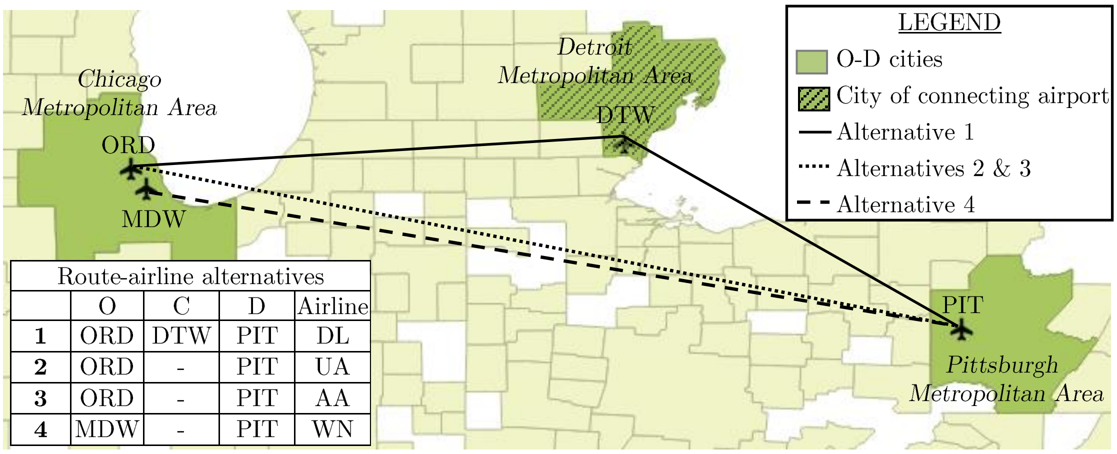
A demand function connects the dependent variable (transport demand) to some explanatory variables, which constitute the factors considered to affect demand. A general formula of air travel demand function is given by:

$$q = f(p, x, \varepsilon) \qquad \textbf{Eq. 4.1}$$

where q is the dependent variable (level of demand), p is the ticket price, x are explanatory (or independent) variables affecting travel demand such as trip distance, level of service and other characteristics related to the specific itinerary, the passenger and so on. ε is the random term of demand. The dependent variable q may be represented by various indicators such as the number of passengers, the number of passenger kilometers or the itinerary market share depending on the type of the demand model used.

This dissertation models city-pair air passenger demand. In a given network, there is a set of Origin-Destination (O-D) cities. In an O-D city pair, potential passengers may have several travel choices; a passenger may choose to travel by air, travel by another transport mode or not travel. If the passenger chooses not to travel by air or not to travel at all, we say that the non-air alternative is picked. If the passenger decides to travel by air, he/she may choose among several route alternatives. Within the air alternative, they may choose from different routes (different O-D airports and direct or non-direct links) offered by different airlines. Therefore, air travel demand is modelled in route-airline level, simply differentiating routes by airlines.

Figure 4.1 illustrates the definition of route-airline alternatives in an O-D city pair. For example, the city pair of Chicago and Pittsburgh (O-D city pair in green) is served by four different route-airline alternatives, including one non-direct and three direct links, as presented in the attached table of Figure 4.1. These air alternatives serve the same O-D cities but can employ different connecting airports or can be offered by different airlines. For example, Alternative 2 differs from Alternative 3 in the fact that the ticketing airlines are not the same.



Route-airline alternatives

	O	C	D	Airline
1	ORD	DTW	PIT	DL
2	ORD	-	PIT	UA
3	ORD	-	PIT	AA
4	MDW	-	PIT	WN

Figure 4.1. Definition of route-airline alternatives in an O-D city pair

Figure notes: O: Origin airport, C: connecting airport, D: destination airport, see Appendices B-1 and B-3 for the airport and airline abbreviations respectively.

The following terminology is used in this dissertation:

- **Market**: A market is defined as a directional O-D city pair. This means that the market "Chicago-Pittsburgh" illustrated in Figure 4.1 is different from the market "Pittsburgh-Chicago". This definition helps to capture potential effects on demand due to different characteristics of the origin city than those of the destination city. In a market there are airline connections, itineraries and segments.
- **Airline connection**: Airline connections represent the potential route-airline alternatives the passengers may choose if the decide to travel by air. A connection is a unique combination of Origin-Connecting-Destination airports and ticketing airline.
- **Segment**: A segment is defined as the non-stop flight between two airports.
- **Itinerary**: An itinerary is a sequence of flights from a passenger's origin to his/her destination. An itinerary may contain only one segment (i.e. a direct itinerary) or more than one segment (i.e. a connecting itinerary).

Our basic unit of observation is the unique combination of "Origin-Connecting-Destination airports and ticketing airline" which is referred to as "airline connection". The air traffic of an airline connection j (q_{jm}) within a city-pair (market) m is equal to the total potential demand of the city-pair (Q_m) times the market share of this airline connection (MS_{jm}), as given in Eq. 4.2.

$$q_{jm} = Q_m \cdot MS_{jm} \qquad \textbf{Eq. 4.2}$$

The total potential demand (Q_m) represents the potential number of travelers between the O-D cities and can be modelled by gravity-type models as a function of demographics and socioeconomic characteristics of the market. A common approach adopted in the empirical literature is to estimate Q_m on the basis of a socioeconomic variable, i.e. $Q_m = k \cdot M_m$, where k is a proportionality factor and M_m is the socioeconomic variable, such as population. This approach provides reportedly reasonable estimates of potential demand if k is set large enough (Hsiao and Hansen, 2011). Based on Berry and Jia (2010), this dissertation uses O-D cities' populations as the market-specific socioeconomic variable and assumes that k is equal to 1. To model the connection's market share, discrete choice models are employed as described next.

4.2 Discrete choice analysis

Discrete choice models describe decision makers' preferences amongst alternatives. Discrete choice analysis relates to demand modeling in the sense that the demand for a specific alternative is represented as the collection of choices made by the decision makers (Garrow, 2010). In this section, an introduction on discrete choice models is presented. We start with an overview on random utility theory and, then, focus on the model which will be used in this dissertation to predict how the air travel pattern may be affected by the implementation of a carbon emission fee.

Discrete choice models estimate the probability of a decision maker to select a good from a finite set of alternatives, based on the attributes of the alternatives and on his preferences (Ben-Akiva and Bierlaire, 2003). According to Domencich and McFadden (1975), the choice process is characterized by four elements: a decision-maker, the alternatives available to the decision-maker, attributes of these alternatives and a decision rule. A decision maker may represent either an individual or a group of individuals. In this dissertation, decision makers are the passengers who aim to travel on an O-D city pair (market). Alternatives represent the competing airline connections over which choices must be made. Each decision-maker is faced with a set of alternatives which exhibit three characteristics (Train, 2003):

- Mutually exclusive alternatives: Passengers (decision makers) make "*discrete choices*", which means that they choose only one alternative from the choice set.
- Exhaustive choice set: All possible alternatives are included.
- The number of alternatives must be finite.

Attributes are characteristics of the alternatives that decision makers take into account during the choice process. Finally, the decision rule is the process used by the decision maker to value the attributes of the alternatives in the choice set and determine his/her choice. In travel behavior analysis, the decision rule of the traveler is usually based on utility theory, where the decision maker's choice lies on the assumption of traveler's utility-maximizing behavior (Ben-Akiva and Bierlaire, 2003; Train, 2003).

In a discrete choice experiment, a passenger i faces a choice among J alternatives and would obtain a certain level of utility from each of them. Each alternative $j=1,...,J$ is characterized by a utility U_{ij}, which is specific to passenger i and alternative j. According to utility maximization theory, the passenger chooses the alternative that provides the greatest utility. Passenger i may choose alternative j over k if and only if:

$$U_{ij} > U_{ik} \ , \forall j \neq k \qquad \textbf{Eq. 4.3}$$

This utility is based on the attributes of the alternative and the passenger and is assumed to be known to the passengers. However, the researcher does not observe all attributes or the decisions of passengers. To capture this uncertainty, utility is decomposed in a deterministic part (V_{ij}) and a random component (ε_{ij}): $U_{ij}=V_{ij}+\varepsilon_{ij}$. V_{ij} is the systematic component of the utility that is known by the researcher up to some parameters; ε_{ij} captures the factors that affect utility but are not included in V_{ij}, and is the sum of errors from various sources such as imperfect information, measurement errors, omission of attributes, but also omission of the characteristics of the traveler that influence his choice. Since the researchers do not know ε_{ij}, they treat these terms as random. Thus, the alternative that the decision maker chooses is random, from the researcher's point of view; this model is known as the Random Utility Model.

Considering the above, Eq. 4.3 can be written in probability terms as shown in Eq. 4.4 where the probability that passenger *i* chooses alternative *j* over *k* is equal to:

$$\begin{aligned} P_{ij} &= Prob\left(U_{ij} > U_{ik} \;\; \forall j \neq k\right) \\ &= Prob(V_{ij} + \varepsilon_{ij} > V_{ik} + \varepsilon_{ik} \;\; \forall j \neq k) \\ &= Prob(\varepsilon_{ik} - \varepsilon_{ij} < V_{ij} - V_{ik} \;\; \forall j \neq k) \end{aligned} \qquad \textbf{Eq. 4.4}$$

This probability is a cumulative distribution. If the density of the random vector $\varepsilon_i=\{\varepsilon_{i1},\ldots, \varepsilon_{iJ}\}$ is denoted as $f(\varepsilon_i)$, this cumulative probability can be rewritten as:

$$P_{ij} = \int_{\varepsilon} I(\, \varepsilon_{ik} - \varepsilon_{ij} < V_{ij} - V_{ik} \;\; \forall j \neq k) f(\varepsilon_i) d\varepsilon_i \qquad \textbf{Eq. 4.5}$$

Where $I(\cdot)$ is the indicator function, which is equal to 1 if the expression in the parenthesis is true and 0 otherwise[12]. We assume there is a continuum of passengers in each market, so that this probability is equal to the aggregate market share of product *j* in market *m* among the subpopulation with characteristics *i*.

Different discrete choice models can be derived under different specifications about the density of the stochastic part of the utility. The most widely used discrete choice model is the Multinomial Logit model (MNL), where it is assumed that the stochastic term is Independent Identically Distributed (iid) with a type I extreme value distribution (also known as the property of Independence of Irrelevant Alternatives-IIA). This independence means that, across passengers and airline connections, the random term of utility (ε_{ij}) for one alternative is independent of (uncorrelated to) the random term of utility for another alternative. This assumption may be inappropriate in some cases since the random terms of the alternatives may be mutually correlated. Consider the nesting structure of the MNL model in Figure 4.2(a). Assume that alternatives 0 to k (which include one non-air alternative and k airline connections) equally share the market (they have the same market shares). The assumption of independence in MNL models implies equal competition between all alternatives and thus a change in characteristic of one of these competing alternatives (from 0 to k) will have the same impact on the market shares of the other alternatives. In other words, MNL models assume IIA and imply proportional substitution across alternatives. However, in the case of Figure 4.2(a) airline connections

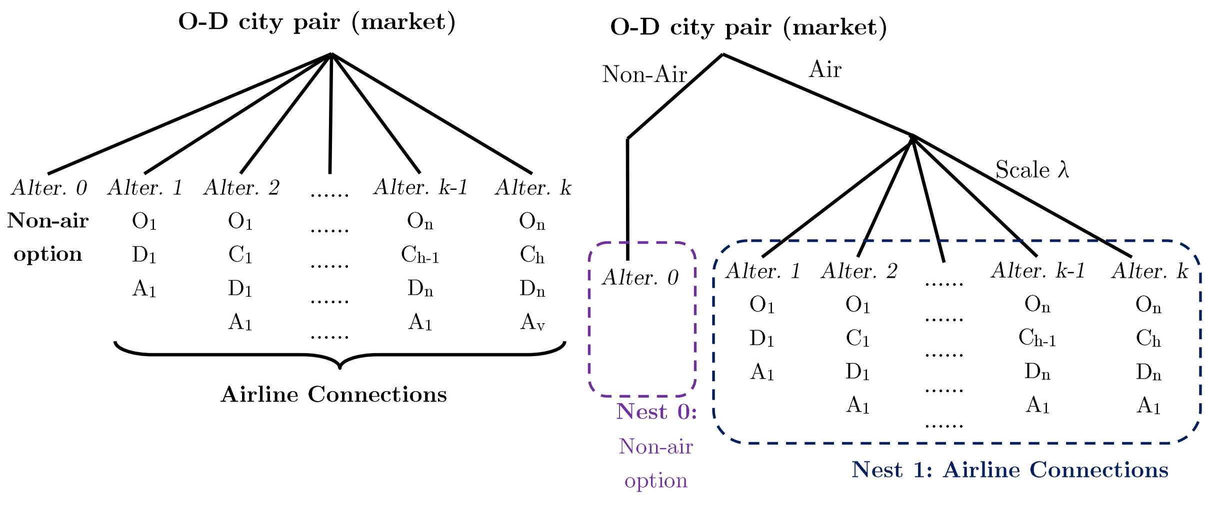
[12] More details on the mathematical framework of discrete choice models can be found in Ben-Akiva and Bierlaire (2003), Ben-Akiva and Lerman (1985), Garrow (2010), Ortuzar and Willumsen (2011), Train (2003).

are likely to be more similar to each other than they are to the non-air alternative due to shared attributes which may be included in the stochastic term of the utility function. This may lead to correlation between the errors associated with airline connections, a violation of the assumptions which underlie the derivation of the MNL. If IIA property does not hold, then the coefficients estimated by a MNL model will be inconsistent.

To avoid the independence assumption within MNL, Generalized Extreme-Value (GEV) models may be developed (Train, 2003) based on a generalization of the extreme-value distribution. The most widely used model within the GEV family is the Nested Logit (NL) model. According to Train (2003), a Nested Logit model is appropriate when the set of alternatives can be grouped into subsets, called nests, in such a way that the following properties hold:

- <u>IIA property holds within each nest</u>: For any two alternatives in the same nest, the ratio of their probabilities is independent of the attributes or existence of all other alternatives. The premise is that other alternatives are irrelevant to the decision of choosing between the two alternatives in the pair.
- <u>IIA does not hold for alternatives in different nests</u>: For any two alternatives in different nests, the ratio of probabilities can depend on the attributes of other alternatives in the two nests.

Following these properties the substitution patterns of the alternatives become more flexible. An improvement in the attributes of one alternative draws proportionately from other alternatives in the nest, but disproportionately from alternatives outside the nest. In the nesting structure shown of Figure 4.2(b), airline connections are grouped in one nest (Nest 1). The non-air alternative (Alter. 0) is separated from the airline connections and is assumed to be the only member of Nest 0. With this nesting structure, the IIA property holds among the airline connections in an O-D city-pair (market), but does not hold between the non-air alternative and each of the airline connections. Potential travelers are more likely to switch from one airline connection to another, than from one airline connection to the non-air alternative.



(a) Multinomial Logit Model (MNL) (b) Two-Level Nested Logit Model (NL)

Figure 4.2 Nesting structures: MNL and NL models

(*Figure Notes*: O_1, ..., O_n: *Origin airport*, C_1, ..., C_h: *Connecting Airport*, D_1, ..., D_n: *Destination airport*, A_1, ..., A_v: *Ticketing airline*, *Alter.1,...,Alter. k: Airline alternatives)*

4.3 Specification of the air travel demand model

As discussed earlier, this chapter estimates an aggregate demand model for air travel in an O-D city pair, where air travel is served by various airline connections (the definition of airline connections in an O-D city pair is depicted in Figure 4.1). A passenger who wants to travel within a market (a pair of O-D cities) 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 ($j=1, 2,...,J$). If the passenger chooses not to travel by air, we say that the non-air alternative is picked ($j=0$). This choice formulation suggests the use of a Nested Logit model, to model the market share function. 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 nesting structure is shown in Figure 4.2(b)[13].

The utility U_{ij} that passenger i obtains when choosing alternative j is given by:

$$U_{ij} = x_j\beta - \alpha p_j + \xi_j + \varepsilon_{ij} \qquad \textbf{Eq. 4.6}$$

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 namely connection-specific, airline-specific and airport-specific variables; a detailed description is given in Section 4.3.2. Parameters β and α are to be estimated and represent the preference for the different attributes of the airline connections and the marginal disutility of price increase respectively.

An important part of this specification is the term ξ_j. This term is used to capture the characteristics of the airline connection that are unobserved to the analyst (recognizing that publicly available aggregate data may omit some of the connections' attributes), but are observed by the potential passenger during his travel decision process. Note that ξ_j is different for each airline connection j but is the same across passengers and so it may be thought as the mean of passengers' valuations of the connection's unobserved characteristics (Berry, 1994). All else equal, travelers are more willing to choose the connections for which ξ_j is high. ξ_j may include exact departure time, in-flight food quality, wi-fi equipment, while other attributes may be related to ticket restrictions, in-advance ticket purchase, frequent-flyer tickets etc. For estimation, the existence of ξ_j implies that ticket prices, as well as other choice variables, could be endogenous (e.g. ξ_j may be correlated with ticket price). In Eq. 4.6, the part $x_j\beta - \alpha p_j + \xi_j$ is common across all passengers (it is only depending on the connection's attributes) and in consistency with Berry (1994) it is called the "mean utility" for airline connection j.

The last part of the utility is the random error term ε_{ij}. Based on Nevo (2011), this term is essential to explaining the fact that passengers who face the same choice set (and prices) may make different choices. The stochastic term represents the distribution of passenger preferences about the mean ξ_j (Berry, 1994). As already mentioned in Section 4.2, different

[13] A Multinomial Logit demand model is also developed for comparison purposes (see Figure 4.2(a)).

discrete choice models can be derived under different specifications about the density of the stochastic part of the utility. Multinomial logit is derived under the assumption that ε_{ij} is iid extreme value across passengers and airline connections. The Nested Logit model is obtained by assuming that the random term of utility $\varepsilon_i=\{\varepsilon_{i1},..., \varepsilon_{iJ}\}$ has the following cumulative distribution:

$$exp\left(-\sum_{k=1}^{K}\left(\sum_{j\in B_k} e^{-\varepsilon_{ij}/\lambda_k}\right)^{\lambda_k}\right) \qquad \textbf{Eq. 4.7}$$

Based on Berry (1994), the stochastic term ε_{ij} can be expressed as $\varepsilon_{ij}=\nu_i(\lambda)+\lambda e_{ij}$. The parameter λ is a measure of the degree of independence within airline alternatives in air nest *g*. In accordance, (1-λ) is a measure of correlation in unobserved factors within each nest. Higher value of λ means greater independence and less correlation. To be consistent with utility-maximizing behavior for all possible values of the explanatory variables, the value of λ must be between 0 and 1. When λ=1 within airline market correlation goes to zero and the nested logit reduces to the standard logit model. Values of λ=0 and λ=0.5 indicate perfect and moderate correlation respectively among the airline alternatives in air nest *g*. $\nu_i(\lambda)$ is a random variable that is constant across airline connections (within the air nest) and differentiates them from the non-air nest. e_{ij} is an independent and identically distributed (iid) random variable across passengers and airline connections following the extreme value distribution. According to Berry (1994) and Cardell (1991), if e_{ij} is an iid extreme value random variable, the variable $\nu_i(\lambda)$ follows a distribution such that $\varepsilon_{ij}=\nu_i(\lambda)+\lambda e_{ij}$ is an extreme value random variable.

The cumulative distribution of the random term of utility ε_{ij} gives rise to the following market share function of alternative $j \in J_g$ (Train, 2003).

$$MS_j = \frac{e^{(x_j\beta-\alpha p_j+\xi_j)/\lambda}\left(\sum_{n\in J_g} e^{(x_n\beta-\alpha p_n+\xi_n)/\lambda}\right)^{\lambda-1}}{\sum_{l=1}^{K}\left(\sum_{n\in J_g} e^{(x_n\beta-\alpha p_n+\xi_n)/\lambda}\right)^{\lambda_l}} \qquad \textbf{Eq. 4.8}$$

where $x_j\beta - \alpha p_j + \xi_j$ denote the mean utility of alternative *j*, J_g is the set of airline connections in the air nest (nest g), *K* are the number of nests in the passengers' choice set (in our case it is equal to 2, i.e. the non-air and air nest).

If we set $D_g = \sum_{j\in J_g} e^{(x_j\beta-\alpha p_j+\xi_j)/\lambda}$, then Eq. 4.8 is equal to:

$$MS_j = \frac{e^{(x_j\beta-\alpha p_j+\xi_j)/\lambda}}{D_g^{1-\lambda}\cdot \sum_g \left(D_g\right)^{\lambda}} \qquad \textbf{Eq. 4.9}$$

The NL model can be decomposed in two logit models so that the NL 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 marginal 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).

$$MS_j = MS_g \cdot MS_{j/g} \qquad \textbf{Eq. 4.10}$$

The conditional share of a specific connection *j*, given that the air nest J_g is chosen is given by a logit probability as follows:

$$MS_{j/g} = \frac{e^{(x_j\beta - \alpha p_j + \xi_j)/\lambda}}{\sum_{j \in J_g} e^{(x_j\beta - \alpha p_j + \xi_j)/\lambda}} \qquad \textbf{Eq. 4.11}$$

Since we work with aggregate market shares, at true parameter values we should have: $MS_j = \widehat{MS}_J(x, p, \xi, a, \beta, \lambda)$, where $\widehat{MS}_J$ and MS_j denote the predicted and true market shares respectively. In the data MS_j is observed and thus model parameters may be defined by matching predicted and actual market shares. However, ξ_j, which enters market shares, is unknown to the researcher, while it enters in a non-linear fashion and is potentially correlated with some explanatory variables. Berry (1994) proposes an estimation procedure which transforms Eq. 4.8 so that parameters enter linearly and exploits the market share MS_0.

Consider that for each market we have a set of J+1 market share equations (J airline connections and the unique non-air alternative) in the J+1 unknowns $\xi_0, \xi_1, .., \xi_J$. In other words, the system is: $MS_0 = \widehat{MS}_0(V_0, \dots, V_J)$, $MS_1 = \widehat{MS}_1(V_0, \dots, V_J)$,...., $MS_J = \widehat{MS}_J(V_0, \dots, V_J)$. Since $1 = \sum_{j=0}^{J} MS_j$ by construction, the equations are linearly dependent and we need to make some normalizations. As the characteristics of the non-air alternative are not identified, the standard practice (Berry, 1994, Nevo, 2011) is to normalize the systematic utility of non-air alternative to zero ($V_0=0 \rightarrow U_{i0}=\varepsilon_{i0}$) and take the difference between the natural logarithms of the market shares of the airline connections minus the non-air alternative. The zero utility normalization for the non-air alternative does not mask the systematic quality differences across the airline connections but we should keep in mind that the utilities from the various alternatives are now actually the differences in utility between the choice of the particular airline connection and the non-air alternative. The use of the non-air alternative in the demand model also plays a significant role because it allows travelers to avoid flying if all airline connections become less attractive. For example, if ticket prices increase at a level where passengers do not prefer to travel by air, the market share of the non-air alternative will increase. Given that $V_0=0 \rightarrow D_0=1$ (as $D_0 = e^{V_0/\lambda} = e^0 = 1$), the market share MS_0 of the non-air alternative is given by Eq. 4.12.

$$MS_0 = \frac{1}{\sum_g \left(D_g\right)^{\lambda}} \qquad \textbf{Eq. 4.12}$$

Given the utility function in Eq. 4.9 and the market share of the non-air alternative in Eq. 4.12, the resulting demand equation gets the linear regression form of Eq. 4.13. The full computational process to obtain Eq. 4.13 is presented in Appendix A.

$$lnMS_j - lnMS_0 = x_j\beta - \alpha p_j + (1-\lambda) \cdot lnMS_{j/g} + \xi_j \qquad \textbf{Eq. 4.13}$$

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 $MS_{j/g}$. Observed characteristics x_j may include frequency, distance, airline dummies and other factor affecting travel demand. Aggregate data on the connections' prices and attributes are obtained from publicly available datasets. The estimation of discrete choice models using aggregate data from the U.S. Department of Transportation is widely spread in the airline industry. The unobserved characteristic ξ_j acts as the disturbance term. β, α and λ are the unknown parameters that need to be estimated. A critical issue when estimating econometric models is endogeneity. This occurs when one or more independent variables are correlated to the disturbance term of the model. In these cases, standard Ordinary Least Squares (OLS) procedures are not directly applicable. In our model, ticket- or flight-level unobserved attributes that are captured by the term ξ_j may be correlated with ticket price p_j and within-group (conditional) market share $MS_{j/g}$. Thus Eq. 4.13 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 6.2.

In this research, the NL model is assumed to express the decision process of travelers within markets. However, results are also presented for the Multinomial Logit model for comparison purposes, where the demand equation takes the form of Eq. 4.14. The full computational process followed to obtain Eq. 4.14 is presented in Appendix A.

$$lnMS_j - lnMS_0 = x_j\beta - \alpha p_j + \xi_j \qquad \textbf{Eq. 4.14}$$

4.3.1 Dependent variable and Market size

The dependent variable is formed by the log difference of market shares minus the non-air option. The market share of an airline connection MS_j is calculated by dividing the number of passengers choosing the specific connection by the market size. In each market, the market share of the non-air alternative MS_0 is computed as $1 - \sum_{j=1}^{J} MS_j$ (for all J products in the market). The number of passengers choosing the specific connection is obtained from publicly available air traffic databases (see Chapter 7). With regard to market size, an accepted approach adopted in the empirical literature is to assume a “market potential” on the basis of a socioeconomic variable, so this dissertation uses O-D cities’ populations as the market-specific socioeconomic variable. In particular, market size Q_m is defined as the geometric mean of O-D cities’ populations.

$$Q_m = \sqrt{POP_O \cdot POP_D} \qquad \textbf{Eq. 4.15}$$

where POP_O and POP_D are the population of the Origin and Destination city respectively. Each Origin and Destination city is linked to one Metropolitan Statistical Area (MSA). A detailed list of the airports and cities included in our sample along with the associated MSAs is presented in Appendix B-2. MSA populations for the study year 2012 are obtained from U.S. Census Bureau (2012).

4.3.2 Determinants of air travel demand

The primary criterion when selecting air travel demand variables is that they represent important determinants of demand. Selecting suitable explanatory variables is one of the key elements to a successful causal model. First, a review on previous air travel demand studies was conducted, which identified the most frequently used explanatory variables (see Table 2.3). Considering that this dissertation addresses air travel demand on aggregate level, macro variables were mainly investigated. Explanatory variables found in the literature are adjusted or modified to the research needs of this study, while new variables are also specified.

Following the above approach, this study considers demand variables which are related to the airline-route characteristics, the airports and the market served and the airlines. The demand variables are grouped in four categories as shown in Figure 4.3. Furthermore, the considered explanatory variables are chosen so that they are available from reliable data sources. In particular, our data sources provide demand information on the number of passengers transported between O-D pairs, itinerary information (ticketing airline, number of stops etc), and price information (quarterly fare charged by each airline for an O-D pair).

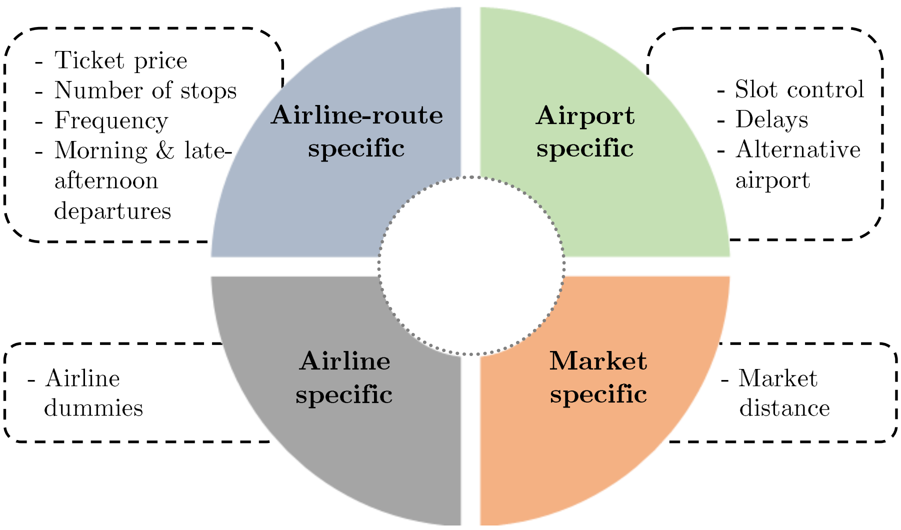


Figure 4.3. Drivers of air travel demand

- <u>Ticket price</u>

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. Thus ticket price has been widely used in itinerary choice models. In some cases where ticket prices are unavailable, other cost shifters, such as jet fuel price, are used as a proxy for airfare. In this work, the price of the sold tickets for round-trip itineraries is derived from publicly available data sources and thus the passenger-weighted average ticket price for each airline connection (unique combination of Origin-Connecting-Destination airports and ticketing airline) is calculated.

Price discrimination techniques may lead to different ticket prices even for the same itinerary offered by the same airline. Airfare deviation may be justified by the ticket class (business or economy class), the number of days the ticket was purchased before the flight and other ticket or travel restrictions (such as non-refundability, minimum stay requirements and Saturday-night stayover). However, our dataset does not contain information on ticket restrictions and does not provide ticket prices separately for business and economy classes. In the absence of more precise data, passenger-weighted average ticket price for each airline connection may account well for O-D travel price.

Such ticket restrictions or unobserved information are captured by the introduction of the term ξ_j in the demand model (Eq. 4.13) as already explained in previous sections. This assumption implies that ticket price is endogenous since it is correlated with the unobserved demand characteristics ξ_j. Since this endogeneity issue may lead to biased parameter estimates if OLS is used, Instrumental Variables methods are employed to cope with endogeneity (see Sections 6.2 and 6.3).

- Number of Stops

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 round-trip itinerary and may take three values: 0 if both outbound and return flights are direct, 1 if either the outbound or the return flight is one-stop, and 2 if both inbound and outbound flights are one-stop.

- Distance

Distance is assumed to have both direct and substitution effects on air travel demand (Bhadra, 2003). Direct effects are related to the propensity to travel and accounts for the fact that travel demand may be negatively affected by distance for very long-distance trips where passengers' willingness to travel is decreasing. From this point of view, a negative coefficient of distance could be expected. On the other hand, distance is considered as an important factor when a passenger chooses travel mode. For example, for short-distance trips both airplanes and ground transportation are competing, while for longer trips air transportation is becoming more competitive. From this point of view, distance is expected to have a substitution effect on air travel demand; thus a positive impact of distance on air travel demand is expected in this case. The latter effect is essential for our model which takes into account the non-air alternative. In this study, distance is introduced in the demand model as the O-D market distance. We should note that market distance is the same for all airline connections competing in a given market. In this way, market distance does not influence demand assignment within the airline market, i.e. the allocation of total O-D city pair demand to the available airline connections. However, it affects demand generation by influencing the market share of airline connections versus the non-air alternative.

- Frequency

Frequency is an important factor in passenger's travel decision-making process, since passenger's utility is expected to increase with higher flight frequency. Since flight frequency is a segment characteristic, a non-direct itinerary includes several frequency variables. For non-direct itineraries, frequency could be calculated as the average number of segment departures. However, the minimum frequency is assumed to be more critical than the average[14] and thus the frequency variable is here calculated as the minimum of segment frequencies. For direct (non-stop) itineraries, itinerary frequency is equal to segment frequency. Following Ben-Akiva and Lerman (1985) and Hansen (1990), the frequency is introduced in logarithmic form for two reasons. First, the effects of adding an additional flight on passenger’s utility (i.e. marginal benefit of frequency) are expected to decrease for increasing frequencies. Second, itinerary frequency is an attribute reflecting the “size” of an alternative and the logarithmic form is most suitable for representing such variables.

[14] It is assumed that adding one more flight on the segment with lower frequency would attract more passengers (higher increase of utility) than adding one more flight on the segment with higher frequency.

- <u>Slot control</u>

Congestion is expected to decrease passenger's utility and, thus, airline connections which pass via congested airports may be less preferred. The variable slot-control is used in the demand model in order to differentiate a more congested airport from the rest airports.

To manage congestion, slot controls are implemented by limiting the number of scheduled flight operations per hour at some airports. IATA's Worldwide Slot Guidelines (IATA, 2015) group airports in three levels according to their degree of congestion: Level 1 (Non-coordinated airport, where capacity adequately meets demand), Level 2 (Schedule facilitated airport, where there is potential for congestion during some periods of the day, week, or season), or Level 3 (Fully coordinated airport, where demand exceeds capacity). All airlines operating at a Level-3 airport must have allocated slots (IATA, 2015). In the United States four airports are slot-controlled: Newark Liberty International Airport[15] (EWR), John F. Kennedy International Airport (JFK), LaGuardia airport (LGA) and Ronald Reagan Washington National Airport (DCA) (GAO, 2012).

By including the slot-control variable in the demand model, we capture the potential negative effect of congestion in slot controlled airports on air travel demand. The variable is equal to the number of slot-controlled airports in the round-trip itinerary.

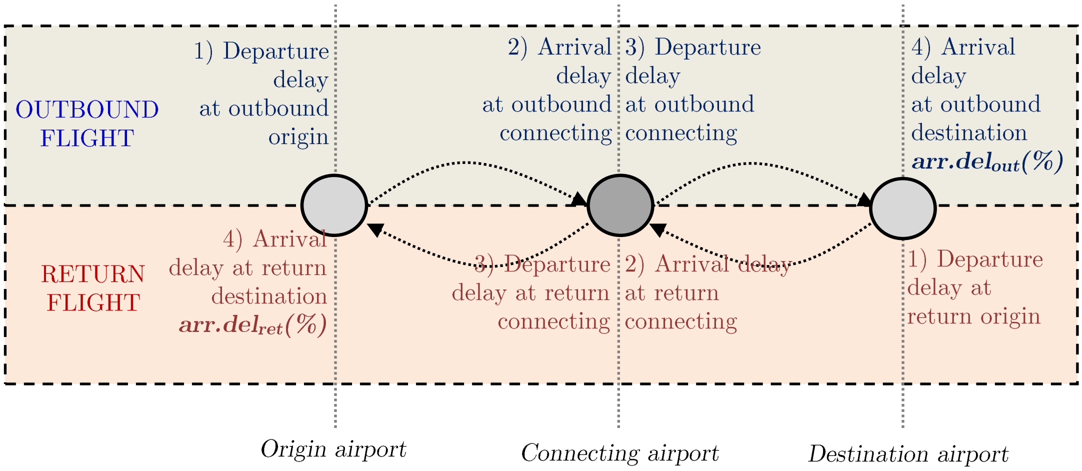
- <u>Delays</u>

On-time performance is another important factor which influences passenger itinerary choices. There are several metrics for on-time performance of a route. The U.S. Department of Transportation (BTS, n.d.) publishes the database "Airline On-Time Performance Data" (OTP) which contains on-time performance data for non-stop domestic flights by major airlines (more details on OTP database are given in Appendix C-1). In this database, departure/arrival delays are given for each reported flight as the difference (in minutes) between scheduled and actual departure/arrival time. Positive and negative delays are used in order to differentiate flights that depart/arrive after (late departures/arrivals) and before (early departures/arrivals) their scheduled time respectively. In other words, negative arrival delay values indicate early arrivals. Another delay indicator in OTP is determined by setting up a delay threshold of 15 minutes: if a flight departure/arrival delay is greater than 15 minutes, it is considered as a delayed flight. In this way, the percentage of flights whose delay is less or more than 15 minutes can be calculated.

As in the case of frequency, delay is a segment indicator and, thus, a non-direct itinerary includes several delay variables as shown in Figure 4.4. For each non-direct airline connection, the following delay indicators may be obtained: (1) departure delay at the origin airport, (2) arrival delay at the connecting airport, (3) departure delay at the connecting airport and (4) arrival delay at the destination airport. For a direct airline connection, only the first (1) and the last (4) indicators are observed. In Pagoni and Psaraki (2015), we experimented with using some of these delay indicators in the demand function. The results suggested that a one-minute arrival delay increase has a larger impact on demand than an equivalent change in departure delay. This is because

[15] The FAA was about to designate EWR as a Level 2 (from October 2016) airport under the IATA's Worldwide Slot Guidelines (FAA, 2016).

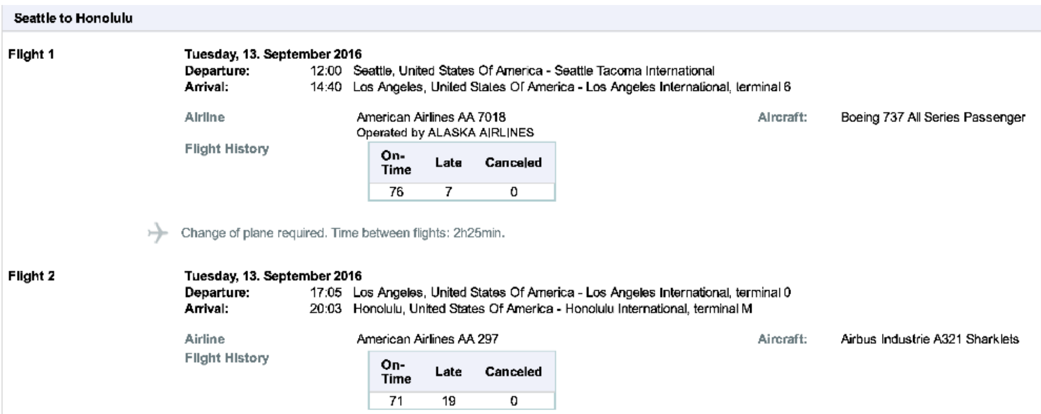
passengers prefer arriving on-time to their destination. Besides, as described below, during the online booking process, passengers are informed only for the arrival and not for the departure on-time performance. Thus the arrival delay is included in the demand model.



Arrival delay variable for the round-trip itinerary $= \sqrt{arr.del_{out} \cdot arr.del_{ret}}$

Figure 4.4. Delay indicators in a non-direct itinerary

Suzuki (2000) notes that market shares may be influenced by passengers' delay experience. Besides, potential passengers may be informed on airline past delays when they book their tickets on the Internet. In particular, most U.S. airlines report the percentage of flights that arrived on-time or late at the destination airport of a selected itinerary. This information is usually given for a past month during the previous quarter as shown in the case of American Airlines in Figure 4.5. The example in Figure 4.5 corresponds to a one-stop flight from Seattle (SEA) to Honolulu (HNL) through the Los Angeles airport (LAX) in September 2016. The information indicate that during July 2016 this flight arrived on time (less than 15 minutes delay) with probability 76% and arrived late (more than 30 minutes delay) with probability 7%. For the flight LAX to HNL, these percentages are 71% and 19% respectively.


Seattle to Honolulu

Flight 1
Tuesday, 13. September 2016
Departure: 12:00 Seattle, United States Of America - Seattle Tacoma International
Arrival: 14:40 Los Angeles, United States Of America - Los Angeles International, terminal 6
Airline: American Airlines AA 7018, Operated by ALASKA AIRLINES
Aircraft: Boeing 737 All Series Passenger
Flight History

On-Time	Late	Canceled
76	7	0

Change of plane required. Time between flights: 2h25min.

Flight 2
Tuesday, 13. September 2016
Departure: 17:05 Los Angeles, United States Of America - Los Angeles International, terminal 0
Arrival: 20:03 Honolulu, United States Of America - Honolulu International, terminal M
Airline: American Airlines AA 297
Aircraft: Airbus Industrie A321 Sharklets
Flight History

On-Time	Late	Canceled
71	19	0

Figure 4.5. Delay information for the one-way itinerary SEA-LAX-HNL by American Airlines

Our hypothesis is that potential travelers make decisions based on information similar to those indicated in Figure 4.5, i.e. delay information for the past quarter. As a proxy to this information, the delay variable of this work takes into account the connection's on-time performance at the quarter prior to decision.

For round-trip itineraries, we observe two arrival delays: that of the outbound flight and that of the return flight. In other words, passengers who book round-trip tickets observe the information in Figure 4.5 and the corresponding information for the return flight (e.g. HNL-connecting airport, if existing-SEA). Using OTP data, we compute the percentage of delayed (using the delay threshold of 15 minutes) arrivals (by airline) for each flight at the quarter prior to passenger's decision. To account for both arrival delays but have a single explanatory variable for delays, the delay variable is constructed as the geometric mean of the percentages for the outbound and the return flights, as shown in Figure 4.4. This value approximates the passengers' perception on round-trip itinerary arrival delays.

- Airline dummies

The airline dummy variables are included in order to capture whether the reputation of an airline affects the travelers' choice. When including dummy variables in a regression model, attention should be paid to the dummy variable trap. This is defined as the situation where two or more variables are highly correlated, i.e. one variable can be predicted from the others. The solution is to drop one of the categorical variables (airlines) and consider it as the base (reference) airline against which the other airlines are compared. In this research, all major airlines are included: Delta (DL), United Airlines (UA), American Airlines (AA), US Airways (US), Southwest (WN) and JetBlue (B6). The rest airlines are represented by two other group variables which contain other legacy and low cost airlines. The US Airways is used as the base airline in the estimation.

A negative coefficient of the dummy variable for a given airline indicates a negative effect on utility associated with that specific airline (in comparison to the reference airline, i.e. the US Airways). If an airline dummy is found to be not statistically significant, it means that travelers are not affected by an airline brand when making a travel decision.

In this dissertation, the above variables are augmented with some additional attributes not formerly used in aggregate models.

- Presence of alternative airport

Another factor that stands out as helping to explain itinerary choice in an O-D city-pair is the presence of alternative airports nearby the passenger's origin or destination city. This effect is strongly evident in multi-airport regions, where the airports compete with each other. Passengers' airport choice (which in turn affects itinerary choice) is not only influenced by airport proximity but also by low ticket prices and other service-related factors (de Neufville and Odoni, 2009). Our aim is to create a variable to control for the possibility that passengers may leave the market and fly from/to other nearby airports. This phenomenon is generally referred to as "airport leakage" to explain that travelers may avoid using the airports in their origin/destination cities, and use other (out-of-region) airports to potentially take advantage of lower fares or more convenient airline services.

Several factors may influence airport choice (Malina, 2010). Since some of them have already been considered for inclusion in the demand function (airport-specific variables), we now control for access distance to the airport and flight availability. When passengers choose among alternative airports, airport proximity is one decision factor. It is assumed that passengers will choose to drive to reach another airport to fly from/to only if it is in close proximity with their travel origin/destination (and other factors are justified, i.e. low price, convenient service). We assume that the distance a traveler is willing to drive to reach an alternative airport is different for short- and medium/long-haul trips[16]. This distance is taken as 60 miles for short-haul flights (which corresponds to about 1 hour driving) and 100 miles for medium/long-haul flights. These values are consistent with existing evidence on airport leakage and are within the distance range given in the booking system of various U.S. airlines. Traditionally the distance a traveler is willing to drive to reach an alternative airport is believed to be 75 miles or less (Dresner et al., 1996, Fuellhart, 2007, Morrison, 2001). Other empirical studies (Suzuki et al., 2004, Leon, 2011) argue that this distance can exceed 150 miles in some circumstances.

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. The “alternative airport” variable is set equal to one if passengers have the opportunity to choose alternative airports either at their origin or destination based on the following conditions:

1. The alternative airport is within a 60- or 100-mile radius (depending on short- or medium/long-haul flight respectively) from the population-weighted centroid of the origin/destination city and
2. It serves the desired destination/origin in the sample period.

For a better understanding of the above process, an example is given in Table 4.1. For the medium/long-haul flight ALB→BUR, there are two potential alternative destination airports: LGB and LAX. Although LGB is closer to Los Angeles centroid, it does not have a connection to ALB in the sample period and thus cannot be considered as alternative destination airport of BUR. LAX is the alternative destination airport since it is within 100-mile radius from the Los Angeles centroid and serves a flight from ALB. For the origin airport, BDL airport satisfies the condition of available connection with the destination airport (BUR) but does not satisfy the proximity condition (distance is greater than 100 miles). In Table 4.1 we also present the itinerary ABQ-ALB which satisfies neither of the two conditions and thus the variable “alternative airport” is set equal to zero.

[16] It is difficult to assess what stage length characterizes a short- or medium/long-haul trip. In this thesis, it is assumed that any flight of less than 750 miles flown (one-way) between O-D airports is a short-haul flight. This corresponds to less than 2 hours flight (for direct and one-stop flights).

Table 4.1 Alternative airport choice definition

Itinerary under consideration		Origin airport				Destination airport				Dummy for alternative O-D airport choice
O-D cities	O-D airports	Close origin airports	Distance between MSA-centroid and close origin airport	Connected with destination?	Alternative origin airport?	Close destination airports	Distance between MSA-centroid and close destin. airport	Connected with origin?	Alternative destination airport	
Albany, NY- Los Angeles, CA	ALB-BUR	SWF BDL	91 123	✓		LGB LAX	21 23	✓	✓	**1**
Albuquerque,NM- Albany,NY	ABQ-ALB	ELP DEN	230 353	✓		SWF BDL	91 123	✓		**0**

The computation of "alternative airport" variable requires the calculation of the population-weighted centroid of each MSA within our sample, since it is assumed that passengers begin and finish their travel at these points. Geographical Information Systems are employed in order to compute population-weighted MSA-centroids using population data from U.S. Census Bureau (2012).

Figure 4.6 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 regions of U.S. have the greatest opportunity to choose alternative airports. This is explained by the existence of many multi-airport regions, such as New York City, Washington/Baltimore, Boston Area, Los Angeles.

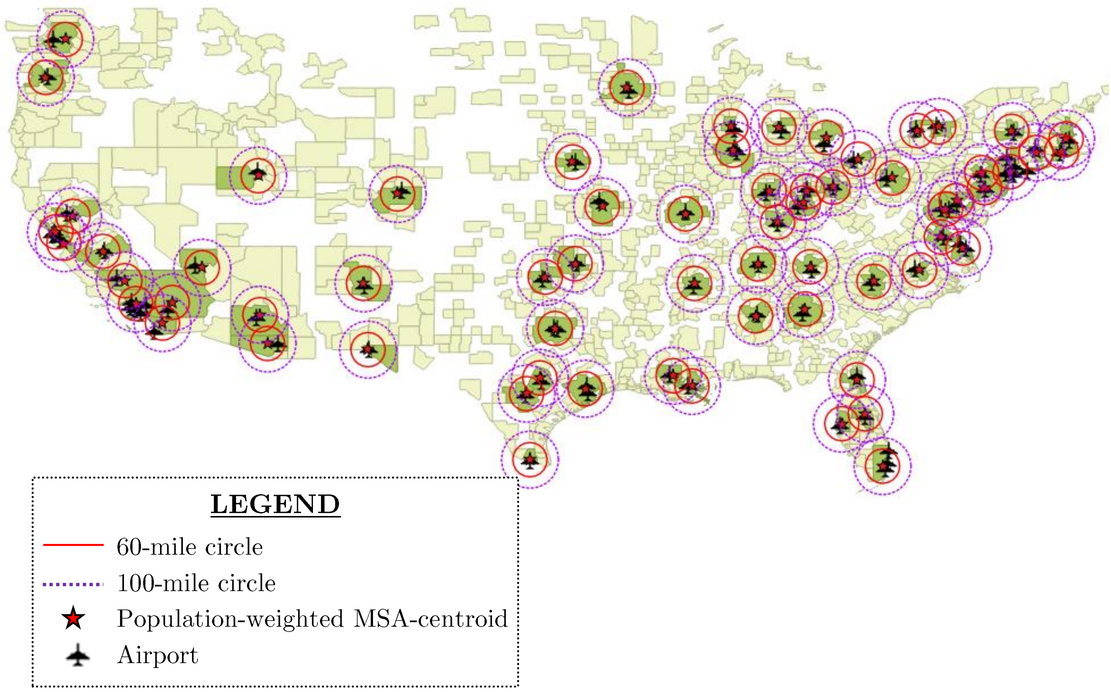


Figure 4.6. Proximity of MSA to alternative airports within 60- and 100-mile radius

Figure 4.7 focuses on the presence of alternative airports for BUR airport, for the case of ALB-BUR itinerary. The value of 100-mile radius is taken as the ALB-BUR itinerary is a long-haul flight. The passenger may choose to fly from LAX airport and then drive to the population-weighted centroid of the Los Angeles MSA.

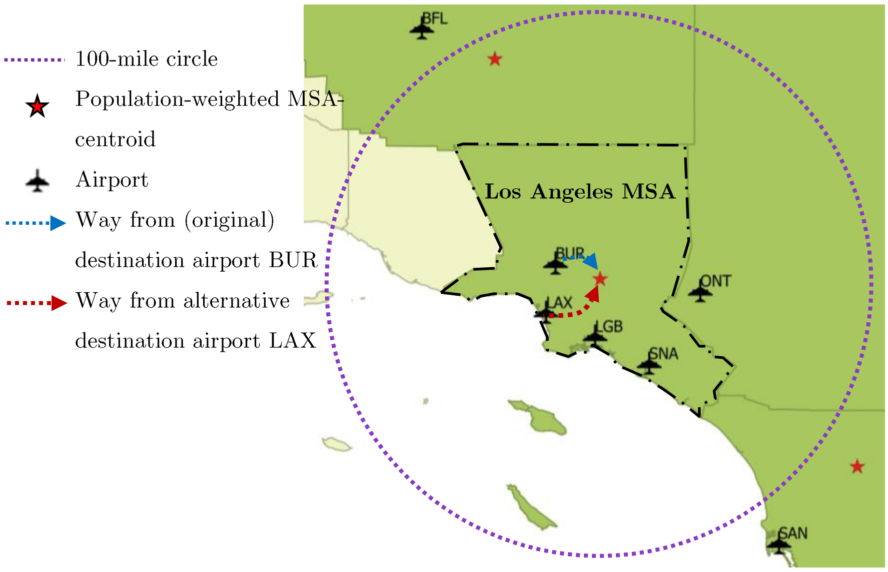


Figure 4.7. Alternative destination airport selection for the ALB-BUR itinerary

The current variable does not directly account for the case of choosing an alternative airport because of very low ticket prices offered by a competing airline even when the alternative airport is far away from the population-weighted MSA centroid. This impact is directly considered by the inclusion of air fare variable in the demand function.

Such cases may occur when low cost airlines serve the market where the air fares may be much lower than those of the full-service airlines. The following discussion is motivated by a characteristic example from the European market and the case of Ryanair. Ryanair is a low cost airline based in Dublin, Ireland, but operating from a variety of UK airports, especially London Stansted. Pitfield (2007) examined several routes from London to European airports and studied the impact of Ryanair's start-up from Stansted on the traffic of full-service airlines operating from Heathrow and Gatwick. The author stated that Ryanair became the dominant carrier at the expense of the full-service airlines, e.g. of British Airways and Lufthansa in the route London-Hamburg, where Hamburg airport was served by British Airways and Lufthansa from London Heathrow (27 miles from the center of London) and Hamburg Luebeck (an airport 40 miles north-east of Hamburg) by Ryanair from London Stansted (45 miles from the center of London). The author concluded that Ryanair expanded the market and took volume of traffic from its competitors.

In our traffic sample, four low cost airlines are active: Southwest (WN), JetBlue (B6), Frontier Airlines (F9) and Virgin America (VX). In the following we focus on Southwest Airlines which is the most active low-cost airline across U.S. markets (it is active in 63% of all markets in the sample; the other LCCs have much lower presence in the sample markets). Figure 4.8 illustrates the differences (expressed in ratios) of ticket prices between Southwest airlines and other active airlines (both full-service and low-cost airlines) in the markets in common. In most cases, within-market average ticket price is 1-1.5 higher than average Southwest's ticket price. In addition, in a notable number of markets Southwest is not the "cheapest" airline, which is indicated by the fact that red points are below the value of 1. This figure shows that for the case of Southwest airlines, the price differences in most markets are not so high in order to have similar effects with the Ryanair's case described above. For the other LCC airlines, for which the price differences (with other active airlines in the market) are higher, our definition of the alternative airport may be less suitable. However, since the other LCC airlines are not active in a large percentage of the U.S. markets, overall it is believed that our definition of the alternative airport is satisfied for the system-wide analysis of the U.S. airline network.

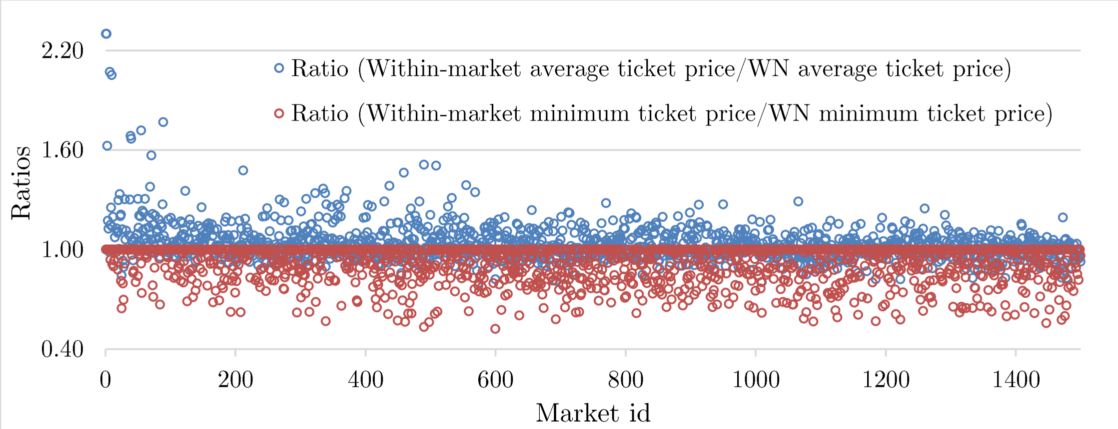


Figure 4.8. Ticket price deviations between Southwest Airlines and other airlines

- <u>Departure time</u>

Common experience suggests that the flight departure time plays a significant role during the air traveler's decision process. From the passengers' perspective, intuitively an itinerary is more attractive if it is offered in the morning, as the travelers will be able to participate in activities at their trip destination. From the airline point of view, it is important to be aware of passengers' preferences on departure time so as to decide appropriate flight schedules to attract more traffic and revenue. 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 to assess the attractiveness of an airline connection based on the time of departure: *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.

Other factors that might impact an airline connection's travel demand within an O-D city pair were examined. Income and airline hubs were candidate variables. Income was considered as an important factor for air travel demand, not only because people with higher incomes travel more, but also because income affects travelers' choices about which transport modes they use. Existing literature indicates that as people get more prosperous, they are likely to devote an increasing share of their incomes to air travel (IATA, 2008a).

Our candidate income variable was constructed as the geometric mean of the per capita income of Origin and Destination cities, but was not found to be statistically significant and was excluded from the demand model. An "airline hub" variable was also examined for the demand function since it was assumed that concentration of traffic in hubs may positively affect demand since airlines can offer more frequent flights. On the other hand, travel time in a hub network increases and may decrease passengers' utility (SSamula, 2008). The definition of airline hub was based on whether a ticketing airline uses an airport as hub. However, it was found that it does not affect air travel demand and was omitted from the demand model.

More details on the demand variables are given in Chapter 7 (Data).

5 Airline behavior

To model airline's behavior we must first define the form of airline's profit function, which is dependent on the airline market demand and the airline-level costs. Given the definition of airline demand (in Chapter 4), Section 5.1 describes the mathematical formulation of the airline's pricing strategy and introduces the assumptions about how airlines interact in each O-D market. Because the marginal costs that enter the airline's optimization functions are not observed, we need to estimate them. In Section 5.2, the marginal cost is determined up to a vector of several cost shifters by using a linear econometric model.

5.1 Airline's Profit Maximization

5.1.1 The market structure of airline industry

As explained in the previous chapter and depicted in Figure 4.1, there are several airlines that serve the same O-D market. These airlines offer differentiated connections and compete with each other in order to attract more passengers. The final payoff of an airline is dependent not only on its own decisions but also on its competitors' decisions. Depending on the market structure, markets can be distinguished in monopolies, oligopolies and markets with perfect competition and markets with monopolistic competition, as indicated in Table 5.1. These structures differ in terms of the number of players in the market, the firm's market power, the degree of differentiation in products etc. In the perfect or pure competition market, there are a large number of firms each producing the same product (also called a standardized or homogeneous product). On the opposite end, a monopoly has only one firm and produces a unique product that has no close substitutes. In the middle are oligopolistic and monopolistic competition. Monopolistic competition is a type of imperfect competition where there are a large number of firms each producing differentiated products and hence are not perfect substitutes. In an oligopoly, there are few firms which produce either a standardized product or a differentiated product. Each firm affects the market (unlike perfect competition) but is also affected by the actions of other firms in the market (unlike monopolies). There are limited entry opportunities of new firms in the market; this is often due to the cost structure of the industry.

Table 5.1. Properties of different market structures

	Monopoly	Oligopoly	Monopolistic competition	Perfect (pure) competition
- Number of firms	One	Few	Many	Many
- Type of product	Unique product (no close substitutes)	Standardized or differentiated products	Similar but differentiated products	Homogeneous
- Entry conditions	No entry	Limited entry	Relatively easy entry/exit	Easy entry/exit
- Market power (control over price)	Complete market power (price setter)	Large amount of market power (price setter-but interdependent behavior)	Limited market power	No market power (price taker)

Airline industry, especially the domestic airline industry in the United States, follows an oligopoly-type structure with the features of oligopoly shown in Table 5.1. First, the U.S. domestic airline market is controlled by a small group of airlines. Table 5.2 presents the market share of the nine largest airlines in the United States based on domestic revenue passenger miles from 2012 to 2015, ranked by the highest market share in 2015. In 2015, American Airlines had the largest market share with 20% after its merger with U.S. Airways. As of 2015, nine major airlines earn 83.5% of U.S. domestic industry revenues. The traffic data are derived from the MIT Airline Data Project (MIT, 2016a).

Table 5.2. Market share of the largest U.S. airlines
(based on domestic revenue passenger miles)

	Airlines	**2012**	**2013**	**2014**	**2015**
1	American	13.0%	12.8%	12.5%	20.0%
2	Southwest	17.5%	17.4%	17.4%	17.9%
3	Delta	16.0%	16.0%	16.6%	16.8%
4	United	16.2%	15.8%	15.2%	14.8%
5	JetBlue	4.9%	5.1%	5.0%	5.2%
6	Alaska Airlines	3.9%	4.1%	4.2%	4.4%
7	Frontier Airlines	1.6%	1.5%	1.6%	1.9%
8	Spirit	1.4%	1.8%	2.1%	2.5%
9	US Airways[17]	8.0%	8.4%	8.2%	-
	Cumulative market share	82.4%	82.7%	82.9%	83.5%

Second, airlines offer differentiated products, i.e. flight connections to a traveler's destination of choice. Although flight connections may externally seem identical, airlines in an attempt to attract higher market share differentiate their connections in terms of product or service quality (e.g. flight frequency, seating accommodations, high quality food etc).

Third, entry into the airline industry is relatively difficult due to various barriers such as high set up costs, legal requirements and brand loyalty. Set up costs include aircraft acquisition costs, marketing costs, terminal rental fees, as well as pilot and crew salaries. These barriers have been significant enough to discourage potential competitors from entering airline industry. Although there may be many "small players" who share a small portion of airline market, they do not affect the major airline players.

[17] Merged with American Airlines in 2015.

The key element of an oligopoly is interdependence, which means that a firm's decisions cannot be made independently of its competitor's decisions. Indeed, airlines are mutually interdependent with each other, since the actions of each airline in the market influences its competitors and the market as a whole. For example, in the attempt to raise revenues, if an airline lowers ticket prices (e.g. by offering discounts on specific itineraries or groups of passengers), other airlines will notice this change immediately. The competing airlines will in turn reduce their airfares, to ensure they remain competitive and they do not loose passengers.

Airline markets, as oligopolies, rely crucially on the strategic interactions between competing players: each airline's actions affect the profits of its rivals and vice versa. The appropriate method to analyze an oligopoly setting, where each player's strategies depend critically upon the behavior of the other players, is game theory. Several papers have used game theory to analyze the interaction of competing airlines (players) in a given O-D trip or a network. Hansen (1990) applied a game-theoretic model to study airlines' frequency competition in a hub-and-spoke network. Pels et al. (2000) used game theory to investigate airport and airline competition in a metropolitan area with multiple departure airports. Adler (2005) developed a two-stage Nash best-response game to analyze the hub-spoke network design issue within a competitive framework. Zito et al. (2011) developed a game approach to model the airlines' choices in a duopolistic short-haul market, where aviation is in competition with ground transportation. The authors focused on pure strategies and estimated a Nash equilibrium on ticket prices and frequencies. Aguirregabiria and Ho (2012) studied the adoption of hub-and-spoke networks by U.S. airlines by assuming that airlines compete in prices. To do this, the authors estimate the Nash–Bertrand equilibrium. Evans and Schäfer (2013) simulated a Nash best-response game to investigate the impact of lower airline operating costs on the resulting flight frequency after introducing lower fuel burn technology into the air transport system. As part of demand and supply models, other studies have employed game theory to examine airline mergers (Doi and Ohashi, 2015; Lee, 2013a), hub-and-spoke networks (Berry et al., 2006), airline code sharing (Shen, 2012) and airline alliances (Gayle and Brown, 2014). The next section introduces the assumptions about how airlines interact in each O-D market and presents the associated mathematical expressions.

5.1.2 Airlines' oligopoly game theoretic model

To describe the oligopoly game developed by the airlines in each O-D market we first specify the game's components:

- The active airlines in each O-D market are the players, i.e. the decision makers in the game. It is noted that players are treated as if they are rational decision makers (they rationally act so as to maximize their payoffs).
- Each player has a specified plan of action (such as setting a price or quantity) for every contingency played by other players, which is called strategy. Generally, a strategy is different from an action in game theory. A strategy of a player can provide for a full description of his/her actions in every feasible situation in the game. In one-stage games, a strategy is simply the player's action taken on that single occasion. However, in multiple-stage games, a player's strategy is a complete

plan of actions and includes, in each stage, all player's possible choices of action conditioning on last stage's results.

- Outcome is the consequence for a player of a specific combination of all players' strategies.
- Payoff is the number attached to an outcome. In this dissertation, the player's payoff corresponds to airline's profit, i.e. each player's (airline) objective is to maximize its profit. It is noted that each airline's profit depends on both its strategies and those of its competitors.

In modelling the airlines' behavior in a competitive airline O-D market, airlines are considered as firms that offer one or more connections in an oligopolistic market. Airlines are modelled as profit maximizing players. The profit π_f of airline f which offers a subset J_f of the J total within-market connections in an O-D market is formed by the difference in revenues and cost as given in Eq. 5.1.

$$\pi_f = \sum_{j \in J_f} \left(p_j \cdot M \cdot MS_j - c_j \cdot M \cdot MS_j \right) - FC_f \Rightarrow$$

$$\pi_f = \sum_{j \in J_f} \left(p_j - c_j \right) \cdot M \cdot MS_j - FC_f \qquad \textbf{Eq. 5.1}$$

where c_j is the (constant) marginal cost of connection j and FC_f is fixed cost of the airline for the different airline connections. Fixed cost could be omitted for simplicity since it is shown in Eq. 5.2 that they drop out of the first order conditions. The terms p_j, M and MS_j were described in Section 4.3 as follows: p_j is the ticket price of connection j, M is the market size, i.e. the potential number of travelers between the O-D cities and MS_j is the market share of alternative j. The marginal cost c_j is not directly provided by the available aggregate data and thus needs to be estimated, as explained in Section 5.2.

As already mentioned above, the objective of each player (airline) in the game is to maximize its profit. In oligopolistic game theory, the competitive behavior between players can be modeled by three competition approaches: (i) Bertrand, (ii) Cournot and (iii) Stackelberg. In Cournot competition, firms compete on quantity, and choose quantities simultaneously. Then price is usually determined by the total output of all firms in the market such that supply equals demand. The Stackelberg model is a strategic game in which firms compete on quantities, but they enter the market sequentially; there is a leader firm, which moves first and then the follower firms move sequentially. In Bertrand competition, firms compete on prices and let the market determine the quantity sold. The most basic and fundamental competition pertains to pricing choices.

In this dissertation, we assume that airlines compete under Bertrand competition and we investigate the game where airlines set ticket prices. In other words, each player has one decision (strategic) variable, the airfare and the objective of the player is to maximize own profit. We assume that flight frequency chosen by each airline is exogenous to their decisions, i.e. flight frequency is not a strategic decision variables in the game.

Assumptions of the basic Bertrand model

- There are a small number of competing firms in the market.

- Firms set prices simultaneously (before observing the price of the rival).
- Firms produce homogeneous products at the same constant marginal cost.
- There are no capacity constraints.
- Firms do not cooperate, i.e. non-cooperative games are developed.

Based on the above assumptions, customers choose the product solely on the basis of price. Bertrand's equilibrium occurs when $price_1 = price_2 = marginal\ cost$. This results in zero profit for both firms. In a duopoly game, neither Player 1 nor Player 2 will set a higher price than the other, since this would yield the entire market to their rival. The result of the model creates a paradox, known as Bertrand's paradox, because if the number of firms goes from one to two, the price decreases from the monopoly price to the competitive price, but does not change as the number of firms become more than two. This is beyond reality, where markets with a small number of firms typically charge a price in excess of marginal cost. The solution to avoid Bertrand's paradox is to relax the assumptions: introduce repeated interaction (which may sustain collusive behavior by the threat of future losses), product differentiation or capacity constraints.

In many real cases, firms produce products that at the least, their consumers perceive as different from a rival's. In this dissertation, we consider that airline connections are differentiated i.e. they differ on a number of characteristics associated with the itinerary, the airline and the airport. In such markets where the products (airline connections) are differentiated the equilibrium is reached for prices above marginal cost and firms are able to make profits (it will be shown in Eq. 5.4).

A fundamental concept of game theory is the equilibrium property of the game. The most widely used equilibrium is the non-cooperative equilibrium of Nash. A Nash equilibrium is the set of strategies from which no single player has an incentive to unilaterally deviate. Under Bertrand competition, the Nash equilibrium may be referred to as Bertrand-Nash equilibrium or a Nash equilibrium in prices. In our airline oligopoly game, each airline (player) chooses a ticket price to maximize its profits given its opponent's pricing (selects its best response given its beliefs about its rivals' pricing strategy). In a Bertrand-Nash equilibrium no airline has incentive to change its pricing strategy, since it cannot improve its profit (holding the prices of all other airlines constant).

In our formulated non-cooperative one-stage game, within each O-D market[18] airlines set their ticket prices under Bertrand competition and product differentiation, taking into account the prices set by competitors. To compute a Bertrand-Nash equilibrium for differentiated airline connections in each O-D market we follow the process shown in Figure 5.1. We construct the profit function of the object airline as given in Eq. 5.1. It is noted that the parameters of the Nested Logit demand model are incorporated (due to the presence of MS_j in the profit function π_f). Also, it is noted that each airline is assumed to behave rationally assuming that its rival behaves rationally; that is each airline's objective is to maximize own profits, believing that all other airlines also maximize their profits. Mathematically this means that we derive object airline's first order conditions of profit

[18] Following Berry and Jia (2010), Gayle and Brown (2014) and Lee (2013) we assume that ticket prices are determined independently across markets.

function with respect to its own price for given rivals' prices (Eq. 5.2) and find the best-response function for the object airline. The market shares for all connections on the object airline network are then estimated by applying the market-share function. Other competing airlines use a similar approach to estimate their ticket prices (by maximizing their profits simultaneously against the airfares of the object airline). In other words, we derive a system of best-response equations, where the vector of optimal price of each airline is obtained by solving the best-response functions of all airlines simultaneously. The optimal price vector is given in Eq. 5.4. Each airline's first-order conditions and optimal price vector depends on both own and its rivals' derivatives with respect to price. The aforementioned steps conclude the first round of interaction; this process is repeated for many more rounds. The process continues until the demand–supply interaction converges.

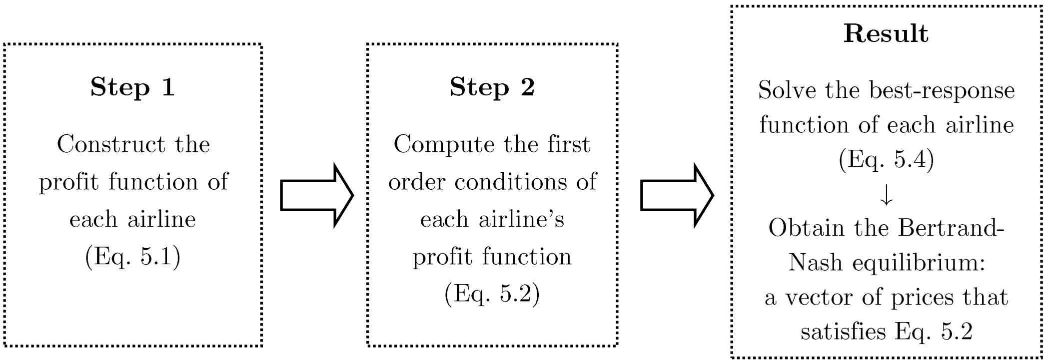


Figure 5.1. Steps followed to obtain the Bertrand-Nash equilibrium

The first order condition of each airline's profit (of Eq. 5.1) yields:

$$\frac{\partial \pi_f}{\partial p_j} = 0 \Rightarrow \sum_{k \in J_f} \left(\frac{\partial p_k}{\partial p_j} \cdot M \cdot MS_k + p_k \cdot M \cdot \frac{\partial MS_k}{\partial p_j} - c_k \cdot M \cdot \frac{\partial MS_k}{\partial p_j} \right) + \frac{\partial FC_f}{\partial p_j} = 0 \Rightarrow$$
$$\sum_{k \in J_f} \left((p_k - c_k) \cdot \frac{\partial MS_k}{\partial p_j} + MS_k \right) = 0 \qquad \textbf{Eq. 5.2}$$

Eq. 5.2 forms a linear system of equations which incorporates ticket prices and marginal cost of all J_f connections of a given airline f in a given market (fixed costs are dropped out of the first order conditions). Let D_{MS_f,p_f} represent the $J_f \times J_f$ matrix of partial derivatives of MS_j with respect to price such that:

$$D_{MS_f,p_f} = \begin{bmatrix} \frac{\partial MS_1}{\partial p_1} & \cdots & \frac{\partial MS_J}{\partial p_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial MS_1}{\partial p_J} & \cdots & \frac{\partial MS_J}{\partial p_J} \end{bmatrix} \qquad \textbf{Eq. 5.3}$$

A pure strategy Bertrand-Nash equilibrium requires that the vector of equilibrium prices satisfy the J_f first order conditions of Eq. 5.2. The existence of such an equilibrium for the case of a nested logit demand model with multiproduct firms has been proven by Anderson and de Palma (1992). Note that the ticket prices of competitors are contained in the market share marginal effects $\partial MS_k / \partial p_j$. In vector notation the Bertrand-Nash equilibrium prices are given by Eq. 5.4.

$$p_f = \left(\underbrace{-D^{-1}_{MS_f,p_f} \cdot MS_f}_{markup} \right) + \underbrace{c_f}_{marginal\ cost} \qquad \textbf{Eq. 5.4}$$

where vectors $p_f = \left[p_1, \ldots, p_{J_f}\right]'$, $MS_f = \left[MS_1, \ldots, MS_{J_f}\right]'$, $c_f = \left[c_1, \ldots, c_{J_f}\right]'$ represent ticket prices, market shares and marginal costs for each $j=1,2,\ldots J_f$ airline connection of airline f within a market. Note that price is split in two terms: the airline markup and the marginal cost. This specification confirms the general pricing rule of economic theory which states that firms charge a relative markup on marginal costs, due to consumers' different willingness to pay for that product in that specific market. D_{MS_f,p_f} represents the $J_f \times J_f$ matrix of partial derivatives of MS_j with respect to price. The elements of the derivative matrix are given by:

$$D = \begin{cases} \dfrac{-a}{\lambda} \cdot MS_j \cdot \left(1 - (1-\lambda) \cdot MS_{j/g} - \lambda MS_j\right), & if\ j = k \\ \dfrac{a}{\lambda} \cdot MS_k \cdot \left((1-\lambda) \cdot MS_{j/g} + \lambda \cdot MS_j\right), & if\ j \neq k \end{cases} \qquad \textbf{Eq. 5.5}$$

Detailed computation of the derivative matrix is presented in Appendix A.

The above approach relies on a static Nash equilibrium in prices and thus rests upon some simplifying assumptions. First, we assume that information is complete (i.e. the payoffs and the characteristics of the game are common knowledge). Second, real airline decisions are not confined to price setting but include other important variables such as flight frequencies and hub choice locations. In our formulated game, we assume that these factors are exogenous to airline's decisions, i.e. flight frequency or hub choice location are not strategic decision variables in the studied game. 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 and address uncertain demand (Donovan, 2005). Our dataset includes aggregate airline- and route-specific data recorded on a quarterly basis. The inclusion of yield management techniques in the above model requires more detailed data, such as historical bookings by flight and fare class for each departure date in order to fully account for ticket restrictions (e.g. advance ticket purchase, Saturday-night stay, different "willingness to pay" for air travel, cancellations, no shows etc). Consideration of the dynamic aspects of revenue management is beyond the scope of this dissertation and is left for future work. In addition, in consistency with the assumptions of the basic Bertrand model and the assumptions of existing literature, the current formulation assumes that there no capacity constraints. In real networks, capacity constraints may be (in some markets) binding for some airlines, resulting in different effects. However, our data provides us with no information at that level of individual flights at a particular day and time, and, thus, we cannot identify potential capacity constrained flights. Finally, the presented game corresponds to a non-cooperative one-shot game. We assume that the airlines are not colluding which is a plausible assumption since collusion is more likely in multi-period games rather than in single-period games.

5.2 Airline cost structure

5.2.1 Airline's marginal cost definition

Marginal cost (or incremental cost) is the change in total costs by adding one more unit of output, which in airline terms concerns the addition of one more passenger. Each airline has a per-passenger marginal cost for each offered connection j, drawn from airline-type and service-type attributes. As already mentioned, this marginal cost for each airline connection j is not directly provided by the available aggregate data and thus needs to be estimated. In general, airline marginal costs are understood as the sum of costs of carrying an additional passenger for a given capacity (which is expected to be constant) plus the costs of providing additional capacity (Brander and Zhang, 1990). In particular, if an extra passenger could be accommodated without adding a flight, then the marginal cost could be constant and equal to the cost of serving a passenger. But if the extra passenger resulted in an extra flight, the marginal cost would be equal to that constant value plus the cost of the extra flight.

Because airline-route marginal costs are not observed, the common approach in the empirical literature is to derive them by the estimation of an econometric model. Three approaches are applicable: (i) marginal cost is derived as a function of route distance and airline-specific average cost and flight length (Brander and Zhang, 1990; Zhang et al., 2014), (ii) the effect of segment density on connection's marginal cost is accounted and the latter is assumed to be derived by a functional form in distance and airline's total passenger flow (Berry et al., 2006; Fageda, 2006), and (iii) marginal costs are assumed to be constant regardless of the level of route traffic density and a marginal cost function consisting of observable cost shifters and unobservable factors is assumed (Berry et al., 1995; Berry and Jia, 2010). To allow for a simple specification of marginal costs, we follow the third approach and assume that marginal cost is given by a linear function of observed cost shifters (w_j) and an unobserved cost error (ω_j) as given in Eq. 5.6. We account for distance, density and other factors' effect through the direct inclusion of relevant variables in the marginal cost empirical specification as explained in Section 5.2.2.

$$c_j = w_j \cdot \gamma + \omega_j \qquad \textbf{Eq. 5.6}$$

The term γ is the vector of coefficients of the connection-specific cost shifters w_j and will be estimated. The vector of cost shifters includes connection, airline and airport specific variables. Under this specification, we allow for different marginal-cost levels for different airlines; i.e. an airline may have some advantages in marginal cost because, for instance, it has invested a fixed cost that helps reduce fuel consumption.

Substituting the marginal cost from Eq. 5.6, the pricing equation for each airline connection in an O-D market is written as:

$$p_j = \left(\underbrace{-D^{-1}_{MS_f, p_f} \cdot MS_j}_{mark-up} \right) + \underbrace{w_j \cdot \gamma + \omega_j}_{marginal\ cost} \qquad \textbf{Eq. 5.7}$$

In the above equation it is shown that the unobserved cost characteristics ω_j affect ticket prices. But, since ticket prices are correlated with market shares, we conclude that ω_j may be correlated with MS_j. Thus market share is considered as endogenous in the pricing equation. Details on the endogeneity issue and the way it is addressed in this thesis are given in Section 6.2.

5.2.2 Determinants of airline connection's marginal cost

Eq. 5.6 along with Eq. 5.7 recovers the marginal cost of each airline connection. Before introducing the marginal cost's explanatory factors the following explanations are in order. The marginal cost of a multi-segment airline connection is the sum of marginal costs of each segment. On an aircraft already in service, the marginal cost of transporting one more passenger is very low-essentially the cost of an additional meal, of the incremental fuel and of the extra passenger fee. But, when an additional flight is required to accommodate the extra passenger, the marginal cost becomes too high. In other words, there are two different units of cost: the traffic cost, which is the marginal cost of carrying one additional passenger and the capacity cost, which includes the costs of accommodating one more flight (Holloway, 2008). Furthermore, marginal cost is primarily a function of variable cost because fixed costs are largely unaffected by changes in passenger traffic (output). Since marginal cost is difficult to measure and cannot be determined from conventional accounting methods, average variable cost has been reported to be used as a proxy for short-run marginal cost (even though it is known that the magnitudes of the two costs may differ substantially) (Macário et al., 2003; Olive, 2002). Although the marginal cost is not equivalent to the average variable cost, we presume the existence of some common cost drivers. Considering the above, this dissertation uses marginal cost variables which are related to connection, airline and airport characteristics.

- Round-trip distance

The distance flown is often acknowledged as an important cost driver. An increase in distance flown may lead to an increase in some variable costs such as fuel costs. Furthermore, a longer route may imply more landings and takeoffs, i.e. longer itineraries are more possible to be non-direct, which may lead to higher fuel costs and airport charges. In the marginal cost function, round-trip itinerary distance is used as explanatory variable.

- Aircraft size

Aircraft size determines a variety of aircraft operating costs, such as fuel and maintenance costs. Other size-related costs include landing fees since they are computed on the basis of the maximum take-off aircraft weight. What drives us to include aircraft size in the marginal cost function is its relationship with fuel costs. Overall, aircraft size along with distance flown can be used as cost variables so as to indirectly capture aircraft fuel cost, which is accounted as a significant factor of a connection's marginal costs. From this point of view we expect a positive coefficient of this variable (increase in the aircraft size may lead to increase of the marginal costs), as indicated in Figure 5.2. The dashed line separates aircraft in two different types: wide-body and narrow-body. It is obvious that wide-body aircraft consume higher amounts of fuel than narrow-body. However, the plot of per seat fuel consumption does not provide so clear conclusions. In Figure 5.3 , apart from wide-body aircraft, the operation of regional aircraft (such as E190, CRJ9, E170 and E145) result in high amounts of per seat fuel.

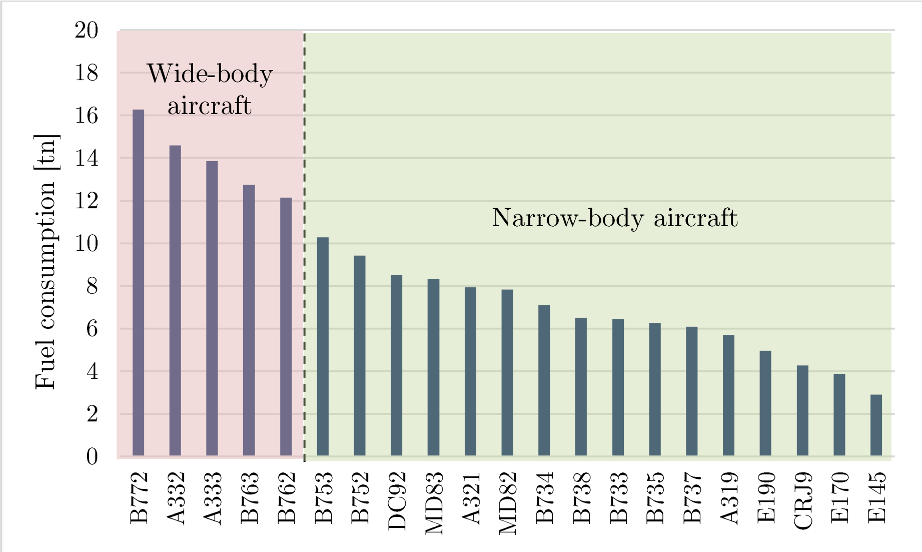


Figure 5.2. Fuel consumption by aircraft type (for a mission of 1000 nm)[19]

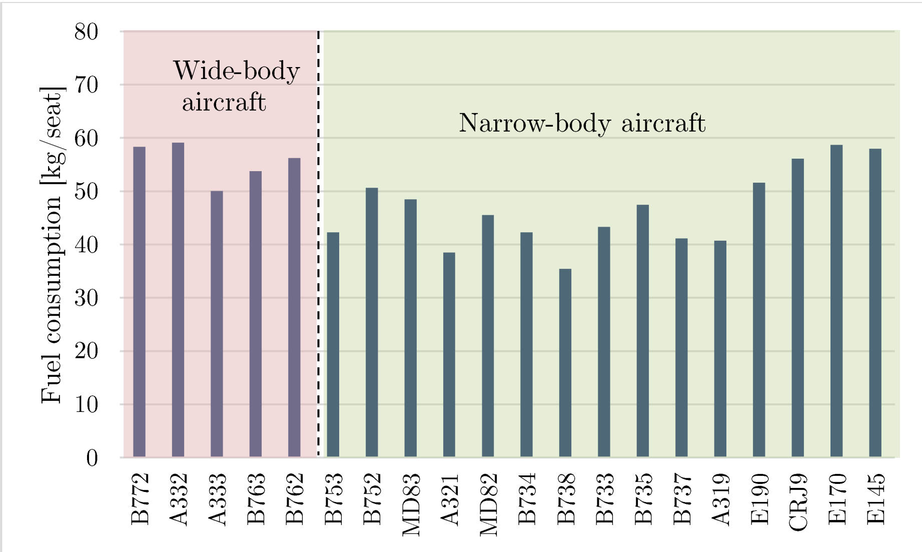


Figure 5.3. Per seat fuel consumption by aircraft type (for a mission of 1000 nm)[19]

Another reason for including the aircraft size in the marginal cost function is to account for the impact of traffic density. Larger aircraft can provide more capacity and transfer more passengers and may be used on routes with denser traffic. From this perspective, itineraries with larger aircraft may have lower per passenger marginal cost. Cost economies of larger aircraft are documented in (Wei and Hansen, 2003; Ryerson and Hansen, 2013).

Therefore, in our model, aircraft size variable is determined by whether the aircraft type is narrow-body or wide-body. Aircraft type is a segment characteristic and, thus, for a non-direct airline connection, several aircraft types may be used. Aircraft size is captured by a dummy variable which is equal to 1 if at least one segment of the itinerary is operated by a wide-body aircraft. The coefficient of this variable will indicate the net effect of the above countervailing forces (fuel cost vs economies of scale) on marginal cost.

[19] The computations of fuel burn have been conducted with the use of EMEP CORINAIR database (2013 version) (EEA, 2013). Seat capacity per aircraft type is given in Appendix B-4.

- <u>Airline hubs</u>

According to SSamula (2008), among the advantages of airline hubs are: i) economies of scale, which are realized through transporting higher traffic densities, thus lowering the per passenger costs, ii) higher flight frequencies, explicitly shown for O-D pairs with low passenger demand, which would otherwise be served by low flight frequencies in a direct flight option and iii) lower cost of travel. Therefore, a variable indicating transfer via hub airports is used to explain if concentration of traffic in hubs affects marginal cost. A dummy variable is constructed which is equal to 1 if the connection departs/connects/ arrives from/to an airport which is a hub for the ticketing airline. A list of the considered airline hubs is provided in Table 5.3 (Appendix B-1 lists corresponding airport codes) and are derived by airlines' official websites. It is noted that Southwest is not included in Table 5.3 since it does not use the hub and spoke system of other airlines, preferring point-to-point routes.

Table 5.3 List of the considered airline hubs

Airline	Airline hubs
American Airlines	ORD, DFW, JFK, MIA, LAX
Alaska Airlines	ANC, LAX, PDX, SEA
Jetblue	JFK
Delta Air Lines	CVG, DTW, ATL, JFK, LGA, MSP, SLC
AirTran Airways	ATL, BWI, MKE, MCO
Frontier Airlines	DEN
Hawaiian Airlines	HNL, OGG
United Airlines	BOS, ORD, CLE, DEN, GUM, IAH, LAX, EWR, SFO, IAD
US Airways	CLT, PHL, DCA, PHX
Virgin America	SFO

- <u>Airline dummies</u>

The airline dummy variables are included in order to capture airline-specific cost effects. All major airlines are included: Delta (DL), United Airlines (UA), American Airlines (AA), US Airways (US), Southwest (WN) and JetBlue (B6). US Airways is used as the base airline in the estimation against which the other airlines are compared. A negative coefficient of the dummy variable for a given airline indicates lower marginal costs in comparison with the base carrier (US Airways). Furthermore, this variable may be used to compare marginal costs between airlines. Figure 5.4 shows the cost per available seat-mile (CASM) for our sample airlines, derived by MIT (2016b). American Airlines stands out as the highest-cost U.S. domestic airline, with its CASM equal to 14.26¢. Also, Delta and United are also among the industry's highest-cost producers.

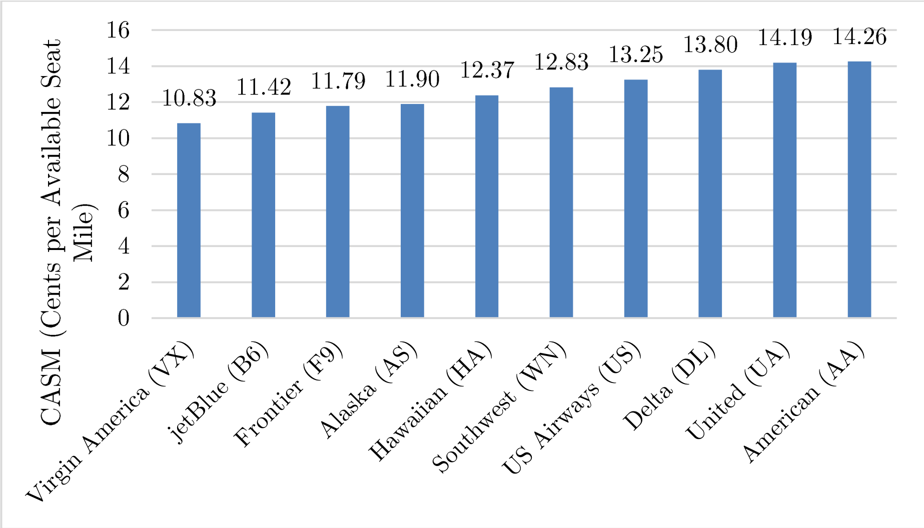


Figure 5.4. Domestic CASM for Individual Carriers (year 2012)

6 Model estimation and policy simulation

To simulate the implementation of a market-based environmental measure in the U.S. airline network, we need to estimate the supply and demand system. Then the estimated equations are used in order to incorporate emissions costs in the airlines' cost functions. Sections 6.1 to 6.3 describe the methodology followed to estimate the system of demand and supply equations, while Section 6.4 presents the approach for simulating the assumed market-based environmental policy.

6.1 System of demand and supply equations

The resulting demand equation for each airline connection j in an O-D market derived from Chapter 4 is:

For the Nested Logit model

$$lnMS_j - lnMS_0 = x_j\beta - \alpha p_j + (1-\lambda) \cdot lnMS_{j/g} + \xi_j \qquad \textbf{Eq. 6.1}$$

For the Multinomial Logit model:

$$lnMS_j - lnMS_0 = x_j\beta - \alpha p_j + \xi_j \qquad \textbf{Eq. 6.2}$$

On the supply side, the pricing equation which gives the best price response function for the ticketing airline serving the connection j (to the airfares of other competing airlines) is derived from Chapter 5 as:

$$p_j = -D^{-1}_{MS_f,p_f} \cdot MS_j + w_j \cdot \gamma + \omega_j \qquad \textbf{Eq. 6.3}$$

Our first task is to estimate the parameters α, β, λ and γ. The system of demand and supply equations (Eq. 6.1 to Eq. 6.3) forms the basis for estimation. Three important issues are discussed below:

- <u>Joint estimation of demand and supply equations:</u> One approach is to estimate the demand equation in isolation (thus estimate the parameters α, β and λ) and then substitute the estimated demand parameters into the price function in order to recover parameter γ. Since demand parameters enter both equations, joint estimation improves efficiency of estimation.
- <u>Non-linearity of parameters</u>: Recall that D_{MS_f,p_f} (see Eq. 5.5) represents the matrix of partial derivatives of MS_j with respect to price. Thus, parameters α and λ enter the pricing function nonlinearly, while β enters both equations linearly. Thus, the estimation method should address this non-linearity issue.

- <u>Endogeneity:</u> The endogeneity of prices and market shares is a critical econometric issue. As already explained in Chapter 4, the term ξ_j may be correlated with ticket price p_j and within-group (conditional) market share $MS_{j/g}$ (demand equation). Similarly, market shares in the pricing equation are endogenous. The above endogeneity issues may lead to biased parameter estimates if Ordinary Least Square estimation method is used. In contrast, Instrumental Variables methods can cope with endogeneity under suitable conditions.

Overall, an estimation method, which addresses both nonlinearity and endogeneity issues, should be used. 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. Details are given in Section 6.2. Moreover handling the inherent presence of nonlinearities, requires the use of generalized moments in connection with instruments. As explained in Section 6.3, in this work, the two-step Generalized Method of Moments estimator is used (Hansen, 1982; Hall, 2005).

6.2 Endogeneity and Instrumental Variables

6.2.1 Sources of endogeneity

A fundamental property in regression analysis is that the independent variables are uncorrelated with the error term. If this property is violated, estimation by Ordinary Least Squares (OLS) methods may lead to biased and inconsistent estimates. In demand models, price endogeneity results in (in absolute terms) under-estimated price coefficients (Mumbower et al., 2014). Endogeneity is said to occur in a regression model if $E[\varepsilon|X_j] \neq 0$, for one or more explanatory variables j (where X_j denotes the explanatory variable(s) and ε the error term of the regression). Endogeneity may arise as a result of (i) Omitted Variables, which occurs when one or more explanatory factors are not included in the regression (e.g. due to data constraints). In this case, these omitted variables are attributed to the error term ε. If these omitted variables are correlated with X_j, then endogeneity arises (because in this way X_j may be correlated with ε). (ii) Measurement Error, which happens when one or more independent variables are not measured perfectly. (iii) Simultaneity, which arises in the context of a simultaneous equations model such as a supply-demand system in economics, in which price influences demand, and demand influences price.

In our model endogeneity arises for two reasons. First, ticket price p_j and within-group (conditional) market share $MS_{j/g}$ may be correlated with the term ξ_j (which acts as the error term of the demand equation) as the latter commonly reflects quality features. ξ_j may include exact departure time, in-flight food quality, wi-fi equipment, ticket restrictions, in-advance ticket purchase, frequent-flyer tickets and other factors which may affect an airline connection's quality and, thus, its ticket price and market share. For example, due to data unavailability we do not observe ticket restrictions of the itineraries, but passengers observe them during the booking process. Tickets with more travel or refundability restrictions are more likely to have lower prices than unrestricted tickets (Puller et al., 2012). If we do not consider this potential endogeneity, the estimated price coefficient and the estimated price elasticity will be biased. Second, the pricing equation indicates that the unobserved cost characteristics ω_j affect ticket prices. But, since ticket prices are correlated with market shares, ω_j may be correlated with MS_j. Thus market share is considered as endogenous in the pricing equation. Figure 6.1(a) illustrates a path diagram highlighting the endogeneity problem in the demand equation. Similar illustration may stand for the pricing equation as well.

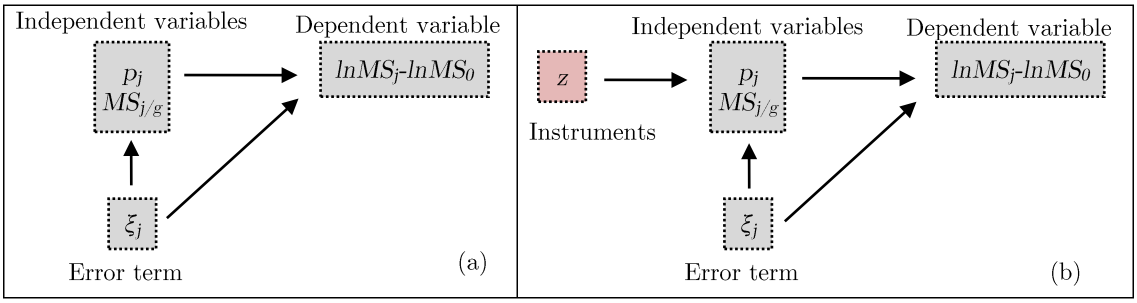


Figure 6.1. Illustration of endogeneity and its solution in the demand equation

The standard practice when right-hand variables are correlated with the error term is to estimate the equation using Instrumental Variable (IV) methods. As shown in Figure 6.1(b), the idea is to find a set of exogenous variables, called instruments, which are (i) correlated with the endogenous variables (instrument relevance) and (ii) uncorrelated with the error term (instrument exogeneity). The satisfaction of these conditions determines that the selected instruments are valid (Stock and Watson, 2010). The selection of valid instruments is not easy and is often controversial. According to Stock and Watson (2010), valid instruments may come from the use of economic theory or the knowledge of the topic being studied and careful attention to the details off the data. Below the selected instruments for the demand and supply equations are discussed.

6.2.2 Instrumental variables

On the demand side, we need to instrument for p_j and $MS_{j/g}$. Therefore, we need to find variables that are correlated with price and within-group market share but are not correlated with the unobserved connection characteristics (demand error term). Following the standard practice, we treat the remaining connection's characteristics x_j as being exogenous; they are assumed to be 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. On the supply side, we need to instrument for MS_j, since it may be correlated with the error term ω_j of the pricing equation. In accordance with the demand-side instruments, we treat the cost-shifting characteristics w_j as being exogenous. We use them as instruments along with additional exogenous variables that are believed to affect MS_j but are uncorrelated with ω_j.

There are several instrumental variables that have been used in the literature, a summary of which is presented in Table 6.1. We have grouped instruments in six categories: demand-side instruments are derived from the first five categories, including cost shifters, market-level and rivals' characteristics and airline's size of operation. Motivated by Mumbower et al. (2014) we also present another type of instruments, the Hausman-type price instruments, which have limited application in the airline industry. Some supply-side instruments are common with demand-side instruments, but other purely supply-side instruments are used as well, described in the sixth category of Table 6.1. The above categories have an intuitive explanation. Cost-shifting instruments are used as demand-side instruments and include variables that have an impact an airline connection cost but are not directly related to the demand error term. Based on this idea, itinerary distance and unit fuel costs have been previously used as instruments. Furthermore, an indicator of whether the origin, destination or connecting airport is a hub for the ticketing carrier has been previously used. In this dissertation, we include an instrument of whether the destination or the connecting airports are hubs for the ticketing airline. The intuition is that airline costs may be affected by hub operation, which may in turn influence ticket prices set by the ticketing airline and corresponding within-group market shares.

According to the supply theory, a product's price is affected by the degree of market competition and market power. As a consequence, market shares are influenced by the overall level of ticket prices. We have grouped market-competition instruments in three sub-categories: market-level characteristics, rival connections' characteristics and airline's size of operation. Market-level characteristics focus on the number of offered connections, the number of active airlines and the number of competitors. This information indicates the degree of within-market competition a connection or its airline is facing, which in turn may affect its ticket price and its market share. In this work, the number of offered connections and the number of airlines in the market are used as demand-side and supply-side instruments. Rival connections' attributes has been also reported as valid instrument for prices and market shares, as they are considered to affect the pricing decision of an airline through within-market competition, but do not enter the utility function and the pricing equation directly. Our instruments along this line 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. In addition, we include the number of destination cities served by direct flights in order to reflect the airline's size of operation at the origin airport which may be related to its price level at the airport. The above market-competition variables are largely determined by the size of a market and are unlikely to respond to the same errors that affect prices and demand. Thus, it is reasonable to assume that they are uncorrelated with the unobserved connection characteristics ξ_j and the unobserved cost shifters ω_j.

Hausman-type price instruments have also been considered in other studies. For example, Mumbower et al. (2014) used the mean ticket prices of the same airline in other markets. Hotle et al. (2015) used the square of the coefficient of variation across the offered fares across different geographic contexts. The idea is that the price of a product in a market will be correlated with the price of a similar product in other market due to common marginal costs (Hausman, 1996).

Finally, purely supply-side instruments include two variables which are indicative of the potential passenger traffic of each connection and each airline. They are defined by the market size divided by the number of connections and by the number of airlines in the market respectively. By this definition, we assume that the potential passenger traffic of each connection and each airline can predict potential market share of each connection and airline (MS_j), but it will be independent of the unobserved cost error term ω_j. Table 6.1

presents various instruments used in previous studies. After a detailed consideration of the above list, we focused on the use of those indicated in the last two columns of Table 6.1. The proposed instruments are selected so as to give reasonable parameter estimates after being tested with the IV diagnostics described in the next section. In Chapter 7, summary statistics of the selected instruments within our traffic sample data are presented.

Table 6.1. Review and selection of instrumental variables

	Type of instruments	**Examples of instruments**	**Used in our model**	
			D	**S**
	1. Cost-shifting instruments	Unit costs of fuel (Hsiao and Hansen, 2011[20]; Israel et al., 2013; Rolim et al., 2016)		
		Itinerary distance (Bhattacharjee, 2016; Chen and Gayle, 2013; Gayle and Brown, 2014; Hotle et al., 2015)		
		Other unit costs (maintenance, insurance, leasing) (Rolim et al., 2016)		
		Fuel price and Aircraft characteristics (the number of seats, operating weight and engine compression ratio of the aircraft) and Airport charges (in per-passenger rate) (Doi and Ohashi, 2015)		
		Hub indicator (whether the origin/destination/connecting airport is hub for the airline) (Berry and Jia, 2010; Israel et al., 2013; Ivaldi et al., 2015; Shen, 2012)	•	
Degree of within-market competition	2. Market-level characteristics	The number of products/routes within a market (Lee, 2013a; Lee, 2013b; Chen and Gayle, 2013)		•
		Number of all airlines (Berry and Jia, 2010)	•	•
		Number of low cost carriers and the number of seats offered in the market (Hotle et al., 2015)		
		Number of competitors, Number of products offered by the airline (Bhattacharjee, 2016; Chen and Gayle, 2013; Gayle and Brown, 2014)		
	3. Rival connections' characteristics	Number of rivals' products (Berry and Jia, 2010; Bhattacharjee, 2016; Chen and Gayle, 2013; Gayle and Brown, 2014; Israel et al., 2013)		
		Percentage of nonstop routes that rivals operate in the same market (Aguirregabiria and Ho, 2012; Berry and Jia, 2010; Israel et al., 2013; Mumbower et al., 2014; Shen, 2012)	•	•
		Number of rival airlines (Israel et al., 2013; Ivaldi et al., 2015)		
		Average distance of rival routes (Berry and Jia, 2010)		
		Average flight frequency of rivals in the market (Ivaldi et al., 2015)		
		Average number of passengers carried by rivals in the market (Ivaldi et al., 2015)		•
	4. Airline's size of operation	Number of cities that the airline serves from the airport (Aguirregabiria and Ho, 2012; Berry and Jia, 2010; Lee, 2013a; Shen, 2012)	•	•
	5. Hausman-type instruments	Mean ticket prices of the same airline in other markets (Mumbower et al., 2014)		
		Square of the coefficient of variation across the offered fares across different geographic contexts (Hotle et al., 2015)		
	6. Other supply-side instruments	By-connection market size (computed as market size divided by the number of connections)		•
		By-airline market size (computed as market size divided by the number of airlines)		•

Note: D: Demand-side instruments, S: Supply-side instruments

[20] Hsiao and Hansen (2011) defined the instrument as the product of the route distance and unit jet fuel cost.

6.2.3 Instrumental Variables diagnostics

To justify the appropriateness of the selected instruments, econometrics' literature (Baum et al., 2003; EViews, 2014) identifies several IV diagnostics which are applied in this work as follows.

The first condition (Instrument Relevance) may be tested by examining the fit of the first stage regressions. Let Z_1 and Z_2 denote the vectors of instruments for the demand and cost equation respectively. These vectors include both the explanatory variables of our system and additional auxiliary variables. The first stage regressions are reduced form regressions of the endogenous variables, i.e. p_j and $MS_{j/g}$ for the demand and MS_j for the pricing equation, on the full set of instruments Z_1 and Z_2 respectively. Two statistics commonly used include the coefficient of determination R^2 and the F-statistic of the first-stage regression. However, for models with multiple endogenous variables, these indicators may not be sufficiently informative. Baum et al. (2003) present an example of a regression with two endogenous variables and two instruments. It is stated that if one of the two instruments is highly correlated with the two endogenous variables, but the other instrument is just noise, then F-statistic and R^2 measures from the two first-stage regressions may not reveal this weakness. In regressions with multiple endogenous variables, the Stock and Yogo (2005)[21] weak instrument test has been proposed. Hence, this test is used to assess the strength of instruments in our model.

The Instrument Exogeneity may be checked via the J-test of overidentifying restrictions, which evaluates the othogonality condition the instruments. This test is applied in the following steps: we estimate the IV regression with the selected instruments and calculate the residuals. Then we regress these residuals on the instrumental variables z and the explanatory variables x. The resulting F of this regression is used to compute the value $m_z \cdot F$, where m_z is the number of instruments. The null hypothesis is that the instruments are exogenous. This test statistic is Chi-squared distributed with degrees of freedom equal to the number of instruments minus the number of endogenous variables.

A Durbin-Wu-Hausman Test is also implemented in order to verify the endogeneity of one or more regressors, e.g. in this thesis, prices and market shares. The statistic is calculated by running a secondary estimation where the test variables (price and market shares) are treated as exogenous rather than endogenous, and then comparing the J-statistic between this secondary estimation and the original estimation. The test is run is Eviews and the null hypothesis H_0 claims that there are no differences between the model in which "the test variables" are treated as endogenous and the model where they are treated as exogenous. The test statistic is distributed as a Chi-squared random variable with degrees of freedom equal to the number of regressors tested for endogeneity. Table 6.2 summarizes the discussed IV diagnostics and the way of evaluation.

[21] The overall strength of the instruments is evaluated through the Stock and Yogo (2005) tabulated critical values of the minimum eigenvalue of the Cragg-Donald statistic.

Table 6.2. Instrumental Variables Diagnostics

	IV tests	Evaluation	Potential conclusion
1	Weak instruments diagnostics H_o: Instruments are weak	Compare Cragg-Donald F-statistic with Stock-Yogo critical values (e.g. at 95% confidence level)	Instruments are not weak
2	Instrument Exogeneity H_o: Instruments are exogenous	Compare test statistic with Chi-squared values	Instruments are exogenous
3	Endogeneity test (Durbin-Wu-Hausman)	Compare Durbin-Wu-Hausman statistic with Chi-squared values	Ticket price and market shares are endogenous

6.3 Estimation

6.3.1 Generalized Method of Moments

To improve the efficiency of demand and supply estimates, the two equations should be estimated jointly. Since some demand parameters (α and λ) enter the supply equation in a nonlinear way, we additionally need a nonlinear system estimation technique. Furthermore, the number of instruments exceeds the number of explanatory variables both in the demand and the supply equation, which means that our model is over identified.

Following the relevant literature, the two-stage nonlinear Generalized Methods of Moments (GMM) estimator is applied for the joint estimation of the demand and supply parameters. GMM estimation was formalized by Hansen (1982). The method requires that a number of moment conditions are specified for the model. For our model, two sets of moment conditions are used: the demand- and the supply-side moments. These moment conditions are functions of the model parameters and the data, such that their expectation is zero at the true values of the parameters. Then a specific objective function represented by the quadratic product of the moment conditions with a symmetric and positive definite weight matrix is minimized to estimate the model parameters. The description of the GMM method relies on the following notation.

- x: exogenous demand variables, x is a $n \times p_1$ matrix
- w: exogenous cost variables, w is a $n \times p_2$ matrix
- ξ: error term in the demand equation, ξ is a $n \times 1$ vector
- ω: error term in the pricing equation, ω is a $n \times 1$ vector
- z_1: demand-side instruments, z_1 is a $n \times k_1$ matrix (where $k_1 > p_1$)
- z_2: supply-side instruments, z_2 is a $n \times k_2$ matrix (where $k_2 > p_2$)
- $u = \begin{bmatrix} \xi \\ \omega \end{bmatrix}$: augmented error, u is a $2n \times 1$ vector
- $z = \begin{bmatrix} z_1 & 0 \\ 0 & z_2 \end{bmatrix}$: demand- and supply-side instruments, z is a $2n \times k$ matrix ($k = k_1 + k_2$)
- $\theta = [\theta_d \quad \gamma]$: vector of unknown demand (ϑ_d) and supply (γ) parameters

where n is the number of observations, p_1 and p_2 are the number of the demand and cost exogenous variables respectively, k_1 and k_2 are the number of the demand and cost instruments respectively.

The exogeneity of the instruments means that there are k_1 and k_2 moment conditions (or orthogonality conditions) for the demand and the supply equations respectively, that should be satisfied at the true value of the parameters. The k_1 moment conditions for the demand are given by $m_d = E[z_1 \xi] = 0$, while the k_2 moment conditions for the supply are given by $m_s = E[z_2\omega] = 0$. To jointly estimate the demand and the supply model, we stack together the above moment conditions as follows:

$$m(\widehat{\theta_d}, \hat{\gamma}) = \begin{bmatrix} m_d \\ m_s \end{bmatrix} = E\begin{bmatrix} z_1{}'\xi \\ z_2{}'\omega \end{bmatrix} = 0 \qquad \textbf{Eq. 6.4}$$

The intuition behind the GMM procedure is to estimate the coefficients $\hat{\theta}_d$ and $\hat{\gamma}$ that minimize the GMM objective function, i.e. the quadratic product of the moment conditions as shown in Eq. 6.5 (Hansen, 1982).

$$\begin{aligned} J(\hat{\theta}_d, \hat{\gamma}) &= m(\hat{\theta}_d, \hat{\gamma})' W_{opt} m(\hat{\theta}_d, \hat{\gamma}) \\ &= u'zW_{opt}z'u \end{aligned} \qquad \textbf{Eq. 6.5}$$

where W_{opt} is a symmetric and positive definite weight matrix, as explained later. Thus GMM estimation solves the following GMM optimization problem.

$$\min_{\widehat{\theta}_d, \hat{\gamma}} \left[\underbrace{m(\hat{\theta}_d, \hat{\gamma})'}_{1\times k} \underbrace{W_{opt}}_{k\times k} \underbrace{m(\hat{\theta}_d, \hat{\gamma})}_{k\times 1} \right] \qquad \textbf{Eq. 6.6}$$

Overall, the two-step GMM estimation method can be described by four stages, as shown in Figure 6.2. First, as explained in Section 6.3.2, the residuals ξ and ω are recovered from the demand and supply equations. Second, we interact the residuals with the instruments in order to get the sample moments of Eq. 6.4 and the objective function of Eq. 6.6. Third, an initial weight matrix is assumed and the first-step GMM estimators $\hat{\theta}_{d,1step}$ and $\hat{\gamma}_{1step}$ are obtained from Eq. 6.6 (by substituting the initial weight matrix). Next, by using the first-step GMM estimators obtained before, the optimal weight matrix W_{opt} is calculated as explained in Section 6.3.3. Finally, given W_{opt}, an iterative approach analogous to the third stage is applied in order to minimize the GMM objective function (by substituting the optimal weight matrix in Eq. 6.6). In this final stage, the optimal GMM estimators $\hat{\theta}_{d,2step}$ and $\hat{\gamma}_{2step}$ are obtained. Since demand parameters α and λ enter the pricing function nonlinearly, we need to do a nonlinear search to recover the coefficients that minimize our objective function over the moments restrictions. An algorithm in the MATLAB environment has been developed for this purpose, where the stopping criterion is set equal to 10^{-5}.

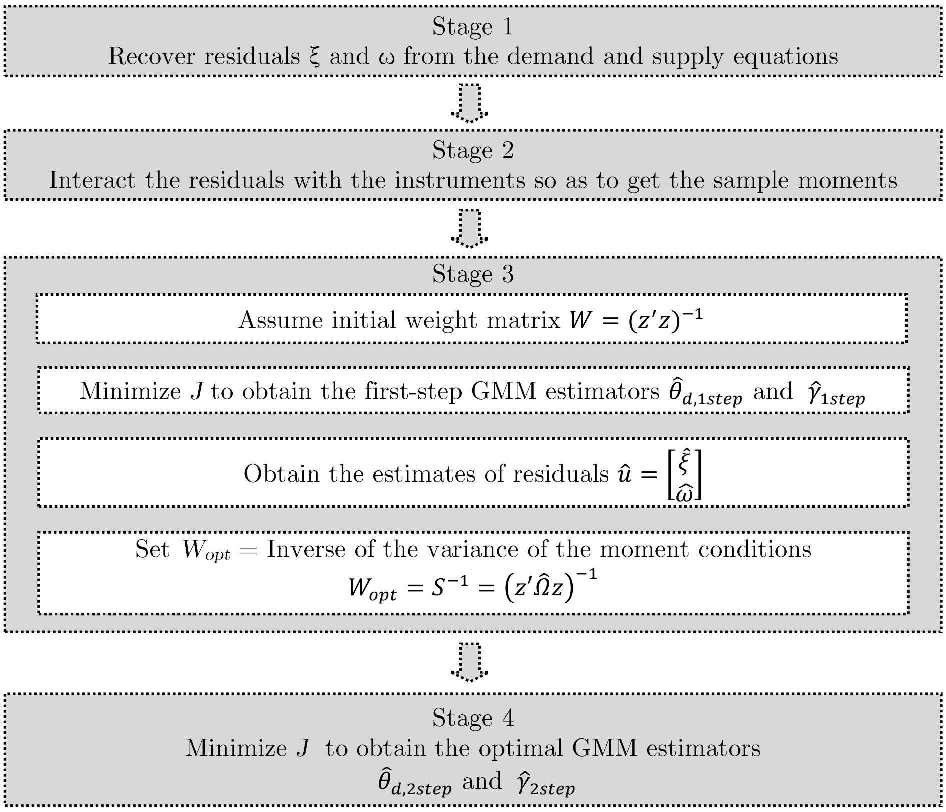


Figure 6.2. Implementation of the two-step GMM estimation

6.3.2 The residuals

This section aims to clarify the way the parameter coefficients enter the moment conditions and the GMM objective function via the residuals ξ and ω. Based on the demand (for the Nested Logit formulation) and supply equations, the vector of residuals (error terms) of the system is given by Eq. 6.7.

$$u = \begin{bmatrix} \xi \\ \omega \end{bmatrix} = \begin{bmatrix} lnMS_j - lnMS_0 - x_j\hat{\beta} + \hat{\alpha}p_j - \left(1 - \hat{\lambda}\right) \cdot MS_{j/g} \\ p_j - w_j \cdot \hat{\gamma} + D_{MS_f,p_f}^{-1} \cdot MS_j \end{bmatrix} \quad \textbf{Eq. 6.7}$$

Where D_{MS_f,p_f} is defined in Eq. 5.3 and Eq. 5.5 as a $J_f \times J_f$ matrix of partial derivatives of MS_j with respect to price, which is non-linearly dependent on the estimated demand parameters α and λ. The vector of residuals is initially interacted with the instruments in order to get the sample moments.

6.3.3 Optimal weight matrix and GMM estimators

The optimal GMM estimators $\hat{\theta}_{d,2step}$ and $\hat{\gamma}_{2step}$ are derived by utilizing optimal weight matrix W_{opt}. In practice, we employ the two step procedure to derive optimal GMM estimators, as shown in Figure 6.2.

In the first step, an initial positive definite weight matrix is assumed. Typically, the Two-Stage Least Squares (2SLS) estimator is used to produce $\hat{\theta}_{d,1step}$ and $\hat{\gamma}_{1step}$. This amounts to using a weight matrix equal to $W = (z'z)^{-1}$ assuming that all error terms are homoscedastic[22]. After estimating the 1st step parameter estimates, we obtain the estimates of residuals $\hat{u} = \begin{bmatrix} \hat{\xi} \\ \widehat{\omega} \end{bmatrix}$.

Given the 1st step residuals, we now proceed to the computation of the optimal weight matrix. Based on Hansen (1982), the optimal weight matrix is the inverse of the covariance of the moment conditions (let denote it as S). Let $\hat{\Omega}$ be the covariance matrix of the disturbance terms. To get an efficient GMM estimator we need to estimate S, and to do this, assumptions about Ω are needed. The most commonly encountered cases in cross–section analysis is heteroskedasticity of residuals. To estimate a heteroscedasticity-consistent estimator of S, the diagonal matrix of squared residuals is taken as (Baum, 2003): $\hat{\Omega} = diag(\hat{u}_1^2, \dots, \hat{u}_j^2, \dots \hat{u}_{2n}^2)$. Then, the optimal weight matrix W_{opt} is given by Eq. 6.8.

$$W_{opt} = \left(z'\hat{\Omega}z\right)^{-1} \qquad \textbf{Eq. 6.8}$$

Finally, we substitute W_{opt} in Eq. 6.5 and solve the minimization problem to obtain the final GMM parameters $\hat{\theta}_{2step} = [\hat{\theta}_{d,2step}, \hat{\gamma}_{2step}]$ (final parameter estimates).

The standard error of the parameter estimates and the statistics to test for statistical significance of estimated coefficients (t-statistic and p-value) are next calculated. For standard errors the asymptotic variance matrix of the GMM estimator is first computed as follows:

$$V(\hat{\theta}_{2step}) = \left\{X'z\left(z'\hat{\Omega}z\right)^{-1}z'X\right\}^{-1} \qquad \textbf{Eq. 6.9}$$

where X denotes the vector of demand and supply regressors (including the endogenous and exogenous variables). The coefficients' standard errors are obtained by computing the square root of the diagonal elements of the asymptotic variance matrix, i.e. $SE = \sqrt{diag\left(V_{\hat{\theta}_{2step}}\right)}$. Then, the t-statistic of each coefficient is calculated as: $t_{\theta_i} = \theta_i / SE_{\theta_i}$.

6.4 Assessment of a market-based environmental policy

6.4.1 Specification of the market-based measure

As described in Section 2.1, different approaches on emissions pricing may be applied in order to reduce aviation emissions. Cap-and-trade programs and emissions levies would provide commercial airlines with an incentive to reduce their emissions in the most cost-effective way. Carbon offsetting is another measure which is currently implemented in aviation only on a voluntary basis and, thus, its success is not guaranteed. However, the ICAO's GMBM concerns a Carbon Offsetting and Reduction Scheme for International Aviation to start on 2021 voluntarily, but continue on a mandatory basis after 2027.

The above measures differ in how they perform under uncertainty about the costs and benefits of reducing emissions. On the one hand, a cap-and-trade policy provides certainty about the quantity of emissions, since the emission cap is set by the scheme a priori. However, allowance prices are determined by the market supply and demand and, thus,

[22] Homoscedasticity describes a situation in which all error terms have the same variance. Under conditional homoscedasticity GMM estimator becomes 2SLS.

can be volatile. So, there may be cases where the allowance prices become too low to create incentives for the airlines to reduce their emissions. In addition, the effectiveness of a cap-and-trade policy depends on other factors, such as the baseline used to project future emissions. Conversely, an emission levy can give a clear price signal that would provide airlines with incentives to adopt sustainable practices. According to economic theory, the emission fee should be set by the scheme at a level that represents the social cost of the emissions. However, an emission levy does not provide any guarantee regarding the desired emissions reduction because the reductions depend on the level of the fee and how firms and consumers respond to the fee.

Overall, the above measures generate an additional cost that becomes part of airline's cost structure. This cost is directly linked to emissions and can be referred to as "emission cost". Despite potential differences, a cap-and-trade system can be viewed as equivalent to a carbon levy scheme applied to aviation, which would explicitly raise airline's marginal costs. This approach is consistent with other studies (Brueckner and Zhang, 2010; Hofer et al., 2010) which state that the imposition of airline emission fees can be viewed as increasing the price of fuel. As a result, regardless of whether the mitigation policies follow a cap-and-trade approach or rely on emission levies, they can all be represented by an economic measure that directly increase the operating costs of the regulated airlines.

Combustion of kerosene (most used fuel by civil aircraft) produces various emissions including carbon dioxide, water vapor, nitrogen oxides, carbon monoxide, hydrocarbons and soot (Brasseur et al., 1998; IPCC, 2007; Lee et al., 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. While CO_2 effects are understood, there are important uncertainties regarding some of the non-CO_2 impacts and the underlying physical processes which require further investigation (ICAO, 2016a). 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, thus, will be the focus of this work.

Considering the above, this dissertation analyzes the implementation of a market-based environmental policy, where airlines pay an extra fee/cost, referred to as "carbon fee/cost", based on their CO_2 emissions. Furthermore, following Gonzalez and Hosoda (2016), we consider carbon fee implementation only on domestic flights and do not account for potential issues of inter-country negotiation. If an aviation carbon fee is not equally applied among countries, airlines may change their operational behavior to remain competitive (e.g., changing airports of choice and/or relocating to "low-fee" countries). Such a problem would not arise if the emission fee is imposed on domestic flights. The study area of this work is the United States.

6.4.2 The rationale of the airline carbon fee

The implementation of the carbon fee will raise the marginal cost of each regulated airline. In the short term, it is believed that the carbon cost will lead airlines to adjust ticket prices so as to reduce profit loss. The strategies of each airline with respect to the ticket price adjustments depend on the airline market structure, i.e. monopoly, oligopoly or perfect competition. Based on Forsyth (2008), in a competitive market, in the short run, a tax increase will impose a loss on airlines in the market. However, in the long run the imposition of a carbon fee may lead the airlines to fully pass through the carbon fee onto the passengers. Then, travel demand will fall depending on the elasticity of demand for flights. The exact amount of price increase depends on the demand elasticity and on the form of the marginal cost function. In this way the airline will face an unambiguous reduction in profit.

In the oligopoly case, airlines will respond to the carbon fee implementation by employing different strategies, such as Bertrand or Cournot strategies, and these will affect outcomes. In this work, we assume that airlines act under Bertrand competition. In order to calculate the changes of ticket prices after the introduction of the carbon fee, we conduct a simulation analysis, where the pre-policy airline's marginal cost ($c_{j,pre}$) is increased by the emission cost. Suppose that a carbon emission unit fee/cost F (in \$/tn CO_2) is introduced for every tonne of CO_2 emitted. The post-policy marginal cost ($c_{j,post}$) is given by:

$$c_{j,post} = c_{j,pre} + F \cdot \sum_{s=2}^{S} \frac{E_{s,j}}{LF_{s,j} \cdot SEAT_{s,j}}, where\ S = \{2,3,4\}, j \in J \qquad \textbf{Eq. 6.10}$$

$E_{s,j}$ 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 and multiplying with the carbon emissions unit cost.

It is assumed that ticket prices will be adjusted as a response to the carbon emission fee, based on the profit maximization behavior of airlines. The change in ticket prices will affect passenger choice and, thus, market shares of a given flight connection may also change. The change in airfares depends on airlines' decision to change their markups or not. If an airline decides not to adjust its markups, the carbon cost will be fully passed onto the passenger. On the other hand, if an airline decides to change its markups the carbon cost pass-through will be different than 100%. The precise value of the adjustment is determined from the new equilibrium associated with the post-policy marginal cost.

The market-based environmental policy is assumed to affect the configuration of airline's marginal cost function as given in Eq. 6.10. We substitute $c_{j,post}$ in Eq. 6.3 and apply a convergent simulation algorithm to obtain a solution to the system pricing equations. The basic elements of the simulation analysis include: (i) the parameter estimates of passenger's utility and marginal cost function, (ii) a market equilibrium assumption (Bertrand-Nash equilibrium) and (iii) the post-policy vector of each airline connection's marginal cost. The equilibrium price vector is found iteratively via a price adjustment process that starts with the benchmark pre-policy equilibrium prices and continues until convergence. This process can be viewed as iterating over airlines' best responses to price changes by all other airlines, until no airline has an incentive to deviate. The new market equilibrium is given by the new vector of ticket prices and the resulting market shares (by substituting post-policy ticket prices in Eq. 4.8). The market share for the non-air alternative is also updated and for an overall ticket price increase it will translate into higher market shares. It should be noted that the formulated model assumes that air travel demand and airlines' price behavior are static, abstracting from any capacity constraints faced by the airlines. This type of demand and pricing dynamic corresponds to the level of individual flights but our data provides us with no information at that level of individual flights at a particular day and time. As a consequence, we cannot identify which flights might be capacity constrained and, thus, we cannot model any changes in network configuration due to the introduction of the considered policy. For example, the market-based environmental policy may result in such air travel demand changes that could encourage the airlines to change their flight frequency or shift to larger or smaller aircraft on specific routes. Also, we cannot account for airlines' entry and exit behavior due to ticket price changes. If these constraints are binding for some airlines, the simulated outcomes will be different from reality.

6.4.3 Carbon price

As already mentioned, one key element is the level of uncertainty associated with the carbon price. For example, an environmental levy guarantees the carbon price in the economic system. In general, price certainty is desirable and a sufficiently high, long-term carbon price will maintain the incentives to invest in low-carbon technology. On the other hand, the price set under an ETS is flexible and depends on the quantity of emission allowances traded in the market (Kossoy et al., 2015). In this way, instabilities in the economic system may be harmful for the carbon market and may distort the ETS's functioning, one of the issues currently being tackled in the EU ETS. The evolution of allowance prices for five national or regional carbon pricing schemes is presented in Figure 6.3. It is noted that a carbon allowance refers to the amount of carbon emitted by the regulated companies (i.e. airlines) and is commonly denominated as one ton of carbon dioxide or its equivalent. Data are derived from various sources including the emission exchanges in Europe, the United States and China. In particular, price data for EU ETS were obtained from the SendeCO2 market (SENDECO2, 2016), California Carbon Allowance (CCA) prices were derived from California Carbon Dashboard (2016), allowance prices at the carbon market of the Chicago Climate Exchange (CCX) were collected from the Intercontinental Exchange (ICE, 2016), allowance prices under the Regional Greenhouse Gas Initiative (RGGI) were obtained from RGGI (2016) and Shanghai carbon prices were derived from the Hong Kong Emission Exchange (2016). From these measures only the EU and the Shanghai ETS mandatory cover aviation emissions. As this dissertation investigates the impact of market-based measures on air transport through the analysis of U.S. aviation industry, it is important to mention the prevailing prices in other non-aviation carbon schemes in the United States. The Chicago Climate Exchange (CCX) was the North America's voluntary trading system for emission sources and offset projects in North America and Brazil. CCX included six greenhouse gases, and traded GHG allowances from 2003 to 2010. CCX ceased trading carbon credits at the end of 2010 due to inactivity in the U.S. carbon markets. In 2013, California launched its cap-and-trade program to lower its greenhouse gas emissions. It included carbon dioxide and other GHG emissions, such as methane, nitrous oxide etc. Initially, the program applied to emissions from electricity and industrial sources, while in 2015 it expanded to fuel distributors, including those of ground transportation and heating fuels. The Regional Greenhouse Gas Initiative (RGGI) is the first mandatory, market-based CO_2 emissions reduction program in the United States. It started in 2009 with the participation of 9 U.S. states (Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island and Vermont). RGGI is composed of individual CO_2 Budget Trading Programs in each participating state where each state's trading program limits emissions of CO_2 from electricity and issues carbon allowances.

Figure 6.3 illustrates the trend in the carbon price in the different carbon pricing systems. Prices of these schemes are not necessarily comparable because of the schemes' differences in terms of the type and the number of sectors covered, the allocation methods etc. However, Figure 6.3 provides for a general view of the prevailing carbon prices. Among the schemes, EU ETS is the most long lasting program and has witnessed the most dramatic plunge. At the beginning of the second trading period (around 2008), the allowance prices reached their peaks with an average of $32.7/ton CO_2. Following the global and European economic crisis, the EU carbon prices fell significantly. The output and emissions of the covered entities were sharply reduced, which led to a large surplus of permits in the EU ETS. The lowest average EU allowance price was observed in 2013 at $5.9 per ton CO_2. Since then, the EU allowance price shows an increasing trend, reaching the price of $8.5 per ton CO_2 in 2015[23]. It should be noted that aviation entered the scheme in 2012 and the directive for aviation was amended in 2014. Carbon allowance were traded in Shanghai's ETS at even lower prices; prices were on average $6 and $4 per ton in 2014 and 2015 (from January to June 2015) respectively.

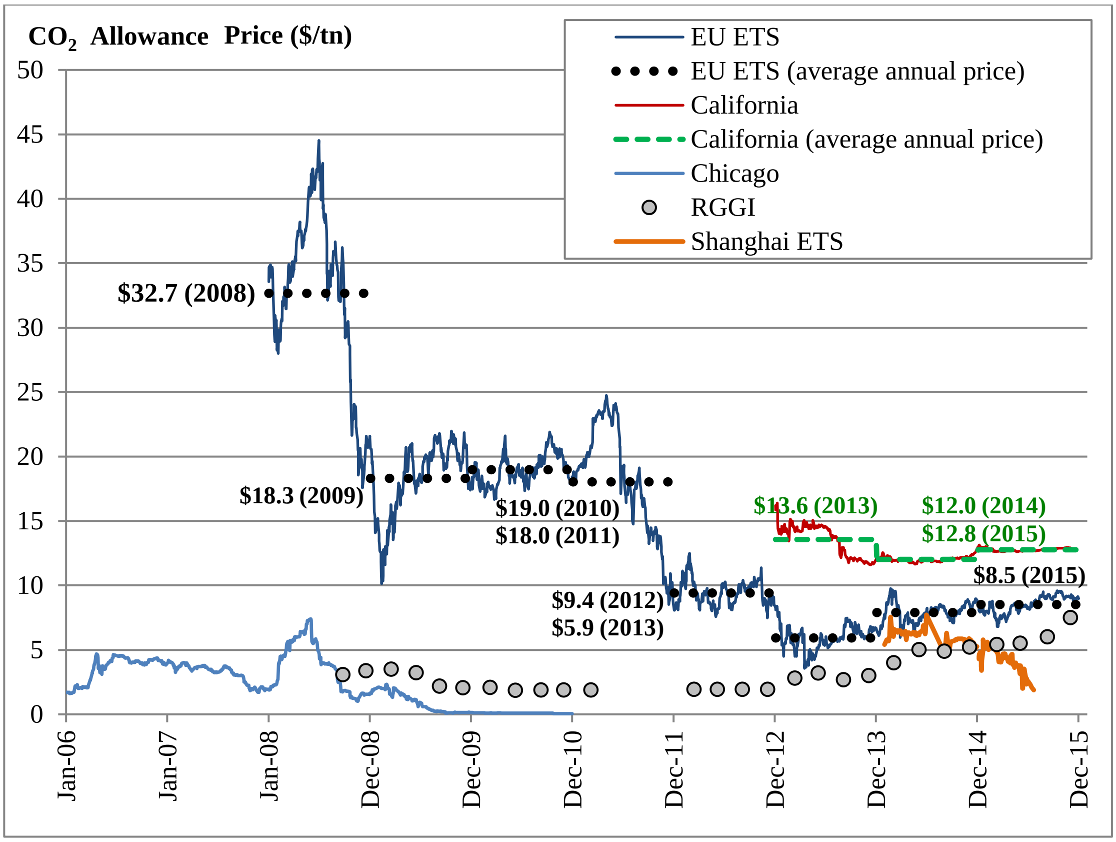
With respect to non-aviation schemes, California's market has slightly higher allowance prices of around $12 to $16 since 2013. In its first year, the average price was $13.6 per ton, while in 2015 carbon was traded at around $12.8. On the other hand, RGGI's prices are very low; for a long period (until the middle of 2014), carbon allowances were auctioned at prices less than $5 per ton (around $2 to $3). Since then, the prices were a bit higher; at the end of 2015 the prices were around $7.5.

Economic theory suggests that emission levies should be set at a level that represents the social cost of emissions (Carlsson & Hammar, 2002). Nonetheless, estimates of the social costs associated with greenhouse gas emissions vary. According to IPCC (2007), the social costs of carbon had an average value of $12 per tonne of CO_2 (in 2005 dollars) with a range of $3 to $95 per tonne (in 2005 dollars). The report also states that the social costs

[23] As of December 2016, EU allowance price level was on average around 5.2€ (which is around $5.5, assuming an average exchange rate of 1€=$1.0567)

of carbon are projected to be significant and to increase over time. In Europe, carbon prices on non-aviation sectors are much higher in comparison to the ETS allowance prices reported earlier. Some examples are given below for 2015 (per ton CO_2); Sweden carbon tax: $130, Finland carbon tax: $64 (for transport fuels), Switzerland carbon tax: $62, Denmark carbon tax: $25, Ireland carbon tax: $22, France carbon tax: $16 (Kossoy et al., 2015).

Based on the above analysis and to account for the uncertainties related to carbon price, this dissertation considers three different scenarios for the carbon price: (i) low scenario, $10 per ton, (ii) medium scenario, $20 per ton and (iii) high scenario, $50 and $100 per ton of CO_2. More details are given in Section 8.2.



Notes: EU ETS: EU Allowance spot price, California: California Carbon Allowance futures, Chicago: Chicago Climate Exchange Carbon spot prices, RGGI: auction prices, Shanghai: Shanghai Emissions Allowance spot price. Exchange rates for the desired time periods were obtained from: http://www.usforex.com/forex-tools/historical-rate-tools/historical-exchange-rates (access on 21.07.16)

Figure 6.3. Allowance prices in implemented carbon pricing instruments

7 Data

Estimation of the supply and demand model and simulation of the market-based environmental policy require a rich dataset with information on airline connection, flight passengers, ticket prices and other explanatory attributes that affect passenger demand and airline marginal cost. In addition, aircraft and airport data is needed for the computation of CO_2 emissions (see also Section 3.4.3 for some data sources used in the CO_2 emissions modelling).

Our study area is the domestic air transport network of the United States, while our study period is the year 2012. This network is selected for several reasons. First, it serves a large part of global passenger traffic, accounting for 27% of global scheduled traffic in terms of revenue passenger kilometers (RPK) in 2012. Also, 2012 U.S. domestic RPKs accounted for 49% of total domestic market (ICAO, 2013c). Second, the U.S. airline network is considered to be a stable competitive market, as it has been deregulated since 1978. Most U.S. markets are served by more than two airlines, thus, providing a suitable ground for applying an oligopoly game between competing airlines. In our traffic sample, in each market there are on average 4.8 airlines. Finally, U.S. is one of the few countries that provides publicly available itinerary traffic data (Garrow, 2010). In particular, the U.S. market-level itinerary traffic data are compiled by the U.S. Department of Transportation (BTS, n.d.) and cover the full itinerary of U.S. domestic passengers which means that one can determine the full composition of traffic in each route area.

This chapter describes the data sources used in this dissertation (Section 7.1). A filtering process is adopted and described in Section 7.2, while the resulting sample data is presented in Section 7.3 along with associated summary tables and statistics.

7.1 Data Sources

Data available by the U.S. Department of Transportation published in the website of the Bureau of Transportation Statistics is used. In particular, three databases are employed: (i) the Airline Origin and Destination Survey (DB1B), (ii) the T-100 Domestic Segment for U.S. Carriers (T-100) and (iii) the On-Time Performance (OTP) database. In addition, 2012 population data from the U.S. Census Bureau (2015) are obtained.

The Airline Origin and Destination Survey (DB1B) reports a 10% sample of domestic airline tickets sold by U.S. airlines. It is the key database of this dissertation and is used to create the flight itineraries and to generate airline connections' market shares, ticket prices and other itinerary attributes presented in Table 7.4. DB1B consists of three sub-components (Market, Coupon and Ticket data) which are properly merged to create the final DB1B dataset as described in Appendix C-1.

The above dataset is merged 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 (T-100) contains monthly domestic non-stop segment data reported by U.S. air carriers. The variables constructed by T-100 include frequency and representative aircraft types. Airline On-Time Performance (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. Each airport in our sample is assigned to their corresponding Metropolitan Statistical Area (MSA). Appendix B-2 presents the MSAs and airports selected and associated population data.

7.2 Cleaning raw data

The DB1B raw data for 2012 included about 36.7 million non-stop segments (DB1B Coupon), 22.7 million directional markets (DB1B Market) and 13.1 million tickets (DB1B Ticket). Figure 7.1 illustrates the data included in the three data tables for an itinerary between the ABE and ATL airports. In this example, the origin airport is ABE and the destination airport is ATL. The ABE-ATL flight is a one-stop flight (connecting airport is CLT) while the return flight is direct. The DB1B Coupon table provides segment-specific information for each domestic itinerary, such as operating airline, origin and destination airports, number of passengers and distance. The DB1B Market table contains directional market characteristics of each itinerary, such as the reporting airline, origin and destination airport, market fare, number of market coupons, market miles flown, and carrier change indicators. Finally, the DB1B Ticket table contains summary characteristics of the entire itinerary, including the reporting airline, itinerary fare, number of passengers, originating airport, roundtrip indicator and miles flown.

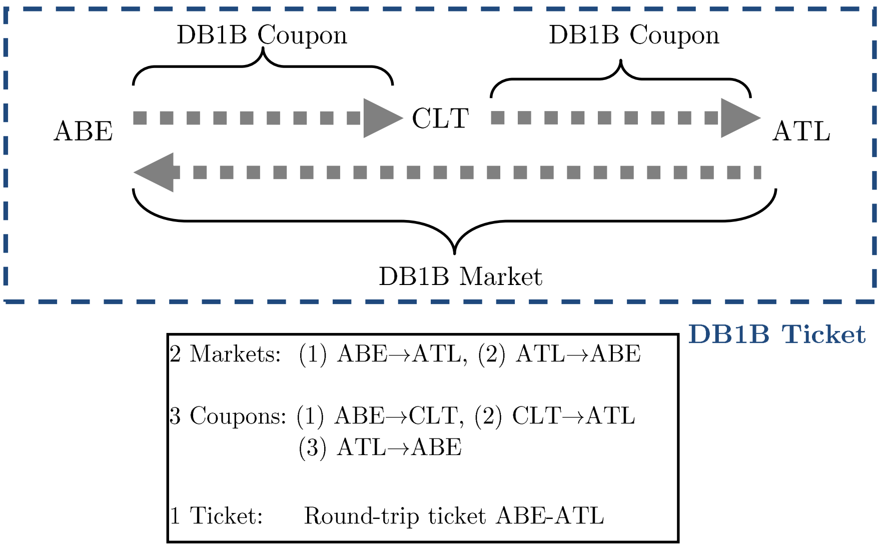


Figure 7.1. Illustration of DB1B data tables

The data used for estimating the model is filtered to ensure relevant and reliable data set. The construction of the final sample follows a well-established procedure (Berry and Jia, 2010; Chi and Koo, 2009; Lee, 2013a; Hsiao and Hansen, 2011) consisting of the following steps. First the DB1B database is filtered based on the following criteria:

1. Round-trip domestic itineraries (68.6% of total tickets) with at most two segments per direction are considered.
2. Tickets with multiple ticketing carriers in the market are omitted, which are about 3.4% of all domestic tickets.
3. Tickets whose fares are indicated as incredible are excluded (around 0.7%).
4. Open-jaw[24] trips are eliminated (around 2.6%), because they are known to be subject to different pricing scheme relative to the ordinary round-trip tickets.
5. Tickets with no data on the ticketing or operating or reporting carrier in a segment of the market are omitted (around 1.3% of all domestic tickets).
6. Tickets with very low and very high air fares are eliminated. Tickets in the fare range of \$25 and \$3000 for a round-trip are retained. These account for 94.6% of all domestic tickets in 2012. The aim is to omit tickets purchased using frequent flyer miles (lower bound) and to restrict the sample to coach-class travel (higher bound).

   Even after the application of the above filtering process, tickets with low fare and long distance were observed in the sample. Longer trips tend to have lower fare per mile because the fixed costs associated with each flight can be spread over a larger number of miles (as shown in Figure 7.2). However, tickets (i) in the bottom and top 5% of the fare per mile distribution and (ii) whose fare is less than 3 cents per mile were excluded from the sample since their fare were unreasonable low/high.

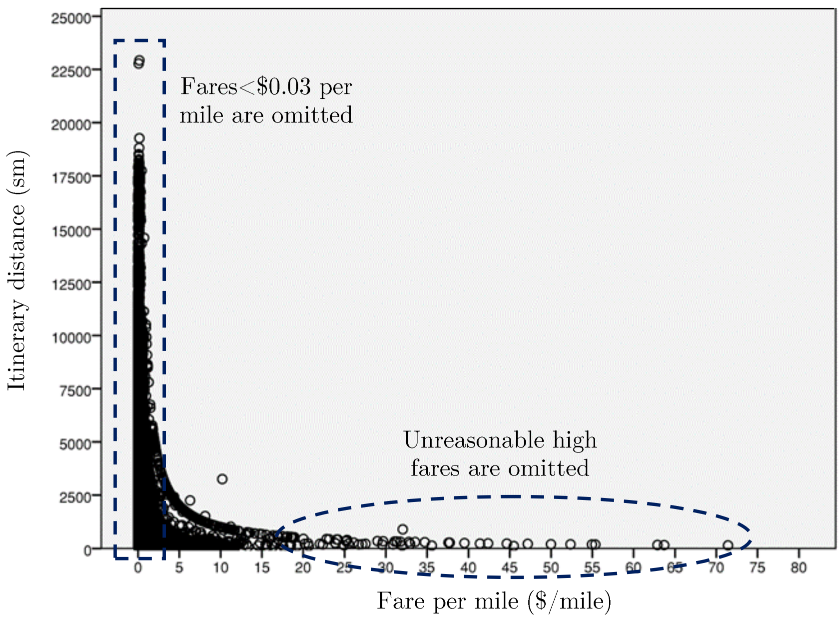


Figure 7.2. Ticket price per mile in relationship with miles flown[25]

[24] An open-jaw ticket is a round-trip ticket in which the traveler does not arrive the same city of departure and/or does not depart from the same city where first landed. A sample open-jaw itinerary might be a flight from SRQ to SLC on the way out and from SLC to MCO on the way back.
[25] It is noted that itinerary distance corresponds to the total miles flown in the round-trip route.

In the second step, we process T-100 and OTP data to be compatible with the DB1B database. Since T-100 and OTP are reported in a monthly basis, and DB1B data are quarterly, we need to aggregate T-100 and OTP in a quarterly basis. Once this is done, edited T-100 and OTP tables include frequency, aircraft and time-related quarterly data. T-100 data tables are filtered as follows:

- Freight traffic data is eliminated from the data. In 2012, these accounted to 13% of all domestic flights and were excluded.
- Records with no data on passengers travelled and departures performed are eliminated.

In OTP tables, some records were excluded from the sample as they were considered as outliers. Flights with unavailable departure/arrival delays and airborne time are discarded. Flights with airborne time shorter than 15 minutes or with departure/arrival delay longer than five hours are also eliminated.

In the third step, we merge the three databases by flight segment and airline. DB1B and T-100 segments are merged by operating airline while DB1B and OTP by reporting airline (details on the merging process of DB1B, T-100 and OTP are given in Appendix C-1). 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 population threshold results in the top 67 MSAs in 2012.

The resulting database had over 3.3 million observations. 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". In this data table, passengers are aggregated over a given itinerary-airline-quarter combination. Thus, for each combination of "O_j-C_j-D_j/A_j,Q_j" we know the total number of passengers travelled. The average ticket price is then computed along with other demand and cost variables, and the final sample data is created.

7.3 Resulting Sample Data

The final sample data has 89,667 airline connections, 13,432 markets[26] (O-D city pairs), 67 origin and destination cities, 91 airports and 11 ticketing airlines. On average, each O-D city pair offered 6.7 flight connections and served 6,446 passengers in 2012, as shown in Table 7.1.

[26] A market is a directional origin and destination city during a specific quarter. Thus, the same itineraries in different quarters are considered as different airline connections in different markets.

Table 7.1. Summary statistics of the traffic sample

Sample data for 2012	
Number of airline connections	89,667
Number of markets (O-D city pairs)	13,432
Number of different cities	66
Number of different ticketing airlines	11
Number of different airports	91
Passengers (in 1000)	86,578

Within market (O-D city pair)	**Mean**	**Std**	**Min**	**Max**
Number of connections	6.7	8.7	1	124
Number of passengers (in 1000)	6.45	16.65	0.05	337.1

DB1B data tables are compiled in a quarterly basis. Table 7.2 presents summary statistics of the resulting traffic sample by quarter during 2012. Based on our traffic sample, air passenger flows are spread during the year, while the second and third quarters receive the majority of passengers (about 51.9% of annual passenger traffic). This is in consistency with the official U.S. Air Carrier Traffic Statistics for 2012 (2nd and 3rd quarter traffic accounts for 52.2% of annual passengers) published on the website of the Bureau of Transportation Statistics (BTS, 2016b).

Table 7.2. Quarterly-based statistics of the traffic sample

	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Total
Number of observations	19,228	23,631	23,296	23,512	89,667
% of observations	21.4%	26.4%	26.0%	26.2%	100%
Number of passengers (in million)	19.1	23.0	21.9	22.6	86.6
% of passengers	22.0%	26.6%	25.3%	26.1%	100%
Distance (sm)	5.8E+07	7.5E+07	7.5E+07	7.4E+07	2.8E+08
% of distance	20.6%	26.7%	26.5%	26.2%	100%
Passenger-miles	1.11E+15	1.73E+15	1.64E+15	1.67E+15	6.15E+15
% of passenger-miles	18.0%	28.1%	26.7%	27.2%	100%

The assessment of the market-based environmental policy relies on an oligopoly game developed by the airlines in each O-D market. As shown in Table 7.3, the sample markets consist of 21.5% monopolies, 21.6% duopolies and 56.9% oligopolies.

Table 7.3. Summary statistics by market structure

	1 airline	2 airlines	3 or more airlines	Total or average
O-D pairs	2,890	2,912	7,630	13,432
Share of O-D pairs	21.5%	21.6%	56.9%	100%
Number of passengers (in million)	1.65	6.05	78.9	86.6
Average ticket price (US$)	520.16	473.35	453.80	458.33

The above table also indicates that ticket price decreases with more active airlines in the market. In particular, in the markets of three or more competitors (which represents the majority of city pairs studied), average ticket prices are 14.6% and 4.3% lower than those associated with 1 and 2 competitors respectively, indicating a high degree of fare competition.

Figure 7.3 presents ticket price and passenger traffic data for the eleven airlines of our traffic sample. On the x-axis, the airlines are grouped in legacy and low cost airlines. Furthermore, “n” indicates the number of airline connections served by each airline (e.g.

Virgin America (VX) ranks last with 327 airline connections). Based on our traffic sample, in 2012, more than half of the passengers flew by legacy airlines (about 54.6%). The low cost airline Southwest (WN) ranks first in passenger traffic with 24.8 million passengers, and Delta Airlines (DL) follows with 14.6 million passengers. Furthermore, Southwest (WN) served about 28 thousand airline connections, while Delta Airlines (DL) follows with about 19 thousand connections. With regard to the average ticket prices by airline, we observe that the average fares of the low cost airlines (WN, B6, FL, F9 and VX) are not much lower that the legacy's fares. This has also been reported in past studies where it is found that the price premium charged by legacy airlines over low cost airlines has eroded. In particular, Borenstein (2011) estimated that the fare premium has decreased from over 90 percent in the early 1990s to over 30 percent in 2009. In our sample, the low cost airline AirTran Airways (FL) had the lowest average ticket price (equal to $348.3). Furthermore, this airline served the shorter round-trip itineraries on average. In our traffic sample, AirTran Airways flew on average 2,689 miles per round-trip itinerary. It is expected that shorter itineraries are cheaper than longer. On the contrary, Hawaiian Airlines had the longest round-trips on average (5,186 miles per round-trip itinerary) and had the highest ticket price.

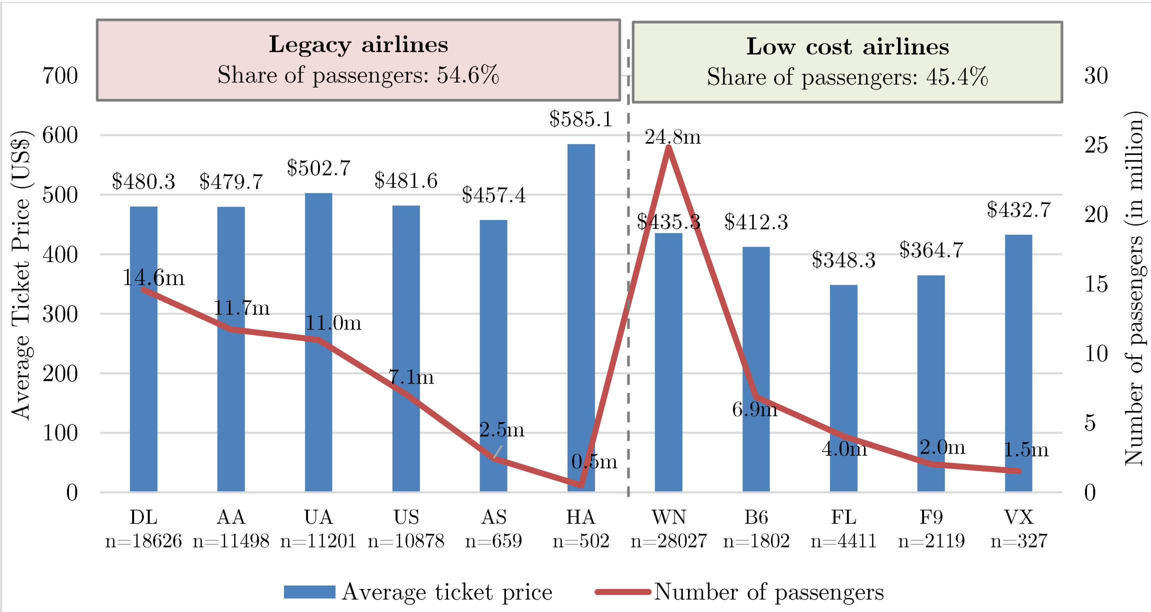


Figure 7.3. Ticket price and passenger traffic data by airline

Table 7.4 summarizes the selected demand and cost variables with descriptive statistics and data source. As already explained, several test runs of the demand and supply models were conducted to choose these variables.

Table 7.4. Summary statistics of demand and cost variables

Variable	Demand/ Cost[a]	Mean (std.dev)	[Min, Max]	Source
- Airline-route specific				
Ticket price [in $100]	D	4.573 (1.35)	[1.16, 13]	DBIB
Number of stops	D	1.556 (0.77)	[0, 2]	DBIB
Round trip distance [in 1000 sm]	C	3.146 (1.49)	[0.17, 10.43]	DBIB
Minimum frequency (flights/quarter)	D	279.89 (191.4)	[12, 1992]	T-100
% of morning departures	D	0.245 (0.17)	[0, 1]	OTP
Aircraft size	C	0.269 (0.44)	[0, 1]	T-100
Per passenger fuel [tn fuel/pax]	C	0.151 (0.06)	[0.01,0.57]	Own-computation[b]
- Airport-specific				
Slot control	D	0.130 (0.36)	[0, 3]	DB1B
Delays	D	0.176 (0.07)	[0, 1]	OTP
Alternative airport	D	0.604 (0.49)	[0, 1]	Own-computation
- Airport-Airline relationship				
Hub	C	0.630 (0.48)	[0, 1]	DB1B
- Market specific				
Market distance [in 1000 sm]	D	1.572 (0.74)	[0.09, 5.22]	DB1B
- Airline dummies				
Jet Blue Airways	D and C	0.021 (0.14)	[0,1]	DB1B
Delta Air Lines	D and C	0.208 (0.41)	[0,1]	DB1B
American Airlines	D and C	0.128 (0.33)	[0,1]	DB1B
Southwest Airlines	D and C	0.311 (0.46)	[0,1]	DB1B
Other legacy airlines	D and C	0.133 (0.34)	[0,1]	DB1B
Other low-cost airlines	D and C	0.074 (0.26)	[0,1]	DB1B

Number of O-D markets: 13,432

Number of airline connections (observations): 89,667

Study period: Year 2012

Table notes: [a] D: Demand variable, C: Cost variable

[b] Fuel for both the LTO and CCD cycles. LTO fuel is based on the ICAO Engine Exhaust Emissions Databank, while CCD fuel is computed on the registration-based typical profiles and by applying the BADA fuel flow coefficients, as explained in Chapter 3.

The ticket price of each round-trip is taken as the passenger-weighted average ticket price. In fact, in a given airline connection, different ticket prices may exist which correspond to different passenger classes (business, economy etc). However, since we do not observe individual passenger information, we cannot identify the passenger class of each ticket record and, thus, do not account for passenger heterogeneity. In 2012, the passenger-weighted average ticket price was equal to $457.3. 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 flights, the variable is equal to zero. On average, each airline connection of the sample had 1.56 stops. The itinerary frequency is calculated as the logarithm of the minimum of segment frequencies. Round-trip distance (cost variable) was on average 3,146 miles, while average market distance (demand variable) is 1,572 sm. Regarding the time-related variables, it is found that in 2012 24.5% of airline connections are offered in the morning period. In addition, on average, 17.6% of flights experienced more than 15 minutes delay during the previous quarter of decision. 26.9% itineraries are served by wide-body aircraft in at least one their segments, while the average fuel consumption is calculated equal to 0.151 tn per passenger. In 2012, each airline connection of the sample passes via 0.13 slot-controlled airports.

The supply and demand models are estimated by using instrumental variables to address endogeneity of ticket prices and market shares. Table 7.5 summarizes the selected demand and supply instrumental variables along with their descriptive statistics, based on the 2012 sample.

Table 7.5. Summary statistics of demand and supply instrumental variables

Instrumental Variable	Demand/ Supply[(a)]	Mean	Std deviation	Min	Max
- Cost-shifting instruments					
Hub indicator (whether the destination airport is hub for the airline)	D	0.103	0.304	0	1
Hub indicator (whether the connecting airport is hub for the airline)	D	0.476	0.499	0	1
- Market-level characteristics					
Number of airline connections within a market	S	17.720	18.778	1	124
Number of airlines within a market	D and S	4.833	2.024	1	10
- Rival connections' characteristics					
Percentage of nonstop routes that rivals operate in the same market	D and S	0.259	0.290	0	1
Average number of passengers carried by rivals in the market	S	100.2	171.89	0	4037.0
- Airline's size of operation					
Number of cities that the airline directly serves from the origin airport	D and S	12.376	13.070	0	60
- Other supply-side instruments					
By-connection market size (in millions)	S	0.384	0.407	0.02	9.29
By-airline market size (in millions)	S	0.790	0.476	0.20	0.48

Table notes: [(a)] D: included in the demand equation, S: included in the supply equation

8 Results

This chapter is divided in two parts; the first part (Section 8.1) presents the results derived from the estimation of the air travel demand model and the airline's behavior model. In detail, the parameter estimates of the models are presented and discussed. Finally, a comparison of estimated and observed passenger demand and ticket prices is undertaken which reveals the goodness of fit of the demand and supply model. In the second part (Section 8.2), our findings obtained by the implementation of the market-based environmental policy are presented. Post-policy equilibrium ticket prices and market shares are estimated. Several issues such as the carbon price variation, the estimated pass-through rate, and the post-policy market concentration are also discussed.

8.1 Model estimation and validation results

When developing an econometric model three main tasks take place: model specification, estimation and validation. In the current section, the model estimation and validation are undertaken. The model specification, where the explanatory variables and the data to be used in the estimation stage are defined, is included in Chapters 4 (demand model), 5 (airline behavior model) and 7 (air traffic data). In the estimation process we obtain the estimation values of the coefficients of the demand and supply parameters. This task is encountered in Section 8.1.1. In Section 8.1.2, the first task of the validation stage, which is to evaluate the estimated model parameters, is included. In particular, the parameter estimates obtained in the estimation stage are evaluated in terms of the expected signs and magnitudes, while statistical tests are performed on their significance. Additional statistical diagnostics are conducted for the instrumental variables used for addressing the ticket price and market shares' endogeneity. Another validation sub-task is also undertaken to establish the goodness of fit of our model. We compare the predicted values of the passenger demand and ticket prices with the values actually observed.

8.1.1 Parameter Estimates

Several test runs were conducted to choose the appropriate demand and cost variables. The final variable set is chosen based on the estimation results and applied statistical tests as well as practical insights based on our intuition and prior literature.

The demand parameter estimates and the associated statistics are reported in Table 8.1 for different demand model specifications. Demand-alone parameter coefficients estimated by the OLS and 2SLS methods are presented for comparison purposes. The OLS and 2SLS comparison reveals the endogeneity issue. Besides, the 2SLS estimates are used to initiate the Generalized Method of Moments (GMM) and obtain the optimal weight matrix, as explained in Section 6.3. In this work, the Nested Logit (NL) model is assumed to express the decision process of travelers within markets. However, estimation results are also presented for the Multinomial Logit (MNL) model for comparison purposes. The estimation results of our final model are presented in Table 8.2, where the air travel demand is modelled by the Nested Logit and is jointly estimated with the supply side by the use of GMM method.

8.1.2 Validation

- Comparison of OLS and 2SLS estimates

In the demand model, ticket price is likely to be correlated with the unobserved-to-researcher characteristic ξ. The OLS estimation ignores the endogeneity of ticket price and therefore the estimates of the price coefficient are most likely biased. To confirm the endogeneity of price we estimate the demand equation using OLS and 2SLS. We compare the results given in columns (3) and (5) of Table 8.1 which correspond to the same model (assumptions of Nested Logit model and demand-alone estimation) except for the method of estimation; column (3) reports OLS estimates, while Column (5) gives 2SLS estimates. Although the estimated ticket price coefficient (-0.175) in column (3) illustrate negative fare impacts on demand, the magnitude of price coefficient in the 2SLS estimates is much larger (in absolute value) than that from OLS. This suggests that the endogeneity of price results in severe bias of the price coefficient estimate if instruments are not used for ticket price.

- Comparison of parameter estimates for the MNL and NL models

We now discuss results from assuming MNL or NL models to model the market share function. We compare the results given in columns (1) and (3) of Table 8.1, which consider MNL and NL models respectively. The estimated coefficient of ticket price is equal to -0.032 for the MNL model and equal to -0.175 for the NL model. MNL and NL models give similar patterns of coefficients for most demand variables, except time-related and delay variables and few airline dummies. The negative coefficients of the percentage of morning departures indicate that the attractiveness of an airline connection is lower in these departure time periods, which is opposed to our intuition and the literature recommendations. Furthermore, in the MNL model the estimated coefficient of the delay variable is positive, meaning that the passengers may be attracted by arrival delays. However, it is unreasonable to expect that delays positively influence passenger itinerary choices. Next, we focus on the value of $MS_{j/g}$'s coefficient. The parameter λ is a measure of the degree of independence within airline alternatives in air nest. Higher value of λ means greater independence and less correlation. The estimated value of *(1-λ)* in the OLS-NL case (column 3) indicates a correlation of 0.44 in the preferences of passengers for air. Based on the above remarks, it is concluded that the Nested Logit model is more preferable than the Multinomial Logit.

Table 8.1. Estimation results for different demand model specifications

Dependent variable: $\ln MS_j - \ln MS_0$						
	Single equation OLS-MNL		Single equation OLS-NL		Single equation 2SLS-NL	
Variable	Coefficient (s.e.)	t-value	Coefficient (s.e.)	t-value	Coefficient (s.e.)	t-value
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-9.823* (0.044)	-220.746	-8.575* (0.033)	-262.440	-7.631* (0.060)	-127.186
Ticket price	-0.032* (0.004)	-8.802	-0.175* (0.003)	-64.660	-0.481* (0.012)	-39.711
$\ln(MS_{j/g})$ *(1-λ)*	-	-	0.440* (0.002)	231.896	0.357* (0.004)	82.503
Number of stops	-1.180* (0.006)	-197.156	-0.906* (0.004)	-201.636	-0.983* (0.005)	-181.695
Market distance	-0.111* (0.007)	-15.441	0.116* (0.005)	21.778	0.381* (0.013)	29.231
ln(minimum frequency)	0.499* (0.007)	74.187	0.474* (0.005)	97.347	0.473* (0.006)	84.907
% of morning departures	-0.009 (0.025)	0.360	0.099* (0.018)	5.573	0.127* (0.020)	6.231
Slot control	-0.537* (0.012)	-43.788	-0.134* (0.009)	-14.836	-0.271* (0.011)	-25.674
Delays	0.111** (0.065)	1.696	-0.318* (0.047)	-6.745	-0.171* (0.054)	-3.545
Alternative airport	-0.603* (0.009)	-68.906	-0.043* (0.007)	-6.326	-0.183* (0.009)	-21.101
Jet Blue Airways	0.765* (0.032)	23.915	0.310* (0.023)	13.317	0.175* (0.029)	6.125
Delta Air Lines	0.124* (0.015)	8.486	-0.103* (0.011)	-9.735	-0.068* (0.012)	-5.506
American Airlines	0.198* (0.017)	11.440	-0.208* (0.013)	-16.475	-0.163* (0.015)	-10.831
Southwest Airlines	-0.110* (0.014)	-7.861	-0.111* (0.010)	-10.907	-0.209* (0.012)	-17.388
Other low-cost airlines	0.429* (0.019)	22.072	0.115* (0.014)	8.158	-0.194* (0.021)	-9.053
Other legacy airlines	-0.123* (0.017)	-7.289	-0.155* (0.012)	-12.638	-0.116* (0.014)	-8.338
Adjusted R^2	0.539		0.758			
F-stat.	4960.7 (prob.=0.00)		12410.8 (prob=0.00)			
Ticket price: $R^2_{adjusted}$ 1st stage					0.415	
F-stat. 1st stage (p-value)					2305.2 (0.00)	
$\ln(MS_{j/g})$: $R^2_{adjusted}$ 1st stage					0.665	
F-stat. 1st stage (p-value)					6565.3 (0.00)	
Number of observations: 89,667						

Notes: OLS-MNL: MNL (single equation) demand model estimated by OLS, OLS-NL: NL (single equation) demand model estimated by OLS, 2SLS-NL: NL (single equation) demand model estimated by 2SLS
Instrumental variables used in the IV methods are given in Table 7.5
*: significant at 1% level, **: significant at 10% level
US Airways is used as the base airline in the estimation

- <u>Final model: System equation GMM-NL</u>

To improve the efficiency of demand and supply estimates, the two equations are eventually estimated jointly. The results from the joint estimation of parameters are reported in Table 8.2 and are discussed next.

The coefficients associated with the explanatory demand variables have the expected sign. As expected, the ticket price has negative effect on air travel demand (-0.46). The estimated value of *(1-λ)* indicates a correlation of 0.347 in the preferences of passengers for air, which reflects moderate substitution possibility among flight connections. The negative coefficient of the number of stops (-0.991) 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 0.36 which reflects the fact that aircraft is the preferred long distance transport mode. The frequency coefficient (0.473) indicates that passenger's utility increases with the number of departures (in logarithmic form). The other indicator of quality of service, namely the percentage of morning departures, has positive coefficient (0.158). This value indicates that airlines attract more passengers if they offer a large percentage of connections during morning hours. On the contrary, market shares are negatively influenced by delays. Arrival delays at the destination airport of more than 15 minutes negatively affect passenger's utility (-0.246). The variable slot-controlled airports is also negatively weighted (-0.278). Flight delays frequently observed at slot-controlled airports may discourage passengers from choosing these airports. The negative coefficient of the variable alternative airport (-0.196) 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.

Table 8.2. Estimation results of the demand and supply system equation

Dependent variable: $lnMS_j$ - $lnMS_0$			**Dependent variable: p_j (fare)**		
Demand variables	Coefficient (s.e.)	t-value	Cost variables	Coefficient (std.err)	t-value
Constant	-7.687* (0.065)	-117.742	Constant	1.651* (0.024)	68.913
Ticket price	-0.460* (0.013)	-34.179	Round-trip distance	0.480* (0.004)	136.798
$\ln(MS_{j/g})$ *(1-λ)*	0.347* (0.005)	74.228	Aircraft size	-0.148* (0.014)	-10.36
Number of stops	-0.991* (0.006)	-163.194	Hub dummy	0.053* (0.020)	2.673
Market distance	0.360* (0.014)	24.909	Jet Blue Airways	-0.837* (0.027)	-29.89
ln(minimum frequency)	0.473* (0.006)	76.687	Delta Air Lines	-0.095* (0.018)	-5.405
% of morning departures	0.158* (0.021)	7.537	American Airlines	-0.162* (0.017)	-9.314
Slot control	-0.278* (0.011)	-25.170	Southwest Airlines	-0.360* (0.023)	-15.820
Delays	-0.246* (0.057)	-4.289	Other low-cost airline	-1.082* (0.016)	-66.630
Alternative airport	-0.196* (0.009)	-22.762	Other legacy airlines	0.085* (0.020)	4.315
Jet Blue Airways	0.178* (0.029)	6.176			
Delta Air Lines	-0.077* (0.013)	-6.133			
American Airlines	-0.156* (0.016)	-9.717			
Southwest Airlines	-0.246* (0.012)	-20.528			
Other low-cost airlines	-0.183* (0.022)	-8.244			
Other legacy airlines	-0.092* (0.016)	-5.746			

Statistics:	
Ticket price: $R^2_{adjusted}$ 1st stage	0.415
F-stat. 1st stage (p-value)	2305.2 (0.00)
$\ln(MS_{j/g})$: $R^2_{adjusted}$ 1st stage	0.665
F-stat. 1st stage (p-value)	6565.3 (0.00)
GMM objective	1020.9
Cragg-Donald F-statistic	806.4 (>Stock-$Yogo_{0.05}$=19.45)
Overid. test p-value (10% signif. Level)	0.00
Durbin-Wu-Hausman test p-value	0.00
Number of observations: 89,667	

Notes: Instrumental variables used in the model are given in Table 7.5
*: significant at 1% level
US Airways is used as the base airline in the estimation

The estimated cost parameters have also the expected sign. The positive coefficient of round-trip distance (0.48) indicates that cost rises with distance travelled. The aircraft size coefficient (-0.148) 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 as well documented in Wei and Hansen (2003) and Ryerson and Hansen (2013). 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, 2013a; 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 (0.053) 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 (-1.082), with Jet Blue Airways being the most cost efficient (-0.837) followed by Southwest Airlines (-0.36). The airline dummies have been constructed by taking the US Airways as the base airline. Thus, the estimated coefficients show the magnitudes of the other airlines' marginal cost in comparison with the base carrier (US Airways).

Before concluding to the model of Table 8.2, we ran several models with different demand and cost variables each time. To choose among the different models, a specific evaluation procedure was followed which included:

- Evaluation of the parameter estimates (e.g. whether they have the expected signs and magnitudes) and their corresponding t-statistics and p-values. For example, in Pagoni and Psaraki (2015), we estimated the models for a smaller time period (we used data for the 1st quarter of 2012) and we experimented with using the "late-afternoon departures" variable in the demand model to assess the attractiveness of an airline connection based on the time of departure (as explained in Section 4.3.2). In this paper the "late-afternoon departures" variable had positive coefficient (equal to 0.14) and was statistically significant. However, in the model developed for the sample of the whole year (2012) this variable was not found to be statistically significant and was excluded from the demand function.
- Due to the endogeneity issue, suitable instrumental variables are used to estimate the model. To justify the appropriateness of the selected instruments, three instrumental variables diagnostics are applied as explained in Section 6.2.3. The statistical package Eviews is used for performing the tests. Cragg-Donald F-statistic for the explanatory power of the instruments is equal to 806.4, which is much higher than the Stock-Yogo critical value for 95% confidence level (equal to 19.45), indicating that the instruments are not weak. The test of the overidentifying restrictions (to check the exogeneity of the instruments) was performed several times for different sets of instruments by regressing the residuals of the IV regressions with the selected instruments. The resulting $m_Z{\cdot}F$ was found less than the chi-squared critical value. The results did not reject the orthogonality condition at the 10% level. Finally, the Durbin-Wu-Hausman test is performed. The test was found statistically significant (p-value=0.00) which means that the null hypothesis (there are no differences between the model in which price and market shares are treated as endogenous and the model where they are treated as exogenous) can be rejected, and thus ticket price and market shares are endogenous. Overall, we conclude that our instruments are exogenous and not weak and that ticket price and market shares are endogenous.

Finally, we measure how well the estimated equations reproduce the observed data by comparing two indicators: the passenger demand, which reveals the goodness of fit of the demand model and the ticket prices, which reflect the characteristics of the supply side. To obtain the estimated data, we substitute the demand and marginal cost estimates of Table 8.2 into Eq. 5.4 and solve the equation for ticket price. Then, the estimated prices are substituted into the market share function (Eq. 4.9) to predict market shares.

Estimated passenger demand is calculated by multiplying the estimated market shares with the respective market size. The results are illustrated in Figure 8.1 which provides a comparison of average observed and estimated ticket prices (upper figure-a) and market shares (lower figure-b). Summed across all airline connections, estimated market shares are only 1.86% higher than the observed data while modeled ticket prices are only 0.72% lower than the observed. Ticket prices are slightly over-estimated for direct flights (0.59%) while they are slightly under-estimated for non-direct flights (0.75%). With regard to market distance, the largest prediction error of ticket price is for markets of more than 2500 sm distance where average ticket prices are over-predicted by 2.1%.

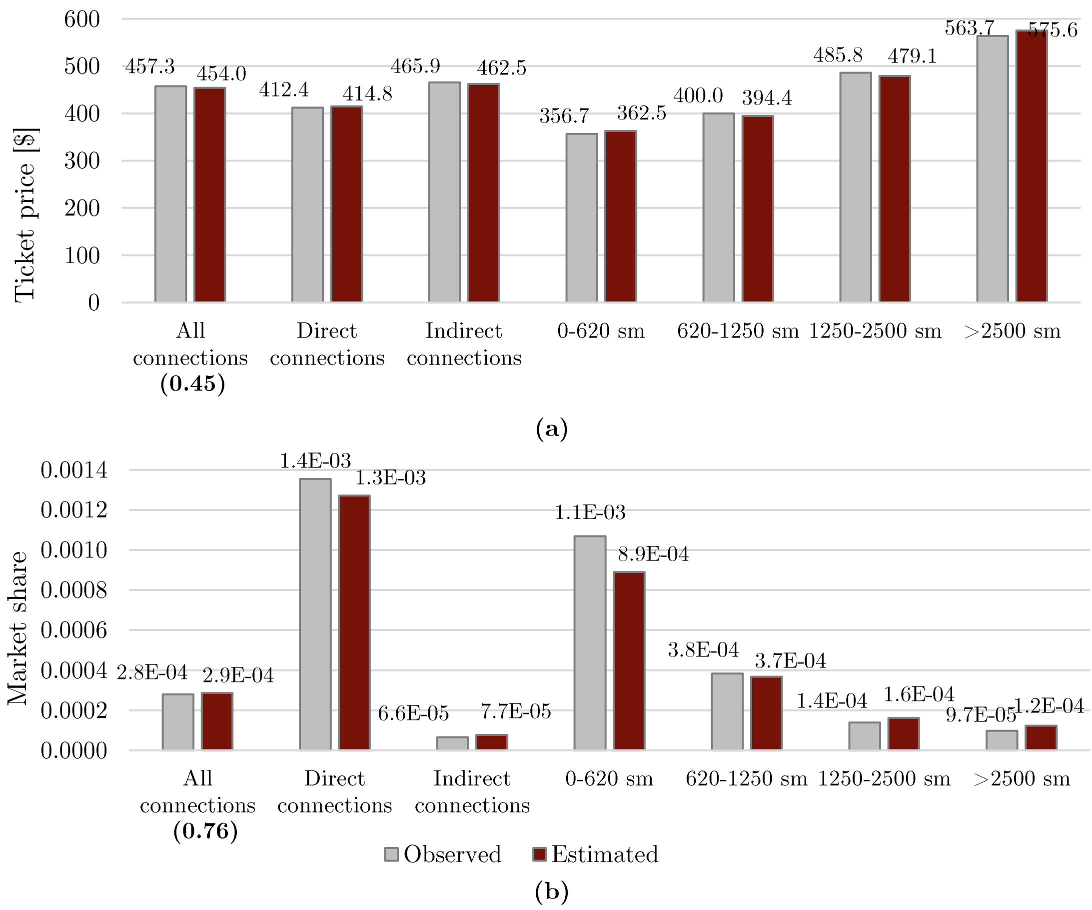


Figure 8.1. Comparison of estimated and observed prices (a) and market shares (b)

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 market shares, it is equal to 0.76, while for the ticket prices it is equal to 0.45 (these values are indicated in parentheses in Figure 8.1), which seem acceptable for cross-sectional data. Also our results indicate that direct connections are better predicted since the squared correlation coefficient for the market shares of the (0.68) is higher than that of the non-direct connections (equal to 0.54). The same applies to the ticket prices as well, similar to what indicated in Figure 8.1. With regard to distance, the better predictions for are obtained for the distance cluster of 620-1250 sm where the squared correlation coefficient is equal to 0.835. For the distance cluster of 0-620 sm the corresponding value is 0.82. All the above findings generally suggest that our model is capable of capturing the dominant effects of passenger demand and ticket prices.

8.1.3 Marginal cost results

Given the price equation (Eq. 6.3) and the estimated coefficients of the demand and supply model, the estimates of marginal costs are obtained for every airline connection. Therefore, a natural test of our model validity to compare our estimates of marginal cost with other studies is facilitated. Our estimates indicate an average marginal cost of $294.80 (averaged for all airline connections in the estimation sample). A direct comparison of this estimation with marginal cost estimates from past studies could be misleading since different traffic samples are used in the estimation (i.e. different time period or ticket prices etc). One idea is to compare the price-cost margin, which is the difference between price and marginal cost as a fraction of price i.e. (p-mc)/p. This value is used as an indicator of market power. Our model yields an average price-cost margin of 0.384, which is consistent with the existing literature, e.g. Shen's (2012) estimate is 0.41, while Alcobendas (2014) and Gayle (2013) report price-cost margins of 0.36 and 0.39 respectively. In cases where the price-cost margin is not reported in the literature, the average marginal cost as a percentage of price is compared (i.e. mc/p). Our estimates indicate that marginal cost constitutes on average the 64.6% of ticket price. This estimate is close to published values, e.g. Lee (2013a) report estimates of 56.8% to 65% depending on the number of airlines in the oligopoly market, while Brown and Gayle (2009) and Gayle and Le (2015) report that on average marginal cost is 68% and 65.7% of ticket price respectively.

8.2 Effects of the market-based environmental policy

The current section assesses the impact of the market-based environmental policy on ticket prices and air travel demand. The analysis is conducted in market, network and airline level. Post-policy equilibrium ticket prices and market shares are estimated. In addition the impact of the studied policy on aviation emissions is assessed. Several issues such as the carbon price variation and the estimated pass-through rate are also discussed.

As explained in Section 6.4, several elements are needed to conduct the simulation analysis of the implementation of the CO_2 emission fee. In particular, apart from the demand and supply model coefficients, pre-policy airline's marginal cost, unit carbon price, load factor data, seat capacities and itinerary carbon emissions are also required. The pre-policy airline's marginal cost is estimated during the demand and supply model estimation. A comparison of pre-policy and post-policy airline's marginal cost is presented in Section 8.2.3.

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 dissertation 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 in Sections 6.4.3 and 2.2 (Table 2.2). To take into account the uncertainties related to carbon price, three scenarios are considered: (i) low scenario, \$10 per ton, (ii) medium scenario, \$20 per ton and (iii) high scenario, \$50 and \$100 per ton 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 (see Table 2.2). The low price was used to approximate the average price of European Union Allowance price during 2012. The prices of \$50 and \$100 per tn CO_2 (high scenario) reflect two more aggressive scenarios for aviation emissions abatement.

Two other significant elements in the considered assessment analysis are the assumed load factor and the seating capacities. Seating capacities are assigned to each segment of the itinerary based on the aircraft type used (seat capacity data by aircraft type is given in Appendix B-4). Load factors are computed by airline and distance combination and are averaged for each quarter in 2012 based on the T-100 database. Since the diagram of load factors by airline and distance combination is scarcely legible, we present average load factors by distance cluster and quarter in Figure 8.2. It is shown that the computed load factors in some distance clusters are different between the different quarters.

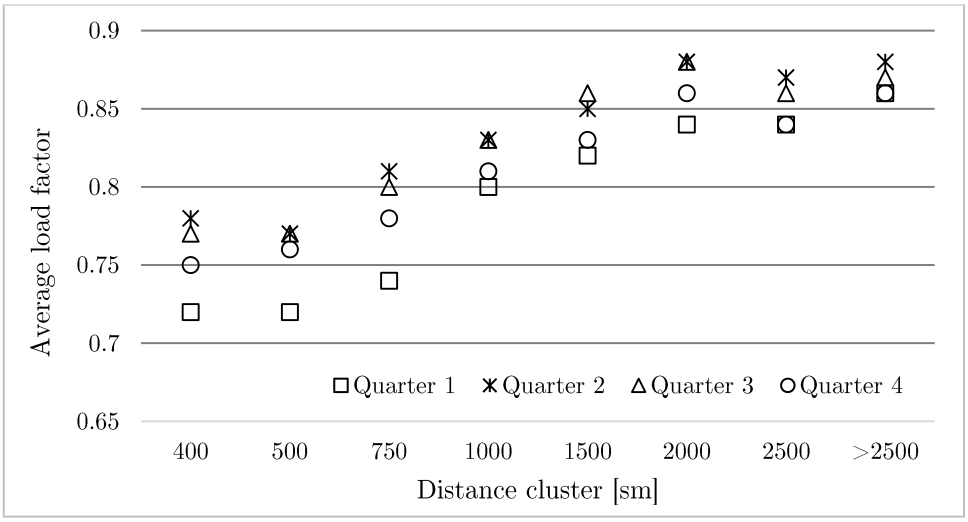


Figure 8.2. Average load factor by distance cluster and quarter

Finally, itinerary carbon emissions are computed in accordance with the methodology developed in Chapter 3.

8.2.1 System-wide analysis

Before presenting the effects of the environmental policy on ticket prices, air travel demand and aviation CO_2 emissions, a brief overview of the carbon footprint of the considered airline network will be presented. It is noted that CO_2 emissions are computed as a function of aircraft fuel consumption, according to the methodology developed in Chapter 3. The registration-based flight profiles are used as representative flight profiles on which BADA's fuel flow rates are employed to compute fuel consumption of each round-trip itinerary of our sample.

Our computations indicate that on average each round-trip itinerary generate 0.17 kg/passenger-sm. However, this value is different for various itinerary distances and aircraft types etc. Figure 8.3 presents the range of flights and CO_2 emissions per passenger-sm in our traffic sample. In accordance with previous studies, CO_2 emissions per passenger-sm tend to decrease as flight distance gets longer. The figure depicts that long distance flights, mainly operated by heavy aircraft, are most efficient in comparison with very short distance flights. On average, itineraries longer than 6,000 miles generate 0.13 kg/passenger-sm, while itineraries with distance from 2,000 to 6,000 miles generate on average 0.15 kg/passenger-sm. Itineraries shorter than 2,000 miles generate on average 0.22 kg/passenger-sm.

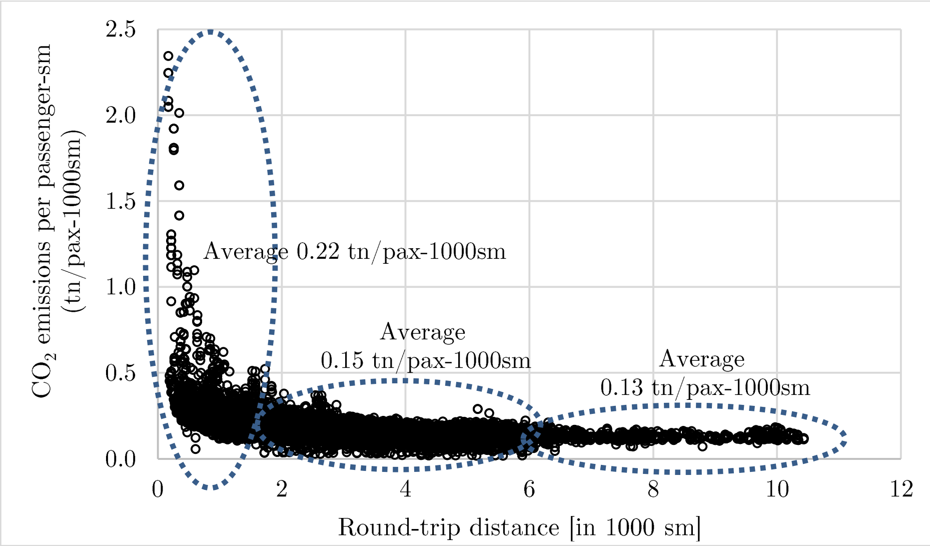


Figure 8.3. Range of flights and CO_2 emission per passenger-km

Next we construct emission maps of the U.S. airspace. These maps enable the identification of critical emission spots including routes, airports and aircraft type. The map construction incorporates the use of Geographical Information Systems in order to import the coordinates of the U.S. airports along with the output data of CO_2 emissions. CO_2 emissions per O-D airport pair are illustrated in Figure 8.4. To provide a clear and readable emissions map, only the 100 most popular U.S. domestic routes for 2012 are considered and designed with direct lines. Figure 8.4 shows the geographical distribution of the CO_2 emissions on the top 100 U.S. domestic routes using the registration-based typical profiles along the CCD cycle. The routes from New York (JFK) to San Francisco (SFO) and Los Angeles (LAX) receive the bulk of CO_2 emissions among the top 100 routes. Furthermore, high amounts of CO_2 are emitted by itineraries between Northeast U.S. airports (e.g. ORD) to west coast's airports (e.g. LAX, SFO) and Hawaii (HNL airport). On the contrary, shorter flights between airports at the Eastern region of U.S. emit the lowest amount of carbon dioxide.

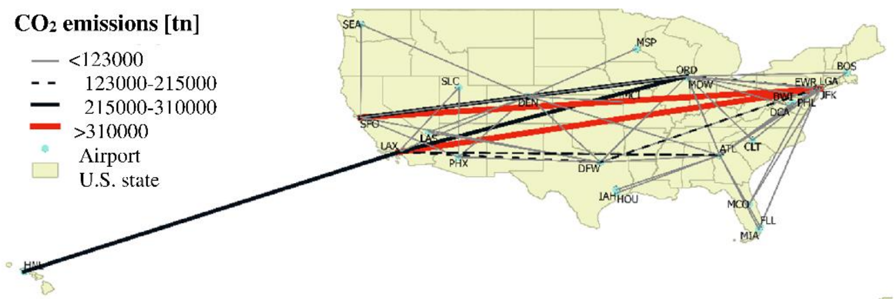


Figure 8.4. CO_2 emissions map of the 100 most popular U.S. routes

Figure 8.4 along with Figure 8.5 provide for an integrated comparison of the annual CO_2 route emissions with reference to the main determinants i.e. aircraft size, flight distance and number of flights. The number of flights in 2012 is illustrated in Figure 8.5(a) and the average aircraft size per O-D airport pair is given in Figure 8.5(b). Longer flights that fly above the entire U.S. airspace (from West to East and vice versa) are operated by larger aircraft with average passenger capacity of more than 190 seats. Short flights are operated by smaller aircraft with seat capacity of 143-190. Although the flights in the route HNL-LAX are few compared to other routes, the annual CO_2 emissions are relatively high due to the long flight distance and the aircraft size used for this route (>190 seat capacity). The same applies to the routes SFO-JFK and LAX-JFK where flight distance and aircraft size are the main factors of high emission values. On the contrary, although the routes ORD-JFK and JFK-ATL have more than 9,000 flights annually, the short distance and relatively small aircraft type (with seat capacity 143-165) lead to relatively low emission values.

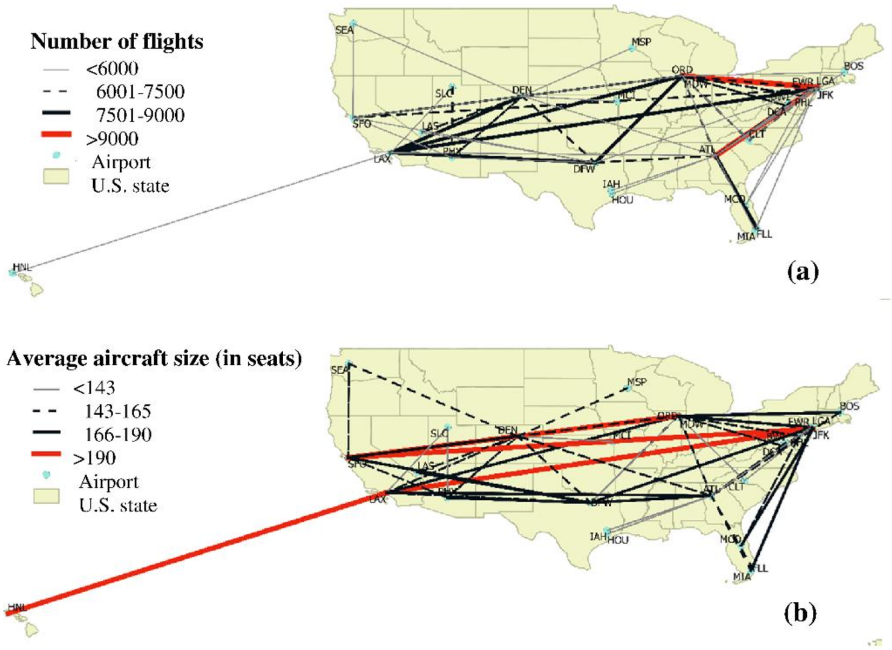


Figure 8.5. Geographical distribution of number of flights (a) and aircraft size (b) for the 100 most popular U.S. routes

The results after the simulation of the market-based environmental policy are presented in Table 8.3. On average the ticket price increases by 1.07% to 10.73% depending on the carbon price set. For the low carbon price scenario (F=10), the carbon cost imposed to the airline for each passenger is on average \$4.75, while this is increased to \$23.77 for the high carbon price scenario of \$50 per ton CO_2. As expected the higher the carbon price, the higher the ticket price increases. The structure of the demand-and-supply model enables that a change in a causal factor may impact both total air travel demand and within-group market shares. In particular, the structure of the oligopoly game (as described in Section 5.1.2) which includes the matrix of partial derivatives of MS_j with respect to price allows for changes in within-group market shares due to ticket price changes among the competitors within the market. After the implementation of the studied environmental policy, on average an itinerary may lose from 0.22% of its within-group market share ($MS_{j/g}$) for a carbon price of \$10 to 2.23% for a carbon price of \$100. In addition, the inclusion of the non-air alternative in the passengers' choice set allows for changes in airline connections' market shares (MS_j) (and thus total air travel demand) due to ticket price changes. Our results indicate that higher airfares after the implementation of the studied policy are followed by a decrease in air traffic. Overall, the simulation results indicate that total passenger traffic will be reduced by 1.47% for the low carbon price scenario, while a relatively high demand decrease of 13.5% may occur for the high scenario of \$100 per ton CO_2. For the medium scenario (F=20), on total 2.91% of passengers may choose not to fly as a result of increased prices.

Table 8.3. Effects of the market-based policy in the U.S. domestic airline network

		Low scenario	Medium scenario	High scenario	
	F (\$/tn CO_2)	F=10	F=20	F=50	F=100
Average effects per airline connection					
Average carbon cost per connection [\$]	Δcost	4.75	9.51	23.77	47.53
Average fare increase per connection [%]	%Δprice	1.07%	2.15%	5.36%	10.73%
Average demand change of within-group connections [%]	%$\Delta MS_{j/g}$	-0.22%	-0.45%	-1.13%	-2.23%
Total effects in the study network					
Reduction in total air travel [%]	%Δpassengers	-1.47%	-2.91%	-7.07%	-13.50%
Reduction in air carbon emissions [%]	%ΔCO_2	-1.88%	-3.73%	-9.02%	-17.05%

Decreased air traffic will lead to lower emission levels for the network under consideration. To accurately compute this effect, the number of "lost" passengers due to the fare increase for each individual flight of an airline should be known. If this information is available, changes in network configuration due to airfare increase could be assessed. For example, the increased ticket prices may result in such air travel demand changes that the airlines might be encouraged to change their flight frequency or shift to larger or smaller aircraft on specific routes. However, our dataset does not provide such detailed information at that level of individual flights at a particular day and time. Instead, aggregate data on the total number of people in 2012 who chose a unique combination of "Origin-Connecting-Destination airports by a specific airline in a quarter of 2012" are available. An illustrative example of the available information for each round-trip airline connection is given in Figure 8.6. In addition, the policy effects on travel demand are mentioned for this example. Although we are able to compute the number of passengers that might stop flying due to ticket price increase, we are not able to know how these passengers are distributed in the various scheduled segment flights of the specific airline in the study quarter of 2012. Thus, we are not able to know how the airline's schedule in each airport-pair segment would change (due to demand decrease) so as to compute the change of CO_2 emissions due to reduced departures of each airline. However, to have an aggregate estimate of the CO_2 emissions reduction due to air travel demand decrease we adopted a simplified assumption that network CO_2 emissions are reduced by the following quantity: number of passengers who stopped flying due to fare increase × per passenger CO_2 emissions. It should be noted that although our approach over-estimates the CO_2 reduction results, it is a satisfying approach to obtain aggregate estimates. Based on the above, the results suggest that CO_2 emissions may decrease by -1.88% to -17.05% depending on the carbon price set due to the air travel demand decrease. It should be also noted that 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. Consequently, the additional traffic of the other transport modes (e.g. car, train etc) would cause an increase in CO_2 emissions. This especially applies to short-distance trips where air transport strongly competes with land transport.

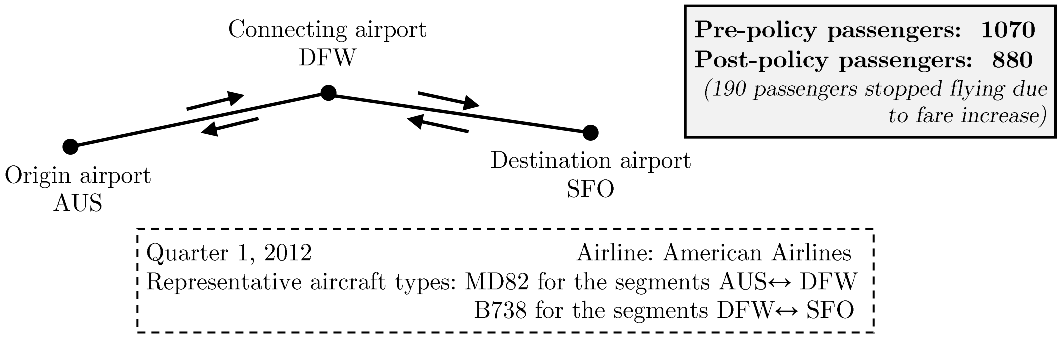


Figure 8.6. Illustration of an airline connection and post-policy demand

The environmental fee constitutes part of the airline cost structure and thus affects profitability. In this study it is assumed that, at least one part of it is passed onto passengers. As shown, price increase beyond a certain level will inevitably lower demand. Market shares of airlines will then be affected, albeit non-uniformly driving down revenues and profitability. In reality, expected airline responses will differ depending on the assessment of the respective impact on market share and will not be confined to a single decision option but a variety of potential decision variable employed in reality (flight frequency, aircraft size, etc). As already mentioned, for instance, if the load factor of the airline connection falls to very low levels, the airline may decide to change its flight frequency or shift to smaller aircraft (given that the flight distance can be covered by smaller aircraft). Although the modelling approach of this dissertation does not capture such airline responses, an attempt is made so as to estimate the effect of the market-based policy on airline's load factor (in the short term). If we assume that the demand decrease is uniformly attributed in load factor decrease, Figure 8.7 presents the cumulative distribution of load factors for the several carbon price scenarios. For comparison reasons, the corresponding curve for the pre-policy load factors is illustrated. Based on the results, before the implementation of the environmental policy the average load factor by itinerary was 0.84, while half of the connections had load factor higher than 0.83. At a carbon price of \$20 per ton CO_2, the average load factor by itinerary was 0.78, while half of the connections had load factor higher than 0.79. The changes get highly sensitive at the price of \$100 per ton CO_2. Average load factor falls to 0.66; this value is the highest level of load factor for the half of connections.

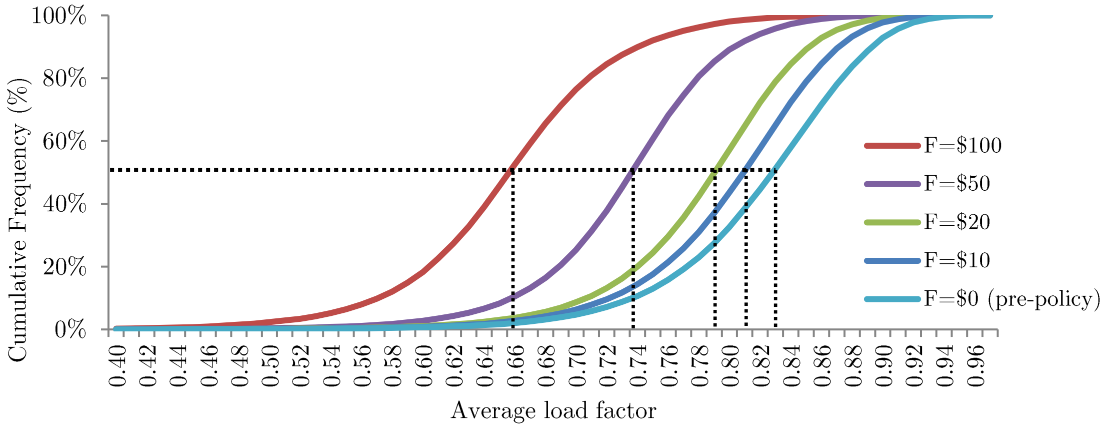


Figure 8.7. Changes in load factor cumulative frequency

On the whole, the above results reveal that the implementation of a carbon policy in the U.S. aviation is expected to cause moderate to significant changes on ticket prices and market shares, depending on the unit carbon price. In the low carbon price scenario (F=10), which is close to the carbon price currently prevailing, ticket prices may increase by 1.07%. This would decrease total passenger demand by 1.47% and network-wide CO_2 emissions by 1.88%.

The effect of the above changes to different distance groups is illustrated in Figure 8.8. Flight connections are grouped in four groups based on their market distance: connections with market distance less than 620 miles (≅1000 km), from 620 to 1250 miles (≅1000-2000 km), from 1250 to 2500 miles (≅2000-4000 km) and greater than 2500 miles (≅4000 km). The distance bounds are selected based on a review conducted by Miyoshi and Mason (2009) on carbon emission levels estimated in various studies for different stage length. For the medium scenario ($ 20/tn CO_2), shorter flights become on average 1.3% more expensive while longer flights' fares increase by about 2.83%. Total air travel demand changes by a range of -1.59% to -6.58% for the shortest and longest flights respectively (for the medium carbon price scenario). Overall, as expected, longer flights experience the greatest impact due to the carbon cost as they generate the largest amount of CO_2 emissions. The large amount of CO_2 emissions are due to several reasons: first, the largest the distance the higher the amount of CO_2 emitted. Second, longer flights are more likely to have one (or more) intermediate stop(s). Thus, the "extra" landing/take-offs result in higher amount of CO_2 emissions. Last, longer flights tend to be served by larger aircraft, as shown in Figure 3.16 where the share of passenger traffic by aircraft type is illustrated for 2012. As we move to higher flight distances, larger aircraft such as Airbus 330-200 (A332) and Boeing 767-300 (B763), 767-400 (B764), 777-200 (B772) serve the flights. Most of these aircraft types burn more fuel and, thus, generate more CO_2 emissions as also indicated in Figure 5.3.

Following the above findings, we may conclude that an airline with a high proportion of long-haul itineraries would experience higher carbon costs and greater impact on demand loss. However, Figure 8.3 indicates that carbon emissions per passenger-miles are lower for long-haul flights in comparison to shorter flights (the value of CO_2 per passenger-miles is a common metric which indicates the flight's efficiency with respect to energy and emissions). Therefore, for a specific airline which serves a large percentage of short-haul flights, the amount of CO_2 emissions and, thus, CO_2 costs are lower in absolute terms (as shown in Figure 8.8) but are higher if we consider the per passenger-mile metric (see Figure 8.3).

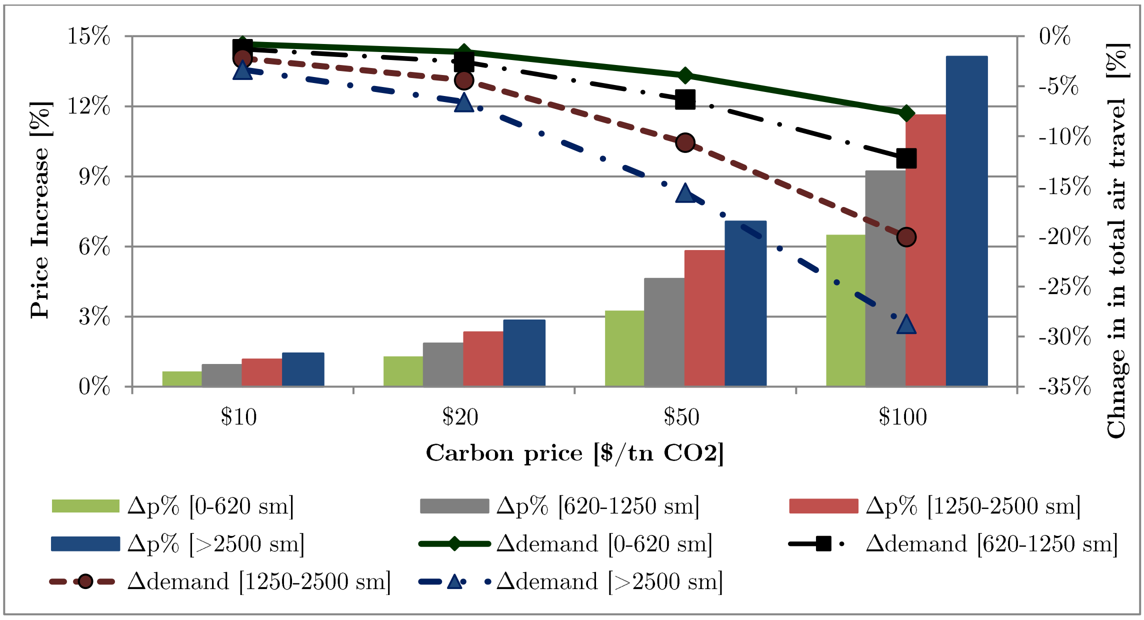


Figure 8.8. Changes in ticket prices and total air travel demand values for different distance groups

Another critical observation is that the CO_2 policy affects direct and non-direct flights differently. Figure 8.9 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 5.7% increase in ticket prices compared to 3.9% for direct flights. For the same carbon price, 10.9% and 6.5% of passengers in connecting and direct flights respectively may choose not to fly after the introduction of carbon policy, due to higher airfare.

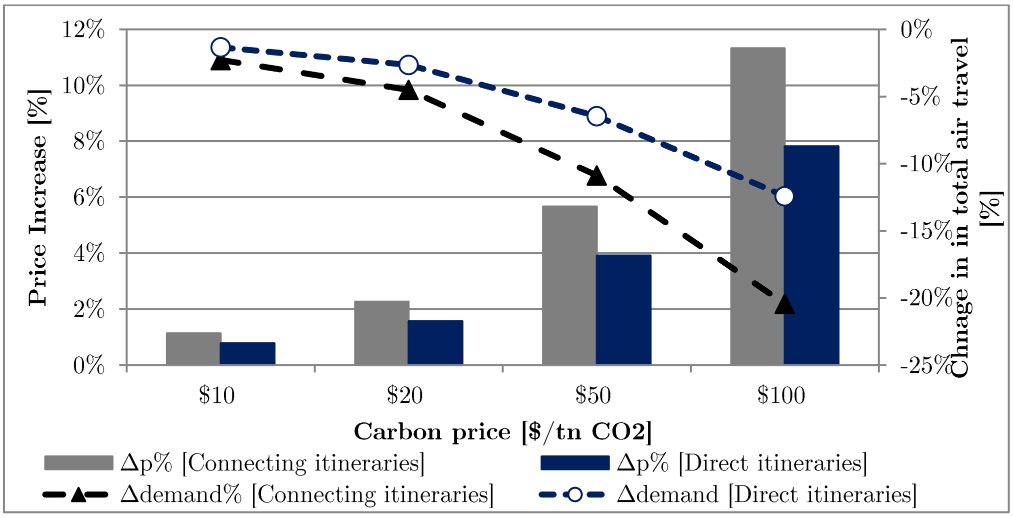


Figure 8.9. Changes in ticket prices and total air travel demand for direct and indirect flights

8.2.2 Market-level analysis

The considered environmental policy is expected to have different impact on markets with different level of competition. For example, it is believed that the number of competitors in a market may influence the magnitude of ticket price increase after the implementation of the studied environmental policy; the higher the number of players in a market, the less the ticket price increase.

To identify the impact of market competition on the effects of the studied environmental policy, markets with similar characteristics have been selected for comparison. Figure 8.10 presents the ticket price increase in relationship with the number of players (airlines) in the market. The results correspond to the low carbon price scenario of $10 per ton CO_2. Similar patterns are observed in the other carbon price scenarios, but with different magnitude. The airfare changes for the whole set of airline connections are illustrated with black points. To examine the trend of ticket price changes with respect to market competition, the airline connections are then split in different categories (every 1000 miles) depending on the roundtrip distance so as to ensure that we compare connections with relatively similar characteristics. Comparing markets with different features (such as flight distance, carbon emissions and thus imposed carbon costs, etc) could lead to misleading interpretations. The linear fit curves for the various roundtrip distances are depicted in different colors. Overall, it is shown that, ticket price increase demonstrates a decreasing trend when we move to a higher number of players (airlines) in the market.

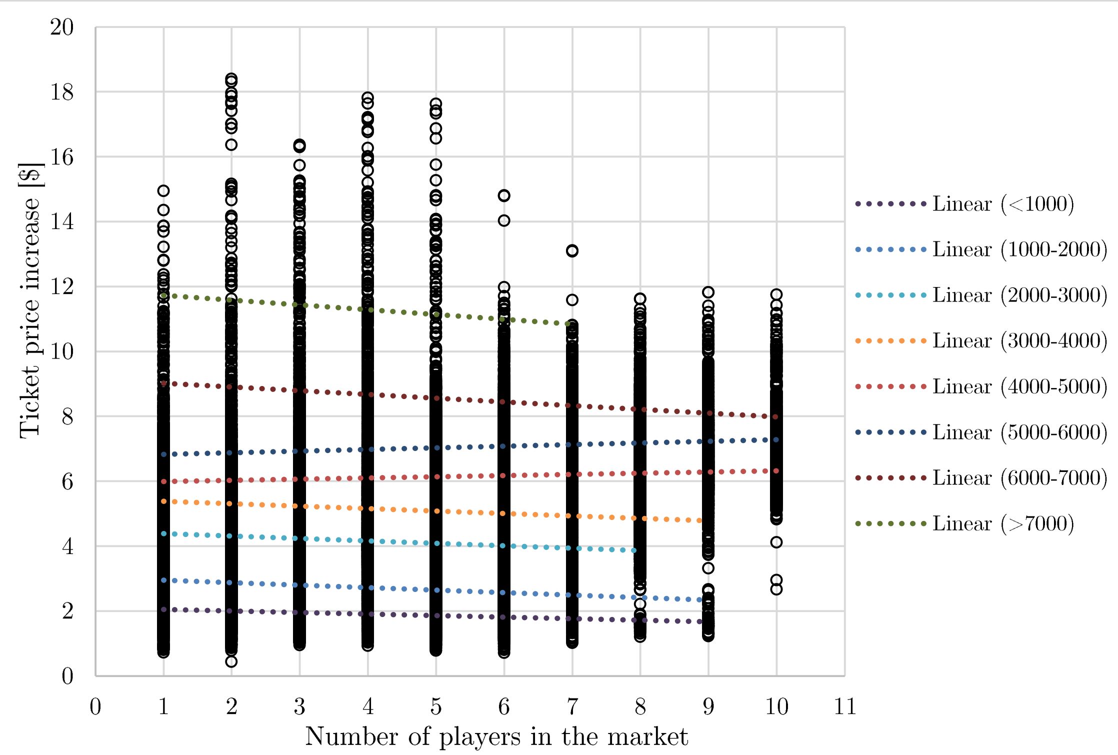


Figure 8.10. Increase in ticket prices in relationship with the number of players in the market[27]

[27] The regressions lines are as follows: Round-trip distance of i) <1000sm: y=2.097-0.048x, ii) 1000-2000sm: y=3.03-0.077x, iii) 2000-3000sm: y=4.46-0.075x, iv) 3000-4000sm: y=5.46-0.075x, v) 4000-5000sm: y=5.95+0.03x, vi) 5000-6000sm: y=6.77+0.05x, vi) 6000-7000sm: y=9.13-0.115x, vii) >7000sm: y=11.88-0.15x, where y is the ticket price increase (in $) and x is the number of airlines in the market.

8.2.3 Airline-level analysis

In this section we focus on the effects of the considered environmental policy on the eleven airlines that are active in our sample network. The policy is expected to affect each airline differently due to differences in the level of each airline's carbon emissions and resulting carbon costs and due to deviations in airlines' ticket prices before the environmental policy. Table 8.4 presents the share of passenger-miles and CO_2 emissions for the sample airlines. Southwest (WN), Delta Air Lines (DL) and United Airlines (UA) rank first in passenger-miles and CO_2 emissions, while Hawaiian Airlines concentrate the lowest share of both indicators. CO_2 emissions efficiency for each airline has been also computed by dividing the amount of CO_2 emissions by the passenger-miles served by each airline in our sample. The magnitude of this indicator depends on the aircraft types used, the distance flown by each airline and the load factor. Thus, average itinerary miles flown and load factor by airlines are presented in Table 8.4.

The highest values of CO_2 emissions per passenger-mile (lowest efficiency) correspond to Virgin America (VX) and JetBlue (B6). Both airlines' itineraries are mainly served by Airbus 321 (about 90% of VX's itineraries and 65% of B6's). This aircraft type is a relatively efficient aircraft type (in terms of fuel consumption and CO_2 emissions) in comparison to the other aircraft types used (see Figure 5.3). However, the lower load factor (compared to the other airlines) results in higher carbon emissions per passenger-mile. The lowest values of CO_2 emissions per passenger-mile (highest efficiency) correspond to Frontier Airlines (F9), Alaska Airlines (AS) and Hawaiian Airlines (HA). Both the aircraft types used (F9's connections mainly served by A319 (80% of them), AS's connections are mainly served by B738 (46%), CRJ9 (12%) and B737 (12%)) and the higher load factors result in higher CO_2 emissions efficiency. For Hawaiian Airlines, the high level of CO_2 emissions efficiency may be mainly explained by the long flights served. HA's itineraries are on average 5186 miles long, which is much longer than the connections of the other airlines.

Table 8.4. Share of passenger-miles and CO_2 emissions by airline

Airline	Share of passenger-miles	Share of CO_2 emissions	CO_2 emissions per passenger-mile (kg/passenger-mile)	Average roundtrip miles (in 1000sm)	Average load factor
VX	2.6%	3.0%	0.172	4.173	0.77
B6	8.8%	9.5%	0.164	3.292	0.83
FL	4.0%	4.2%	0.160	2.673	0.79
AA	14.6%	15.4%	0.159	3.445	0.81
US	8.5%	8.7%	0.154	3.225	0.84
DL	17.5%	17.5%	0.152	3.234	0.84
UA	15.4%	15.0%	0.149	3.410	0.84
WN	21.8%	21.1%	0.147	2.854	0.80
F9	2.6%	2.2%	0.129	3.318	0.89
AS	2.9%	2.4%	0.123	3.044	0.87
HA	1.3%	1.1%	0.122	5.186	0.87

Due to the carbon cost the marginal cost of each airline are increased. Figure 8.11 illustrates the airlines' marginal cost before and after the studied environmental policy for the medium carbon price scenario (F=$20). The stars next to the airlines' names indicate the LCC airlines. LCC airlines have lower marginal costs in comparison to other airlines, both before and after the environmental policy. Above the bars the average carbon cost per connection by airline is given.

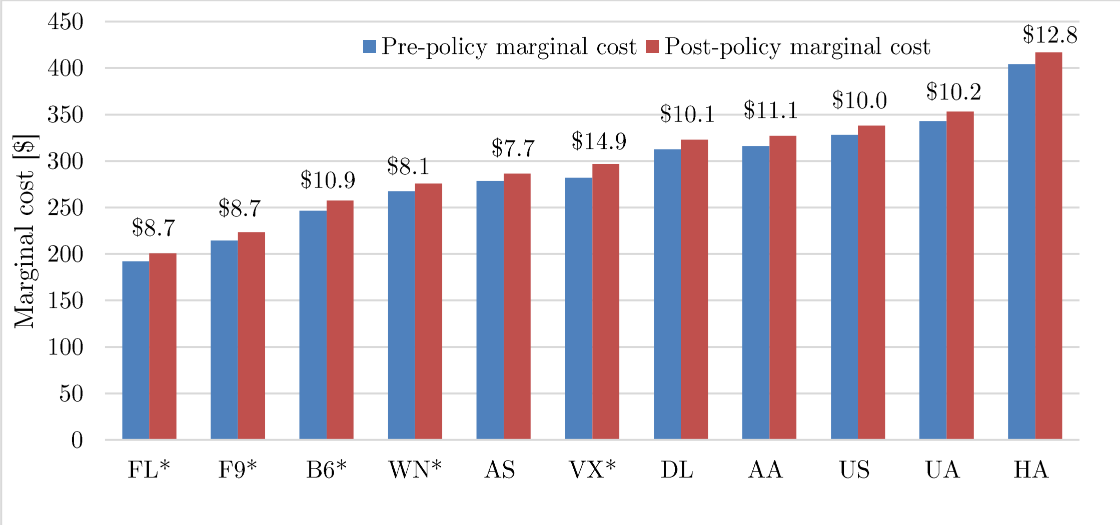


Figure 8.11. Airlines' marginal cost before and after the environmental policy (for the medium scenario F=$20/tn CO_2)

The effects of the policy on ticket prices for the same carbon price scenario are shown in Figure 8.12. Legacy airlines are illustrated in grey bars, while low cost airlines' changes are given in the light brown bars. We observe that low-cost airlines face the largest price increase, except Southwest Airlines. Based on our simulation results, Virgin America's prices are likely to increase by 3.4%, followed by three other LCC airlines: JetBlue, AirTran and Frontier. This large effect for LCCs may be explained by the pre-policy prevailing ticket prices and the carbon cost implied under the environmental policy. For example, Frontier and AirTran have a relatively low carbon cost in comparison with other airlines (see Figure 8.11). However, due to their low pre-policy ticket prices (Frontier and AirTran have on average the lowest pre-policy prices, $365.6 and $347.6 respectively), the percentage price increase (2.4% and 2.5% respectively) after the environmental policy is higher than in other airlines. For the cases of Virgin America and Southwest Airlines, the high and low effects respectively may be explained by both the high/low carbon cost and the pre-policy ticket prices (on average Virgin America has the 4^{th} lowest ticket prices while Southwest Airlines ranks 5^{th}).

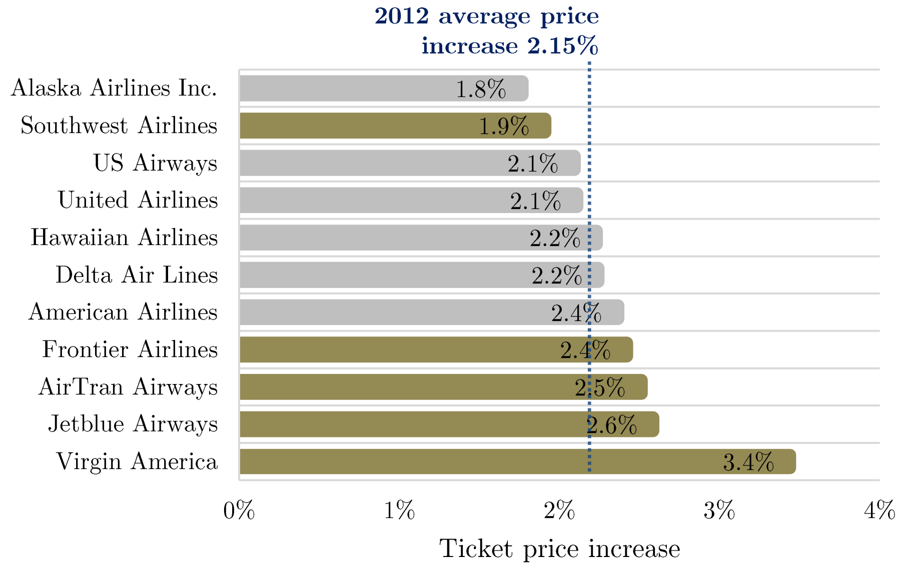


Figure 8.12. Ticket price changes by airline (for the medium scenario F=$20/tn CO_2)

Similar patterns are observed for the rest of the carbon price scenarios (10, 50 and 100). However, the level of price increase depends on the scenario applied.

As indicated in Table 8.3, ticket price 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 0.22% for the low scenario and 2.23% for the highest carbon price. This means that competition distortions are expected to be rather low. Our results are in agreement with the findings 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).

This dissertation assumes that the market-based environmental policy is uniformly imposed to the different airline connections and airlines of the studied network (all airlines and airports are subject to the considered policy). This is the reason why market share changes mainly occur between the airline alternatives and the non-air alternative; in other words, due to the massive ticket price increase the travelers are more likely to stop flying than shifting to competing airline connections. In case the market-based policy treated airlines or airports or airline connections in different way (i.e. emissions cost imposed to some of the airline connections in the market), then the results might indicate more intense conditional market share changes among the airlines. This case could be applicable, for instance, if an airport in the given network imposed extra fees for the emissions generated during landings and take-offs (while other airports in the same network did not).

8.2.4 Carbon cost pass-through rate

Airlines' decision on the level of CO_2 cost pass-through rate is an important determinant of the impact of the examined market-based measure on aviation. Consistent with airlines' profit maximizing behavior in competitive markets, most studies claim that airlines may pass the entire cost of CO_2 emissions to passengers (Forsyth, 2008; Hofer et al., 2010; Miyoshi, 2014; Sgouridis et al., 2011). On the other hand, some studies support that airlines' competition may not enable the full pass through of CO_2 cost to passengers (Boon et al., 2007; Morrell, 2007; Scheelhaase et al., 2010; Malina et al., 2012) and that pass through rate depends heavily on the type of competition (Oxera, 2003).

In this dissertation, the cost pass through rate (*PTR*) is not pre-determined but it is computed within the supply-and-demand model as the ratio of the ticket price change (Δp) to the change in marginal cost (which is equal to the carbon cost) as follows:

$$PTR\ [\%] = \frac{\Delta p}{CO_2 cost} \cdot 100 \qquad \textbf{Eq. 8.1}$$

Our estimation results indicate that CO_2 cost pass through rates vary between 89% and 140%. However, for the 99.5% of the sample airline connections, the PTR ranges from 95% to 112%, while on average the level of PTR is equal to 100.4%. Among the sample airlines, Virgin America and JetBlue Airways have the lowest pass-through rate (99.1% and 99.4% respectively), while Alaska and Southwest Airlines have the highest pass-through rate on average (101.6% and 101.2% respectively). Figure 8.13 shows the distribution of the pass through rates for the sample connections (for clarity reasons PTR greater than 115% are not presented).

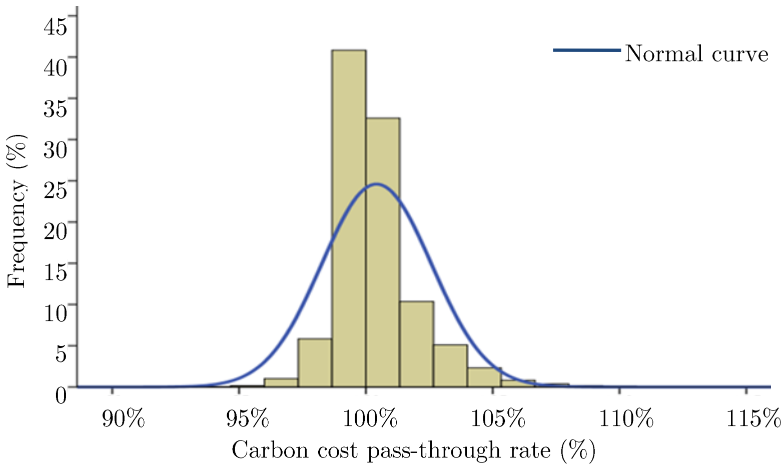


Figure 8.13. Distribution of the resulting CO_2 cost pass-through rates

9 Conclusions and Recommendations

This chapter summarizes the main conclusions of the work undertaken. Moreover, recommendations for research are outlined.

9.1 Modelling approach and key research findings

This dissertation analyzes the airline industry from different perspectives, including passenger choices, airline decisions, market competition, and aircraft carbon emissions and resulting carbon cost in a regulated environment. In particular, it shows how airlines may adjust their pricing strategies and how passengers may change their travel choices in view of a market-based environmental policy within a competitive airline network. For this purpose, a modelling approach, mainly used in the industrial organization economics literature, is extended within the context of transportation engineering, so as to suitably represent the airline network to which market-based environmental policies may induce airfare and demand changes, influenced by air passenger choices, airline decisions and imposed carbon cost. One important feature of this dissertation is that, after computing aircraft carbon emissions by regulated itinerary, the corresponding carbon cost is introduced as a shifter in the airline's marginal cost function. A portion of the induced environmental cost may be passed onto the passengers, resulting in increased ticket prices. The adjustment of ticket prices in response to the carbon cost is determined by a Nash equilibrium in prices. Then, air passenger travel choices are modelled through discrete choice analysis.

Various conclusions can be drawn regarding the methodological approach developed in this dissertation. First, contrary to the majority of aggregate studies, which employ linear regression models of passenger traffic, in this study air travel demand in an origin-destination city pair is modeled by discrete choice models of passenger behavior, while the supply side is formulated as a profit maximization problem for each active airline in a competitive market with multiple players (competing airlines).

This analysis provided useful information on the key determinants of the utility function of air passengers and the airlines' marginal cost. Several macro-level variables identified in the literature are adjusted or modified for inclusion in the demand model such as ticket price, connection's frequency, arrival delays, airline dummies, while additional explanatory variables not formerly used in aggregate models, such as the presence of alternative airport nearby the origin or the destination city and connection's departure time, are also specified.

Due to the form of data used, some characteristics of the airline connection may be unobserved to the analyst but are known to the potential passenger during his travel decision process. A single term capturing these unobserved characteristics is included, the existence of which implies that some demand variables, could be endogenous. Endogeneity issues that arise from the correlation of ticket price and within-group market share with the error term of the demand function necessitates the use of Instrumental Variable method for the estimation of model parameters, since the use of Ordinary Least Squares method could lead to biased parameter estimates. Specifically, the estimation results obtained from different specifications of our demand model confirm endogeneity. Although the estimated ticket price coefficient (-0.175) derived from the OLS estimation illustrates a negative fare impact on demand, the magnitude of price coefficient in the 2SLS estimates (which is much larger in absolute value) suggests that the endogeneity of price results in severe bias of the price coefficient estimate if instruments are not used for ticket price. Therefore, for the joint estimation of the nonlinear demand-and-supply model bypassing endogeneity issues the two-step Generalized Method of Moments is used. The application of diagnostic statistical tests enabled to use valid and relevant instrumental variables.

The structure of the demand-and-supply model, which introduces the non-air alternative in the upper level of the nested logit model (in the demand model) and incorporates the partial derivative of competing connections' market share in the pricing equation of each airline, enables that a change in a causal factor may impact both total air travel demand (or equally the market share MS_j) and within-group market shares ($MS_{j/g}$). Furthermore, the estimation results obtained from different specifications of our demand model suggest that the Nested Logit model is preferable than the Multinomial Logit for the representation of the passenger' choice process in the air travel market.

To feed the CO_2 emission model with flight profile data the LTO phase is separated from the CCD phase. Second, big datasets of air traffic and flight track information over a wide range of U.S. domestic flights are employed to conduct an extensive analysis of past aircraft altitude profiles. Two different methods are used; the first uses a novel combination of clustering and landmark registration techniques exploiting the information of the entire trajectory of historic flights, while the second relies on the point mass BADA model, which has been used by several researchers in the past. A detailed comparison of the operational characteristics obtained by the above methods is conducted for the first time to determine the suitable method for further provision of reliable CO_2 emission estimates for large scale networks, similar to our study U.S. airline network. Finally, the construction of typical flight profiles, and their corresponding fuel burn and CO_2 emission values, for various combinations of "aircraft-distance-flight direction" is done in a novel fashion.

The developed modelling approach is applied to the large-scale network of the United States. The registration-based method performs significantly better than the BADA-based estimation in terms of predicting the operational characteristics of a flight, since the first fundamentally relies on operational data and can capture actual flight performance more reliably. Despite the substantial difference in the estimated flight characteristics between the two profile estimation methods, the difference in the estimates of fuel consumed and CO_2 emissions is less pronounced. On network-wide level, BADA-based typical profiles are estimated to consume 6.3% less fuel in comparison to registration-based profiles. The comparison of the two methods with the two latest versions of the widely-used EMEP CORINAIR database showed that its last version (EMEP CORINAIR 2013) gives similar results with our methods, especially for the registration-based profiles. Finally, our network-wide estimates generally agree with other published estimates for the U.S. airspace, which provides a good indication of the validity and reliability of our methods and results at network wide level.

Large datasets on air itineraries from different sources are processed to form the final traffic sample for estimation and policy simulation. The estimated model parameters have the expected signs, are statistically significant and intuitively appealing.

The simulation analysis revealed that the implementation of an environmental market-based policy in the U.S. aviation could have some significant effects on ticket prices, air travel demand and resulting CO_2 emissions for high ranges of carbon unit price. In this dissertation, different carbon price scenarios ($10, $20, $50, $100 per ton CO_2) are assumed so as to capture different situations of the carbon market. Based on our simulations, for the low carbon price scenario ($10), which is close to the carbon price currently prevailing, ticket prices may increase by 1.07%. This would decrease total passenger demand by 1.47% and network-wide CO_2 emissions by 1.88%. If the most aggressive carbon price scenario is assumed ($100), the ticket prices may increase by about 10.7% while the air travel industry may, in turn, face significant losses in terms of passenger demand (losing about 13.5% of passengers who may stop flying due to higher prices). Currently very low carbon prices exist in several carbon markets (a bit lower than $10 per ton CO_2) such as EU ETS, Shanghai's ETS, as depicted in Figure 6.3. Despite the considerable amount of volatility in the dynamics of the carbon price, the adoption of the aggressive scenarios of $50 and $100 per ton CO_2 is not possible given current trends.

Taking into account our simulation results for the low carbon price scenario of $10 per ton CO_2 (which is close to the prevailing price) and the aviation industry ambitious goal (ICAO, 2016a) to reduce net aviation CO_2 emissions by 50% until 2050 (relative to 2005 levels), this dissertation suggests that **airlines and policy makers may need to turn to alternative approaches to ensure economic and environmental sustainability**. Our analysis suggests that CO_2 emissions pricing certainly contributes to a reduction in CO_2 emissions. Nevertheless, it seems that such low levels of carbon price would not trigger more significant changes in the air transport sector so as to act as a stand-alone measure. A combination of different policies (e.g. technological improvements, operational changes etc) could be needed to effectively work towards the environmental target. Moreover, policy makers should not ignore the potential passenger shift from air travel to other transport modes, which is partly captured in this thesis as the non-air option. This especially applies to short-distance trips where air transport strongly competes with land transport.

Demand shift between airline connections may be slightly affected by a market-based environmental policy. In particular, the within-group air travel demand change may be only -0.22% for the low scenario ($10) and -2.23% for the highest carbon price ($100), indicating that competition distortions are expected to be rather low. This concluding remark is consistent with other studies which have investigated environmental policies in European or other markets.

The above result ignores the distinction between legacy and low cost airlines. The airline-level analysis indicates that all low-cost airlines, except Southwest Airlines, may face the largest price increase. The larger effect on LCCs may be explained by the pre-policy prevailing ticket prices and the carbon cost implied under the environmental policy. The latter is, in turn, influenced by the load factor, the miles flown and the aircraft type used by each airline. Furthermore, another important finding is that the levels of ticket price increase may vary depending on the size of the market. In particular, the market-level analysis showed that ticket price increase decrease when a higher number of players enter the market. Finally, the results show that longer flights experience the greatest impact in terms of price increase and demand decrease due to the carbon cost as they generate the largest amount of CO_2 emissions, while 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.

Another important dimension is the level of CO_2 carbon cost pass-through onto the passengers. CO_2 cost pass through rates vary between 89% and 140%. However, for the vast majority of the sample airline connections, the pass through rate ranges from 95% to 112%, while on average it is equal to 100.4%. This value is consistent with the assumptions adopted in most existing studies (as reported in the relevant column of Table 2.2) while it is far from the 35% or 50% assumptions which were used by few researchers.

9.2 Research limitations and Future Research

This dissertation has dealt with passenger travel choices and airline pricing responses under market-based environmental policies in a competitive environment. Recommendations for further research are presented below.

The current modelling approach assumes that the decision process of an air passenger is described by a Nested Logit model formulation, which is regarded as providing reasonable substitution patterns among the air alternatives while remaining computational manageable. Future research could consider other discrete choice models; for example the use of mixed logit could allow the demand coefficients to vary over decision makers rather than being fixed (Train, 2003). Random coefficients logit and probit models accounting for variations in tastes among potential consumers can also be considered. The inclusion of random price coefficients could extend the current modelling approach by allowing two or more passenger types (e.g. leisure, business etc) and thus different demand changes to less price sensitive passengers.

One assumption in our analysis is that ticket price is the key decision variable in the airline strategy towards an externally imposed environmental fee. In future research, additional decision variables actually considered by airlines such as frequency or hub choice location could be examined. This will require a stepwise formulation of the oligopoly game among the competing airlines and will have to address demanding computational challenges.

In transportation modelling, it is usual to model trips based on their purpose. In this dissertation, trip purpose is not taken into account since such information is not available in the publically available databases. A fruitful area of future research is to account for trip purpose in the demand model, if relevant data are available.

Future research could strengthen the validity of flight profile estimation methods under different assumptions. For example, the current approach only considers flight profiles with constant cruise phase. This approach could be strengthened by including additional carefully chosen registration points and by dealing with suitable warping functions. Furthermore, in the current research no information on local conditions (e.g. meteorological data) are used due to data unavailability. Our analysis could be augmented to incorporate local conditions at the origin destination airports. This is believed to provide more reliable estimates for the BADA-based flight profiles. Finally the accuracy of fuel burn and CO_2 emissions could be enhanced by tackling existing shortcomings of the BADA model such as the nonconsideration of wind speed, delays, cancellations, or reroutings as well as the approximate estimation of aircraft weight.

Application of the proposed methodology to a region where an environmental measure is already in place would be worth to study as it would offer the opportunity to validate the simulation results of the model and investigate any currently unidentified limitations. The European region is one candidate region, where the EU ETS is currently implemented. However, to the level of our knowledge, such aggregate itinerary data, with information of ticket prices and other itinerary attributes are not, at least, publicly available. Moreover, the model could simulate alternative environmental policies. A subsequent comparison of the simulation results could shed light to the effectiveness of the different policies under consideration.

Extension of the static setup considered in this work to dynamic environments is another promising avenue for further research. This is a considerably harder research task but worth to be pursued as airlines are known to engage in strategic interactions making decisions that take into account estimated of future profitability discounted to present values. In addition demand has dynamic elements as passengers make travel decisions based on prior experience. State space models, dynamic programming decompositions, Markov perfect and Bayesian equilibria provide a natural modeling framework for the study of the above dynamic setup.

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Appendix A

A-1. Demand model equations

Demand model equations for the Nested Logit (Eq. 4.13) and the Multinomial Logit (Eq. 4.14) are derived as follows:

Nested Logit Demand Model

Recall that: $MS_j = \frac{e^{V_j/\lambda}}{D_g^{1-\lambda} \cdot \sum_g (D_g)^{\lambda}}$, $D_g = \sum_{j \in J_g} e^{V_j/\lambda}$, $MS_0 = \frac{1}{\sum_g (D_g)^{\lambda}}$ and $MS_{j/g} = \frac{e^{V_j/\lambda}}{\sum_{j \in J_g} e^{V_j/\lambda}}$.

Divide MS_j by MS_0 :

$$\frac{MS_j}{MS_0} = \frac{\frac{e^{V_j/\lambda}}{D_g^{1-\lambda} \cdot \sum_g (D_g)^{\lambda}}}{\frac{1}{\sum_g (D_g)^{\lambda}}} = \frac{e^{V_j/\lambda}}{D_g^{1-\lambda}}$$

(Note that: 0 denotes the non-air nest, the utility V_{i0} of the non-air nest is normalized to zero) (A.1)

Take logarithms of (1):

$$lnMS_j - lnMS_0 = ln\left(e^{\frac{V_j}{\lambda}}\right) - ln\left(D_g^{1-\lambda}\right)$$

$$= \frac{V_j}{\lambda} - (1-\lambda) \cdot ln\left(D_g\right) \tag{A.2}$$

Take logarithms of $MS_{j/g}$:

$$lnMS_{j/g} = ln\left(\frac{e^{V_j/\lambda}}{\sum_{j \in J_g} e^{V_j/\lambda}}\right) = ln\left(e^{V_j/\lambda}\right) - ln\left(D_g\right) \Rightarrow$$

$$ln\left(D_g\right) = \frac{V_j}{\lambda} - lnMS_{j/g} \tag{A.3}$$

$$(A.2) \xrightarrow{(A.3)} lnMS_j - lnMS_0 = \frac{V_j}{\lambda} - (1-\lambda) \cdot \left(\frac{V_j}{\lambda} - lnMS_{j/g}\right)$$

$$= \frac{V_j}{\lambda} - (1-\lambda) \cdot \left(\frac{V_j}{\lambda} - lnMS_{j/g}\right)$$

$$= \frac{V_j}{\lambda} - \frac{V_j}{\lambda} + lnMS_{j/g} + \lambda \cdot \frac{V_j}{\lambda} - \lambda \cdot lnMS_{j/g}$$

which gives the linear regression form for the NL demand model (Eq. 4.13):

$$lnMS_j - lnMS_0 = x_j\beta - \alpha p_j + (1-\lambda) \cdot lnMS_{j/g} + \xi_j$$

Multinomial Logit Demand Model

In this case the nesting structure shown in Figure 4.2(a) is assumed. Recall that the utility of passenger i (U_{ij}) for a product j in a market m, is given by:

$$U_{ij} = x_j\beta - \alpha p_j + \xi_j + \varepsilon_{ij}$$

Where $x_j\beta - \alpha p_j + \xi_j = V_j$ is the systematic component of the utility and the stochastic term ε_{ij} is Independent Identically Distributed with a type I extreme value distribution.

The aggregate market share MS_j of connection j (including the non-air alternative, *j=0*) among the *J* connections in a market is given by the following logit formula:

$$MS_j = \frac{e^{V_j}}{\sum_{j=0}^{J} e^{V_j}} = \frac{e^{x_j\beta-\alpha p_j+\xi_j}}{\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}} \text{ for all } j=0,1,\ldots,J \tag{A.4}$$

We normalize the systematic utility of the non-air alternative to zero, thus:

$$MS_0 = \frac{e^0}{\sum_{j=0}^{J} e^{V_j}} = \frac{1}{\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}}$$

Divide MS_j by MS_0:

$$\frac{MS_j}{MS_0} = \frac{\frac{e^{x_j\beta-\alpha p_j+\xi_j}}{\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}}}{\frac{1}{\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}}} = e^{x_j\beta-\alpha p_j+\xi_j} \tag{A.5}$$

Take algorithms of (5):

$$lnMS_j - lnMS_0 = ln\left(e^{x_j\beta-\alpha p_j+\xi_j}\right) = x_j\beta - \alpha p_j + \xi_j \tag{A.6}$$

which gives the linear regression form for the MNL demand model (Eq. 4.14):

$$lnMS_j - lnMS_0 = x_j\beta - \alpha p_j + \xi_j$$

A-2. Elasticities

We first compute the derivatives $\partial MS_j/\partial p_j$ and $\partial MS_k/\partial p_j$. These derivatives are used to obtain (i) the own and cross price elasticities and (ii) the Jacobian D of the market share function with respect to prices (used in Chapter 5).

$$D = \begin{bmatrix} \frac{\partial MS_1}{\partial p_1} & \cdots & \frac{\partial MS_J}{\partial p_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial MS_1}{\partial p_J} & \cdots & \frac{\partial MS_J}{\partial p_J} \end{bmatrix}$$

The Nested Logit and the Multinomial Logit model are treated separately.

<u>Nested Logit model</u>

Recall that: $MS_j = \frac{e^{V_j/\lambda}}{D_g^{1-\lambda} \cdot \sum_g (D_g)^\lambda}$, $D_g = \sum_{j \in J_g} e^{V_j/\lambda}$ and $MS_{j/g} = \frac{e^{V_j/\lambda}}{\sum_{j \in J_g} e^{V_j/\lambda}}$.

$$\frac{\partial MS_j}{\partial p_j} = \frac{\left(e^{\frac{V_j}{\lambda}}\right)' \cdot D_g^{1-\lambda} \cdot \sum_g (D_g)^\lambda - e^{\frac{V_j}{\lambda}} \cdot \left(D_g^{1-\lambda} \cdot \sum_g (D_g)^\lambda\right)'}{\left(D_g^{1-\lambda} \cdot \sum_g (D_g)^\lambda\right)^2} \tag{A.7}$$

$$\left(e^{V_j/\lambda}\right)' = \left(e^{(x_j\beta-\alpha p_j+\xi_j)/\lambda}\right)' = \frac{-a}{\lambda}\cdot e^{(x_j\beta-\alpha p_j+\xi_j)/\lambda} = \frac{-a}{\lambda}\cdot e^{V_j/\lambda}$$

$$\left(D_g\right)' = \left(\sum\nolimits_{j\in J_g} e^{V_j/\lambda}\right)' = \frac{-a}{\lambda}\cdot e^{V_j/\lambda}$$

$$\left(\sum\nolimits_g \left(D_g\right)^{\lambda}\right)' = \lambda\cdot D_g^{\lambda-1}\cdot D_g' = \lambda\cdot D_g^{\lambda-1}\cdot\frac{-a}{\lambda}\cdot e^{V_j/\lambda} = -a\cdot e^{V_j/\lambda}\cdot D_g^{\lambda-1}$$

$$\begin{aligned}\left(D_g^{1-\lambda}\cdot\sum\nolimits_g \left(D_g\right)^{\lambda}\right)' &= \left(D_g^{1-\lambda}\right)'\cdot\sum\nolimits_g\left(D_g\right)^{\lambda} + D_g^{1-\lambda}\cdot\left(\sum\nolimits_g\left(D_g\right)^{\lambda}\right)' \\ &= (1-\lambda)\cdot D_g^{-\lambda}\cdot\left(D_g\right)'\cdot\sum\nolimits_g\left(D_g\right)^{\lambda} + D_g^{1-\lambda}\cdot\left(\lambda\cdot D_g^{\lambda-1}\cdot\left(D_g\right)'\right) \\ &= (1-\lambda)\cdot D_g^{-\lambda}\cdot\frac{-a}{\lambda}\cdot e^{V_j/\lambda}\cdot\sum\nolimits_g\left(D_g\right)^{\lambda} + \lambda\cdot\frac{-a}{\lambda}\cdot e^{V_j/\lambda} \\ &= -\alpha\cdot e^{V_j/\lambda}\cdot\left(\frac{1-\lambda}{\lambda}\cdot D_g^{-\lambda}\cdot\sum\nolimits_g\left(D_g\right)^{\lambda} + 1\right)\end{aligned}$$

$$(\mathrm{A.7}) \to \frac{\frac{-a}{\lambda}\cdot e^{V_j/\lambda}\cdot D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda} - e^{V_j/\lambda}\cdot\left(-\alpha\cdot e^{V_j/\lambda}\cdot\left(\frac{1-\lambda}{\lambda}\cdot D_g^{-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}+1\right)\right)}{\left(D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}\right)^2}$$

$$= \frac{\frac{-a}{\lambda}\cdot e^{V_j/\lambda}\cdot D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}}{\left(D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}\right)^2} - \frac{e^{V_j/\lambda}\cdot\left(-\alpha\cdot e^{V_j/\lambda}\cdot\left(\frac{1-\lambda}{\lambda}\cdot D_g^{-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}+1\right)\right)}{\left(D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}\right)^2}$$

$$= \frac{\frac{-a}{\lambda}\cdot e^{V_j/\lambda}}{D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}} - \frac{-\alpha\cdot e^{V_j/\lambda}\cdot\left(e^{V_j/\lambda}\cdot\frac{1-\lambda}{\lambda}\cdot D_g^{-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda} + e^{V_j/\lambda}\right)}{\left(D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}\right)^2}$$

$$= \frac{-a}{\lambda}\cdot MS_j - \frac{-\alpha\cdot e^{V_j/\lambda}}{D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}}\cdot\left(\frac{e^{V_j/\lambda}\cdot\frac{1-\lambda}{\lambda}\cdot D_g^{-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}}{D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}} + \frac{e^{V_j/\lambda}}{D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}}\right)$$

$$= \frac{-a}{\lambda}\cdot MS_j + a\cdot MS_j\cdot\left(\frac{(1-\lambda)\cdot e^{V_j/\lambda}}{\lambda\cdot D_g} + MS_j\right)$$

$$= \frac{-a}{\lambda}\cdot MS_j + a\cdot MS_j\cdot\left(\frac{1-\lambda}{\lambda}\cdot MS_{j/g} + MS_j\right) \Rightarrow$$

$$\frac{\partial MS_j}{\partial p_j} = \frac{-a}{\lambda}\cdot MS_j\cdot\left(1-(1-\lambda)\cdot MS_{j/g} - \lambda MS_j\right)$$

The derivative $\partial MS_k/\partial p_j$ is computed as follows:

$$\frac{\partial MS_k}{\partial p_j}=\frac{\frac{\partial}{\partial p_j}\left(e^{V_k/\lambda}\right)\cdot D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}-e^{V_k/\lambda}\cdot\frac{\partial}{\partial p_j}\left(D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}\right)}{\left(D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}\right)^2} \tag{A.8}$$

Note that: $\frac{\partial\left(e^{V_k/\lambda}\right)}{\partial p_j}\quad=0.$

Thus (A.8) is written as:

$$\frac{\partial MS_k}{\partial p_j}=\frac{-e^{V_k/\lambda}\cdot\left(-\alpha\cdot e^{V_j/\lambda}\cdot\left(\frac{1-\lambda}{\lambda}\cdot D_g^{-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}+1\right)\right)}{\left(D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}\right)^2}$$

$$=\frac{-e^{V_k/\lambda}}{D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}}\cdot\left(\frac{-\alpha\cdot e^{V_j/\lambda}\cdot\frac{1-\lambda}{\lambda}\cdot D_g^{-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}}{D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}}+\frac{-\alpha\cdot e^{V_j/\lambda}}{D_g^{1-\lambda}\cdot\sum_g\left(D_g\right)^{\lambda}}\right)$$

$$=-MS_k\cdot\left(\frac{-\alpha\cdot(1-\lambda)}{\lambda}\cdot\frac{e^{V_j/\lambda}}{D_g}-\alpha\cdot MS_j\right)$$

$$=-MS_k\cdot\left(\frac{-\alpha\cdot(1-\lambda)}{\lambda}\cdot MS_{j/g}-\alpha\cdot MS_j\right)\Rightarrow$$

$$\frac{\partial MS_k}{\partial p_j}=\frac{a}{\lambda}\cdot MS_k\cdot\left((1-\lambda)\cdot MS_{j/g}+\lambda\cdot MS_j\right)$$

Overall, the elements of the **derivative matrix** are given by:

$$D=\begin{cases}\frac{-a}{\lambda}\cdot MS_j\cdot\left(1-(1-\lambda)\cdot MS_{j/g}-\lambda MS_j\right), & if\ j=k\\ \frac{a}{\lambda}\cdot MS_k\cdot\left((1-\lambda)\cdot MS_{j/g}+\lambda\cdot MS_j\right), & if\ j\neq k\end{cases}$$

The own-price (j=k) and cross-price (j≠k) elasticities are given by:

$$\eta_{j,p}=\begin{cases}\frac{a}{\lambda}\cdot p_j\cdot\left(1-(1-\lambda)MS_{j/g}-\lambda MS_j\right), & if\ j=k\\ \frac{a}{\lambda}\cdot p_j\cdot\left((1-\lambda)\cdot MS_{j/g}+\lambda\cdot MS_k\right), & if\ j\neq k\end{cases}$$

<u>Multinomial Logit model</u>

Since $MS_j=\frac{e^{V_j}}{\sum_{j=0}^{J}e^{V_j}}=\frac{e^{x_j\beta-\alpha p_j+\xi_j}}{\sum_{j=0}^{J}e^{x_j\beta-\alpha p_j+\xi_j}}$ the derivative $\partial MS_j/\partial p_j$ is computed as follows:

$$\frac{\partial MS_j}{\partial p_j}=\frac{\left(e^{x_j\beta-\alpha p_j+\xi_j}\right)'\cdot\sum_{j=0}^{J}e^{x_j\beta-\alpha p_j+\xi_j}-e^{x_j\beta-\alpha p_j+\xi_j}\cdot\left(\sum_{j=0}^{J}e^{x_j\beta-\alpha p_j+\xi_j}\right)'}{\left(\sum_{j=0}^{J}e^{x_j\beta-\alpha p_j+\xi_j}\right)^2}$$

But: $\left(e^{x_j\beta-\alpha p_j+\xi_j}\right)'=-a\cdot e^{x_j\beta-\alpha p_j+\xi_j}$

and $\left(\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}\right)' = -a \cdot e^{x_j\beta-\alpha p_j+\xi_j}$

$$\frac{\partial MS_j}{\partial p_j} = \frac{-a \cdot e^{x_j\beta-\alpha p_j+\xi_j} \cdot \sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}}{\left(\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}\right)^2} + \frac{e^{x_j\beta-\alpha p_j+\xi_j} \cdot a \cdot e^{x_j\beta-\alpha p_j+\xi_j}}{\left(\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}\right)^2}$$

$$= \frac{-a \cdot e^{x_j\beta-\alpha p_j+\xi_j}}{\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}} + a \cdot \frac{e^{x_j\beta-\alpha p_j+\xi_j}}{\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}} \cdot \frac{e^{x_j\beta-\alpha p_j+\xi_j}}{\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}}$$

$$= -a \cdot MS_j + a \cdot MS_j \cdot MS_j \Rightarrow$$

$$\frac{\partial MS_j}{\partial p_j} = -a \cdot MS_j \cdot \left(1 - MS_j\right)$$

The derivative $\partial MS_k/\partial p_j$ is computed as follows:

$$MS_k = \frac{e^{x_k\beta-\alpha p_k+\xi_k}}{\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}}$$

$$\frac{\partial MS_k}{\partial p_j} = \frac{\left(e^{x_k\beta-\alpha p_k+\xi_j}\right)' \cdot \sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j} - e^{x_k\beta-\alpha p_k+\xi_k} \cdot \left(\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}\right)'}{\left(\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}\right)^2}$$

$$= \frac{0 \cdot \sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j} - e^{x_k\beta-\alpha p_k+\xi_k} \cdot \left(-a \cdot e^{x_j\beta-\alpha p_j+\xi_j}\right)}{\left(\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}\right)^2}$$

$$= a \cdot \frac{e^{x_k\beta-\alpha p_k+\xi_k}}{\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}} \cdot \frac{e^{x_j\beta-\alpha p_j+\xi_j}}{\sum_{j=0}^{J} e^{x_j\beta-\alpha p_j+\xi_j}} \Rightarrow$$

$$\frac{\partial MS_k}{\partial p_j} = a \cdot MS_k \cdot MS_j$$

For the Multinomial Logit model, the elements of the **derivative matrix** are given by:

$$D = \begin{cases} -a \cdot MS_j \cdot \left(1 - MS_j\right), if\ j = k \\ a \cdot MS_k \cdot MS_j, \quad if\ j \neq k \end{cases}$$

The own-price (j=k) and cross-price (j≠k) elasticities are given by:

$$\eta_{j,p} = \begin{cases} -a \cdot p_j \cdot \left(1 - MS_j\right), \ if\ j = k \\ a \cdot p_j \cdot MS_j, \quad if\ j \neq k \end{cases}$$

Appendix B

B-1. Study Airports

IATA Code	Airport Name	IATA Code	Airport Name
ABE	Lehigh Valley Intl.	LGA	LaGuardia
ABQ	Albuquerque Intl. Sunport	LGB	Long Beach Airport
ALB	Albany Intl.	LIT	Bill and Hillary Clinton Nat Adams Field
ATL	Hartsfield-Jackson Atlanta Intl.	MAF	Midland Intl.
AUS	Austin - Bergstrom Intl.	MCI	Kansas City Intl.
BDL	Bradley Intl.	MCO	Orlando Intl.
BFL	Meadows Field	MDW	Chicago Midway Intl.
BHM	Birmingham-Shuttlesworth Intl.	MEM	Memphis Intl.
BLI	Bellingham Intl.	MFE	McAllen Miller Intl.
BNA	Nashville Intl.	MHT	Manchester-Boston Regional
BOI	Boise Air Terminal	MIA	Miami Intl.
BOS	Logan Intl.	MKE	General Mitchell Intl.
BTR	Baton Rouge Metropolitan/Ryan Field	MSP	Minneapolis-St Paul Intl.
BUF	Buffalo Niagara Intl.	MSY	Louis Armstrong New Orleans Intl.
BUR	Bob Hope	OAK	Metropolitan Oakland Intl.
BWI	Baltimore/Washington Intl.	OGG	Kahului Airport
CAK	Akron-Canton Regional	OKC	Will Rogers World
CHS	Charleston AFB/Intl.	OMA	Eppley Airfield
CLE	Cleveland-Hopkins Intl.	ONT	Ontario Intl.
CLT	Charlotte Douglas Intl.	ORD	Chicago O'Hare Intl.
CMH	Port Columbus Intl.	ORF	Norfolk Intl.
COS	City of Colorado Springs Municipal	PBI	Palm Beach Intl.
CVG	Cincinnati/Northern Kentucky Intl.	PDX	Portland Intl.
DAL	Dallas Love Field	PHF	Newport News/Williamsburg Intl.
DAY	James M Cox/Dayton Intl.	PHL	Philadelphia Intl.
DCA	Ronald Reagan Washington National	PHX	Phoenix Sky Harbor Intl.
DEN	Denver Intl.	PIT	Pittsburgh Intl.
DFW	Dallas/Fort Worth Intl.	PSP	Palm Springs Intl.
DTW	Detroit Metro Wayne County	PVD	Theodore Francis Green State
ECP	Northwest Florida Beaches Intl.	RDM	Roberts Field
EGE	Eagle County Regional	RDU	Raleigh-Durham Intl.

ELP	El Paso Intl.	RIC	Richmond Intl.
EWR	Newark Liberty Intl.	RNO	Reno/Tahoe Intl.
FAT	Fresno Yosemite Intl.	ROC	Greater Rochester Intl.
FLL	Fort Lauderdale-Hollywood Intl.	RSW	Southwest Florida Intl.
GEG	Spokane Intl.	SAN	San Diego Intl.
GRR	Gerald R. Ford Intl.	SAT	San Antonio Intl.
GSP	Greenville-Spartanburg Intl.	SAV	Savannah/Hilton Head Intl.
HNL	Honolulu Intl.	SBA	Santa Barbara Municipal
HOU	William P Hobby	SDF	Louisville Intl.-Standiford Field
HPN	Westchester County	SEA	Seattle/Tacoma Intl.
HSV	Huntsville Intl.-Carl T Jones Field	SFO	San Francisco Intl.
IAD	Washington Dulles Intl.	SJC	Norman Y. Mineta San Jose Intl.
IAH	George Bush Intercontinental/Houston	SJU	Luis Munoz Marin Intl.
IND	Indianapolis Intl.	SLC	Salt Lake City Intl.
ISP	Long Island MacArthur	SMF	Sacramento Intl.
JAC	Jackson Hole	SNA	John Wayne Airport-Orange County
JAN	Jackson Medgar Wiley Evers Intl.	STL	Lambert-St. Louis Intl.
JAX	Jacksonville Intl.	SWF	Stewart Intl.
JFK	John F. Kennedy Intl.	TPA	Tampa Intl.
LAS	McCarran Intl.	TUL	Tulsa Intl.
LAX	Los Angeles Intl.	TUS	Tucson Intl.
LBB	Lubbock Preston Smith Intl.	TYS	McGhee Tyson

B-2. Metropolitan Statistical Area Population

Metropolitan Statistical Area (MSA) population data for the study year 2012 were obtained from the U.S. Census Bureau. The next table presents the MSA and airports selected and associated population data.

MSA name	MSA Code	Population (2012)	Airports included in our sample
New York-Newark-Jersey City, NY/NJ/PA	35620	19,831,858	EWR, LGA, JFK, ISP, HPN, SWF
Los Angeles-Long Beach-Anaheim, CA	31080	13,052,921	LAX, LGB, BUR, SNA
Chicago/Naperville-Elgin, IL/IN/WI	16980	9,522,434	ORD, MDW
Dallas-Fort Worth-Arlington, TX	19100	6,700,991	DFW, DAL
Houston-The Woodlands-Sugar Land, TX	26420	6,177,035	HOU, IAH
Philadelphia-Camden-Wilmington,PA/NJ/DE/MD	37980	6,018,800	PHL
Washington-Arlington-Alexandria,DC/VA/MD/WV	47900	5,860,342	DCA, IAD
Miami-Fort Lauderdale-West Palm Beach, FL	33100	5,762,717	FLL, MIA, PBI
Atlanta-Sandy Springs-Roswell, GA	12060	5,457,831	ATL
Boston-Cambridge-Newton, MA/NH	14460	4,640,802	BOS
San Francisco-Oakland-Hayward, CA	41860	4,455,560	OAK, SFO
Riverside-San Bernardino-Ontario, CA	40140	4,350,096	ONT, PSP
Phoenix-Mesa-Scottsdale, AZ	38060	4,329,534	PHX
Detroit-Warren-Dearborn, MI	19820	4,292,060	DTW
Seattle-Tacoma-Bellevue, WA	42660	3,552,157	SEA

Minneapolis-St.Paul-Bloomington, MN/WI	33460	3,422,264	MSP
San Diego-Carlsbad, CA	41740	3,177,063	SAN
Tampa-St. Petersburg-Clearwater, FL	45300	2,842,878	TPA
St. Louis, MO-IL	41180	2,795,794	STL
Baltimore-Columbia-Towson, MD	12580	2,753,149	BWI
Denver-Aurora-Lakewood, CO	19740	2,645,209	DEN
Pittsburgh, PA	38300	2,360,733	PIT
San Juan-Carolina-Caguas, PR	41980	2,315,683	SJU
Charlotte-Concord-Gastonia, NC-SC	16740	2,296,569	CLT
Portland-Vancouver-Hillsboro, OR/WA	38900	2,289,800	PDX
San Antonio-New Braunfels, TX	41700	2,234,003	SAT
Orlando-Kissimmee-Sanford, FL	36740	2,223,674	MCO
Sacramento--Roseville--Arden-Arcade, CA	40900	2,196,482	SMF
Cincinnati, OH/KY/IN	17140	2,128,603	CVG
Cleveland-Elyria, OH	17460	2,063,535	CLE
Kansas City, MO/KS	28140	2,038,724	MCI
Las Vegas-Henderson-Paradise, NV	29820	2,000,759	LAS
Columbus, OH	18140	1,944,002	CMH
Indianapolis-Carmel-Anderson, IN	26900	1,928,982	IND
San Jose-Sunnyvale-Santa Clara, CA	41940	1,894,388	SJC
Austin-Round Rock, TX	12420	1,834,303	AUS
Nashville/Davidson/Murfreesboro/Franklin, TN	34980	1,726,693	BNA
Virginia Beach-Norfolk-Newport News, VA/NC	47260	1,699,925	ORF, PHF
Providence-Warwick, RI-MA	39300	1,601,374	PVD
Milwaukee-Waukesha-West Allis, WI	33340	1,566,981	MKE
Jacksonville, FL	27260	1,377,850	JAX
Memphis, TN/MS/AR	32820	1,341,690	MEM
Oklahoma City, OK	36420	1,296,565	OKC
Louisville/Jefferson County, KY/IN	31140	1,251,351	SDF
Richmond, VA	40060	1,231,980	RIC
New Orleans-Metairie, LA	35380	1,227,096	MSY
Hartford-West Hartford-East Hartford, CT	25540	1,214,400	BDL
Raleigh, NC	39580	1,188,564	RDU
Birmingham-Hoover, AL	13820	1,136,650	BHM
Buffalo-Cheektowaga-Niagara Falls, NY	15380	1,134,210	BUF
Salt Lake City, UT	41620	1,123,712	SLC
Rochester, NY	40380	1,082,284	ROC
Grand Rapids-Wyoming, MI	24340	1,005,648	GRR
Tucson, AZ	46060	992,394	TUS
Urban Honolulu, HI	46520	976,372	HNL
Tulsa, OK	46140	951,880	TUL
Fresno, CA	23420	947,895	FAT
Albuquerque, NM	10740	901,700	ABQ
Omaha-Council Bluffs, NE/IA	36540	885,624	OMA
Albany-Schenectady-Troy, NY	10580	874,646	ALB
Bakersfield, CA	12540	856,158	BFL

Knoxville, TN	28940	848,350	TYS
El Paso, TX	21340	830,735	ELP
Allentown-Bethlehem-Easton, PA/NJ	10900	827,171	ABE
Baton Rouge, LA	12940	815,298	BTR
McAllen-Edinburg-Mission, TX	32580	806,552	MFE
Dayton, OH	19380	800,972	DAY

B-3. Airline Codes

IATA Airline Code	Airline Name	Airline Type
AA	American Airlines Inc.	Legacy
AS	Alaska Airlines Inc.	Legacy
B6	Jetblue Airways Corporation	Low cost
DL	Delta Air Lines Inc.	Legacy
F9	Frontier Airlines, Inc.	Low cost
FL	AirTran Airways, Inc.	Low cost
HA	Hawaiian Airlines, Inc.	Legacy
UA	United Airlines, Inc.	Legacy
US	US Airways, Inc.	Legacy
VX	Virgin America Inc.	Low cost
WN	Southwest Airlines Co.	Low cost

B-4. Aircraft types

The following table presents the aircraft types included in our traffic sample along with:

- The equivalent aircraft type, to be used for the CO_2 emissions calculations by EMEP CORINAIR and BADA databases,
- The engine type and the number of engines, to be used for the CO_2 emissions calculations by the ICAO Engine Exhaust Emissions databank,
- Their classification in narrow-body or wide-body to be used in the marginal cost function of Chapter 5, and
- The seating capacity, which is used to calculate the per-passenger CO_2 emissions. Depending on the airline policy, seating capacity may vary even for the same aircraft type. In our work, seat capacities are obtained by aircraft manufacturers' manuals assuming two-class seating configuration.

Aircraft	**Equivalent Aircraft for EMEP CORINAIR**	**Equivalent Aircraft for BADA model**	**Engine**	**# of engines**	**Engine type**		**Aircraft size**		**Seat capacity**
					Jet	**Turboprop**	**Narrow-body**	**Wide-body**	
A318	A318	A318	CFM56-5B9	2	•		•		107
A319	A319	A319	IAE V2522-A5	2	•		•		124
A321	A321	A321	CFM56_5B	2	•		•		185
A332	A332	A332	TRENT 772B	2	•			•	246
A333	A333	A333	CF6 80E1 A2	2	•			•	300
AT72	AT72	AT72	PW124	2		•			68
B712	B712	B712	BR715-C1-30	2	•		•		106
B733	B733	B733	CFM56-3B1	2	•		•		149
B734	B734	B734	CFM56-3B2	2	•		•		168
B735	B735	B735	CFM56-3B1	2	•		•		132
B737	B737	B737	CFM56-7	2	•		•		148
B738	B738	B738	CFM56-7B	2	•		•		184
B752	B732	B752	RB211-535E4	2	•		•		186
B753	B753	B753	PW2037	2	•		•		243
B762	B762	B762	PW4062	2	•			•	216
B763	B763	B763	PW4060	2	•			•	237
B764	B763	B764	PW4062	2	•			•	296
B772	B772	B772	GE90-90B	2	•			•	375
CRJ1	CRJ1	CRJ1	CF34-3A1	2	•		•		50
CRJ2	CRJ2	CRJ2	CF34-3B1	2	•		•		50
CRJ7	CRJ9	CRJ9	CF34-8C5	2	•		•		78
CRJ9	CRJ9	CRJ9	CF34-8C5	2	•		•		76
DC95	DC94	DC94	JT8D-11	2	•		•		139
DH8A	DH8A	DH8A	PW120	2		•	•		37
DH8C	DH8C	DH8C	PW120	2		•	•		50
DH8D	DH8D	DH8D	PW150A	2		•	•		78
E120	E120	E120	PW118	2		•	•		30
E135	E145	E135	AE 3007A1E	2	•		•		37
E145	E145	E145	AE 3007A1	2	•		•		50
E170	E170	E170	CF34-8E5	2	•		•		66
E190	E190	E190	CF34-10E6	2	•		•		96
J328	D328	E135	AE 3007A1E	2	•		•		30
MD82	MD82	MD82	JT8D-217C	2	•		•		155
MD83	MD83	MD83	JT8D-219	2	•		•		155
MD90	MD83	MD83	JT8D-219	2	•		•		172
SF34	SF34	SF34	GE CT7-9B	2		•	•		30

Appendix C

C-1. Data process from the Bureau of Transportation Statistics

Three databases for airline statistics are used: the Airline Origin and Destination Survey (DB1B), the T-100 Domestic Segment for U.S. Carriers (T-100) and the On-Time Performance (OTP) database.

Airline Origin and Destination Survey (DB1B)

DB1B is a 10% sample of domestic airline tickets sold by U.S. airlines including detailed data on flight fares, itineraries (Origin, Connecting and Destination airports), ticketing and operating carriers for each flight segment and the number of passengers. These data are given in a quarterly basis through three data tables: DB1B Coupon, DB1B Market and DB1B Ticket. Each directional market is given a unique identification number "Mkt_id". For each ticket the identification number is "Itin_id". These numbers are used as keys in order to merge these DB1B tables as shown in Figure C.1

DB1B COUPON

Itin_id	Mkt_id	Seq_num	Coupons	Year	Quarter	Origin	Destination	Trip break	Ticketing airline	Operating airline	Reporting airline	Passengers	Distance
2012152	201215201	2	3	2012	1	CLT	ATL	X	US	US	16	1	226
2012152	201215201	1	3	2012	1	ABE	CLT		US	16	16	1	481
2012152	201215202	3	3	2012	1	ATL	ABE	X	US	US	16	1	692

Key to merge DB1B Coupon and DB1B Market

DB1B MARKET

Itin_id	Mkt_id	Market coupons	Year	Quarter	Origin	Destination	Reporting airline	Ticketing airline	Operating airline	Passengers	Market fare	Market miles flown
2012152	201215201	2	2012	1	ABE	ATL	16	US	99	1	224.4	707
2012152	201215202	1	2012	1	ATL	ABE	16	US	US	1	219.64	692

Key to merge DB1B Market and DB1B Ticket

DB1B TICKET

Itin_id	Coupons	Year	Quarter	Origin	Round trip	Online	Dollar cred	Reporting airline	Passengers	Itin_fare	Distance	Miles flown
2012152	3	2012	1	ABE	1	0	1	16	1	444	1399	1399

Figure C.1. Methodology to merge DB1B data tables

To supplement the characteristics of the constructed itineraries, two additional databases are used: the T-100 Domestic Segment for U.S. Carriers (T-100) and the On-Time Performance (OTP) database, as explained below.

T-100 Domestic Segment for U.S. Carriers (T-100)

The T-100 table contains non-stop segment data for domestic flights within the boundaries of the U.S. The data are given in a monthly basis and include operating airline, origin and destination airports, aircraft type, available capacity, number of departures, aircraft hours etc. We use T-100 data to supplement airline connections' characteristics with flight frequency and representative aircraft type for each non-stop segment of the itinerary. Table C.1 explains the computation process for flight frequency and representative aircraft type. Flight frequency is extracted in quarterly basis (by summing the monthly frequency). The representative aircraft type is the one with the higher utilization rate in the quarter. The keys to merge T-100 data with DB1B are: Year, Quarter, Origin and Destination airports and Operating airline (see Figure C.2).

Table C.1. Extracted characteristics from T-100 table

	Year	Quarter	Month	Departures	Frequency (flights/ quarter)	Airline	Origin	Destination	Aircraft type	Representative aircraft type
ABE-CLT	2012	1	1	6	**102**	16	ABE	CLT	CRJ-200ER	**RJ-700** (with 73 departures/ quarter)
	2012	1	1	22		16	ABE	CLT	CRJ -700	
	2012	1	2	2		16	ABE	CLT	CRJ -200ER	
	2012	1	2	23		16	ABE	CLT	CRJ -700	
	2012	1	3	21		16	ABE	CLT	CRJ -200ER	
	2012	1	3	28		16	ABE	CLT	CRJ -700	
CLT-ATL	2012	1	1	88	**675**	US	CLT	ATL	A320	**A319** (with 407 departures/ quarter)
	2012	1	1	140		US	CLT	ATL	A319	
	2012	1	2	17		US	CLT	ATL	A321	
	2012	1	2	84		US	CLT	ATL	A320	
	2012	1	2	118		US	CLT	ATL	A319	
	2012	1	3	1		US	CLT	ATL	B737-400	
	2012	1	3	2		US	CLT	ATL	B737-300	
	2012	1	3	29		US	CLT	ATL	A321	
	2012	1	3	47		US	CLT	ATL	A320	
	2012	1	3	149		US	CLT	ATL	A319	

Airline On-Time Performance (OTP)

The Airline On-Time Performance (OTP) table contains on-time arrival data for non-stop domestic flights by major airlines. The data are given flight-by-flight and include origin and destination airports, flight numbers, reporting airlines, scheduled and actual departure and arrival times, departure and arrival delays, taxi-out and taxi-in times etc. We use OTP data to construct delay and time-related variables for the demand model and to compute average taxi-in/out times for each U.S. airport (which are used in the CO_2 emissions model). The keys to merge OTP data with DB1B are: Year, Quarter, Origin and Destination airports and Reporting airline (see Figure C.2).

Extracted data from T-100						
Year	Quarter	Operating Airline	Origin	Destination	Representative aircraft type	Frequency (flights/quarter)
2012	1	US	CLT	ATL	A319	675
2012	1	16	ABE	CLT	RJ-700	102

Key to merge T100 and DB1B

DB1B COUPON													
Itin_id	Mkt_id	Seq_num	Coupons	Year	Quarter	Origin	Destination	Operating Airline	Trip break	Ticketing airline	Reporting airline	Passengers	Distance
2012152	201215201	2	3	2012	1	CLT	ATL	US	X	US	16	1	226
2012152	201215201	1	3	2012	1	ABE	CLT	16		US	16	1	481

Key to merge OTP and DB1B

Extracted data from OTP							
Year	Quarter	Origin	Destination	Reporting Airline	Airborne time (avg)	Departure on time 15 [%]	Arrival on time 15 [%]
2012	1	ABE	CLT	16	81.75	0.93	0.71
2012	1	CLT	ATL	US	44.50	0.90	0.83
AVG: Average, POS: Positive, NEG: Negative							

Figure C.2. DB1B, T-100 and OTP merging