Three Essays on the Economics of Air Transportation

Thèse

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Résumé

Cette thèse est constituée de trois essais en économie du transport aérien. Le premier essai, intitulé *"Effects of Corruption on Efficiency of the European Airports"*, établit un lien entre la corruption et l'efficacité opérationnelle des aéroports européens. Plusieurs États ont privatisé et commercialisé leurs aéroports publics dans le but d'améliorer l'efficacité de leurs opérations. Cependant, un niveau élevé de corruption dans le pays pourrait compromettre la réalisation de cet objectif. La littérature économique suggère que l'exposition à la corruption peut interférer dans l'allocation des ressources, surtout lorsqu'il s'agit de grandes infrastructures. En utilisant des données sur 47 aéroports européens observés au cours de la période de 2003 à 2009 et un indicateur de corruption provenant de "International Country Risk Guide", nous montrons que la corruption a des effets négatifs sur l'efficacité des aéroports et l'ampleur des impacts dépend des structures de propriété et de gestion des aéroports (public, privé et mixte). En particulier, la corruption réduit l'efficacité des aéroports privés. Ces derniers deviennent même moins efficaces que les aéroports publics lorsque l'environnement est fortement corrompu. Nous concluons que la privatisation n'améliore pas nécessairement la performance des aéroports lorsque la corruption est élevée.

Le deuxième essai, intitulé *"Flexible Estimation of an Airport Choice Model : The Case of Quebec Airports"*, analyse les déterminants de choix des voyageurs entre un aéroport régional et une plate-forme de correspondance aéroportuaire au Québec. Parmi les modèles les plus populaires, nous explorons le logit à coefficients fixes et variables, le logit additif généralisé et les estimateurs de probabilités conditionnelles de noyaux pour variables continues et discrètes. Les modèles empiriques utilisent les résultats d'une enquête sur la qualité des services aux aéroports réalisée auprès des passagers embarquant à l'un des deux aéroports principaux de Québec en 2010. Les résultats économétriques soulignent l'importance de la fréquence de vol et de l'accessibilité à l'aéroport dans le choix des voyageurs. Le prix du service, la raison du déplacement ainsi que la destination et l'horaire du vol paraissent aussi pertinents. Bien que les modèles logistiques testés ont des fondements théoriques basés sur les modèles d'utilité aléatoire, les tests économétriques d'adéquation de la forme fonctionnelle rejettent ces modèles. Les estimateurs de noyaux offrent une alternative flexible pour capturer des non-linéarités et des effets d'interaction entre les variables explicatives qui échappent aux modèles logistiques.

Le troisième essai, intitulé *"When Hotelling Meets Vickrey – Spatial Differentiation and Service Timing in the Airline Industry"*, développe un modèle de concurrence duopolistique entre deux aéroports desservis chacun par un transporteur. Les transporteurs offrent un seul vol vers une même destination. L'interaction entre les aéroports et les transporteurs est modélisée à l'aide d'un jeu séquentiel à trois étapes. Dans un premier temps, les aéroports fixent (simultanément) la taxe aéroportuaire chargée aux transporteurs et annoncent la plage horaire disponible pour le vol. Ensuite, les transporteurs fixent chacun l'heure de leur vol. À la dernière étape, les transporteurs décident du prix du voyage. Les voyageurs, répartis sur un espace géographique linéaire de taille fixe et dotés de préférences hétérogènes pour les heures de départ, choisissent le couple aéroport-transporteur en fonction du prix du billet d'avion, du coût de déplacement vers les infrastructures et du coût de déshorage (coût monétaire de partir avant ou après l'heure préférée). Ce cadre d'analyse est utilisé pour explorer l'impact de l'emplacement géographique des aéroports et de l'horaire du vol sur les taxes aéroportuaires, les prix du billet d'avion, la demande des voyageurs et les profits. Les résultats montrent qu'un aéroport qui bénéficie d'une meilleure localisation géographique charge une taxe aéroportuaire plus élevée que son concurrent et que son transporteur profite également de cet avantage en localisation pour accroître ses prix vis-à-vis du transporteur concurrent. Lorsque les coûts opérationnels des transporteurs ne dépendent pas de l'heure de départ, ils fixent un horaire identique et la concurrence pour attirer les voyageurs se fait exclusivement par les prix des billets. Si leurs coûts varient selon l'heure de départ, les transporteurs différencient en général leur horaire, et cela même lorsque ces coûts horaires sont identiques entre transporteurs. La différenciation des temps de départ permet aux aéroports et aux transporteurs de se concurrencer en horaire, ce qui peut réduire ou renforcer l'avantage géographique.

Abstract

My thesis is composed of three essays on the economics of air transportation. My first essay, entitled *"Effects of Corruption on Efficiency of the European Airports"*, analyzes the effect of corruption on airport productive efficiency in Europe. Many governments have privatized and commercialized their airports in order to improve efficiency of their operations. However, this objective may not be achieved if the business-operating environment is very corrupt. According to the economics literature, corruption may be a hindrance to efficiency, especially when it comes to large infrastructures. Using an unbalanced panel data of 47 major European airports from 2003 to 2009 and the corruption measure provided by International Country Risk Guide (ICRG), we show that corruption has a negative impact on airport operating efficiency and the effect depends on the ownership form (private, public and mixed). Airports under mixed public-private ownership with private majority achieve lower levels of efficiency when located in more corrupt countries. They even operate less efficiently than fully and/or majority government owned airports in highly corruption environment. We conclude that privatization may not lead to efficiency gains in countries that suffer from higher levels of corruption.

My second essay, entitled *"Flexible Estimation of an Airport Choice Model: The Case of Quebec airports"*, explores the determinants of passengers' choice between a primary hub and a secondary airport in Quebec. Among the most popular models, we explore fixed- and random-coefficients logistic models along with two flexible alternatives including an additive logistic model and a kernel-based conditional density with continuous and discrete variables. Using an original dataset from the 2010 Airport Service Quality survey conducted in Quebec airports, we show that flight frequency, access time and access mode to airports, among others, are the main factors of airports' choice across all specifications. Airfare, the reason for travel, flight destination and departure times also appear to have significant impacts. While the logistic models have strong theoretical foundations based on the random utility models, the recent kernel-based tests reject these specifications. The nonparametric kernel estimators provide flexible tools to capture non linearities and interactions effects between selected explanatory variables without imposing shape constraints on the conditional probability.

My third essay, entitled *"When Hotelling Meets Vickrey - Spatial Differentiation and Service*

Timing in the Airline Industry", investigates rivalry between transport facilities in a model that includes two sources of horizontal differentiation: geographical location and departure time. We explore how both sources influence facility fees and the price of the service offered by downstream carriers. The interactions between the facilities and their carriers are represented as a sequential three-stage game in fees, departure times and fares with simultaneous choices at each stage. Travellers' cost includes a fare, a transportation cost to the facility and a schedule delay cost, which captures the monetary cost of departing earlier or later than desired. One carrier operates at each facility and schedules a single departure time. We show that duopolistic competition drives to an identical departure time across carriers when their operational cost does not vary with the time of day, but generally leads to distinct service times when this cost depends on the time of the day. When a facility possesses a location advantage, it can set a higher fee and its downstream carrier can charge a higher fare. Departure time differentiation allows the facilities and their carrier to compete along an additional differentiation dimension that can reduce or strengthen the advantage in location.

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To my parents, Jean and
Christine

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I can always count on friends and family gave me the strength and courage to overcome every academic challenge. For that, I kindly thank Maude, Emmanuelle, Nicholas-James, Sarah, Nasro, Mélissa, Steph, Constantinos and Spiros, with whom I shared joys and doubts during my academic journey. I do not forget friends and family from Madagascar for their encouragement. No words of mine can express my gratitude to Tiana and Jony for their hospitality and for always being by my side during my doctoral studies.

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Avant-propos

Les chapitres de la présente thèse sont constitués d'un article publié et de deux documents de travail, qui sont en cours de rédaction dans le but de les soumettre à des revues scientifiques avec comité de lecture.

Le chapitre 1 est un article réalisé avec mon co-directeur Denis Bolduc, les professeurs Tae Oum et Jia Yan ainsi que Dr. Yap Yip Choo. Cet article intitulé "Corruption Effects on Efficiency of the European Airports", dont je suis la principale auteure, a été publié dans le journal scientifique avec comité de lecture *Transportation Research Part A: Policy and Practice*, Volume 79, September 2015, Pages 65−83.

Le deuxième chapitre est un article réalisé avec mon directeur de thèse, Carlos Ordás Criado. Je suis l'auteure principale de cet article. Le troisième chapitre est un article co-écrit avec mon directeur de thèse, Carlos Ordás Criado, et le professeur André de Palma.

Introduction

In the 1970s and 1980s, many governments around the world embraced the international trend towards airline deregulation and airport privatization. Starting with the three airports in London area (Heathrow, Gatwick, and Stansted) in 1987, many airports in Europe, New Zealand and Australia have already been or are in the process of being privatized.[1] In the US, airports are still owned by states but operations of some commercial airports are transferred to either a branch of government (mostly municipal or metropolitan government) or an airport or port authority set up by government. As for Canada, government set up local not-for-profit corporations − airport authorities − to manage major airports. The main goal of privatization and management restructuring of airports is to increase efficiency of their operations, as higher efficiency contributes significantly to regional development, by reducing travel costs of consumers and boosting employment.[2] Besides, some evidence suggest that privatized airports exhibit higher efficiency than the public ones (Oum et al., 2006, 2008).

Since the 2000s economists have been arguing that corruption may interfere in the allocation of resources and then affect efficiency of infrastructures. Svensson (2005) and Dal Bó and Rossi (2007) agree that efficiency losses due to corruption are particularly damaging when it affects large infrastructures. In the aviation industry, Yan and Oum (2014) conclude that corruption engenders input misallocation and reduces productivity of publicly-owned airports. If there exists a negative link between airport efficiency and corruption, efficiency gains from privatization may not be guaranteed in a high corruption environment. The first chapter of this dissertation attempts to empirically test whether this negative relationship between efficiency and corruption exists for European airports, and evaluate if the corruption effects depend upon different forms of airport management and ownership (private, public and mixed). From this study, we offer additional empirical evidence on the effect of corruption on airport efficiency, by using a sample of European airports observed over the 2003 − 2009 period and

[1] The majority (or minority) stakes of a large number of airports have been sold to private owners. For example, the majority stakes in Copenhagen Kastrup International Airport, Vienna International Airport, and Rome's Leonardo Da Vinci Airport have been sold to private owners.

[2] Brueckner (2003) studied the link between airline traffic and urban economic development and shows that a 10% increase in passenger enplanements in a metropolitan area boosts the employment in service-related industries by approximately 1%. This result implies that an airport expansion that would generate a 50% increase in traffic would raise service-related employment in the metropolitan area by 185 000 jobs.

the corruption index provided by International Country Risk Guide (ICRG). The empirical results suggest that airport efficiency is affected by corruption, but the effect depends upon the ownership form. As expected, private airports are more efficient than the public ones, when the country-level corruption is low. However, they operate less efficiently than public airports in a high corruption environment. We conclude that efficiency gains from privatization may be cancelled out by the negative effects of corruption.

The airline deregulation and airport privatization have also promoted development of regional airports, and created opportunity for competition between medium regional and large airline-hub airports. Despite the wide range of studies on airport competition, rivalry between regional and main airports has attracted less attention in the economics literature. The second chapter of this dissertation uses state-of-art estimation methods to explore the determinants of the choice between a regional and the closest airline-hub airports, and quantify their impacts on the conditional choice probability. As previous literature mostly uses the family of random utility models based on logistic specifications to analyze airport competition (see for example Pels et al. (2000, 2003); Ishii et al. (2009)), we empirically test whether the functional forms of the logistic models are correctly specified, and further explore more flexible estimation methods including Generalized Additive models (GAM) and fully nonparametric kernel estimators. Using an original dataset from the 2010 Airport Service Quality (ASQ) survey in Quebec Jean Lesage (YQB) and Montreal Pierre-Elliot Trudeau (YUL) international airports, we show that the choice of a regional facility is strongly linked to the access time and access mode to the airport, flight frequency, departure time, flight destination, reason of flight and passengers' characteristics such as age and gender. Results of the specification tests based on the methods proposed by Fan et al. (2006) and Li and Racine (2013) suggest that both fixed- and random-coefficients logit and GAM models are misspecified from an econometric viewpoint. We report the results of alternative fully nonparametric kernel estimators by means of plotting 3-dimensional devices to give a representation of the interaction effects between continuous and discrete regressors on the conditional probability, often ignored in the literature.

The third chapter of this dissertation discusses strategic interactions between large airline-hub and medium regional airports in a duopolistic market. Empirical evidence suggests that demand for services at an airport is strongly linked to the price of the service offered, access time and cost to the airport and flight departure/arrival times (Pels et al. (2000, 2003); Ishii et al. (2009); Brey and Walker (2011)). Theoretical researchers often borrow the Hotelling (1929) framework to study the pricing mechanism of facilities and downstream carriers when travellers' transportation costs exist (Basso and Zhang (2007)) and to analyze competition in scheduling times (van der Weijde et al. (2014)) while they use the Vickrey (1969) framework to model consumers' value of time and scheduling delay cost.[3] The third chapter of this disser-

[3]The schedule delay cost is defined as the difference between the preferred and the actual departure/arrival

tation attempts to bring Hotelling (1929) and Vickrey (1969) frameworks together to analyze pricing and scheduling decisions of rival carriers and facilities. The model incorporates both spatial differentiation and service timing. It also considers important characteristics of the aviation industry that most of the previous literature have neglected: a captive market, which captures the difference between large and small/medium airports, and the vertical relationship between carriers and airports. In the analysis we consider a three-stage sequential game with multiple agents (airports, airlines and consumers). In the first stage, profit-maximizing airports receive commercial revenues and set the aeronautical fees to be charged to carriers. In the second stage, two cases are studied: (i) when departure times are exogeneously set and carriers compete in fares and (ii) when departure times are simultaneously chosen prior to fares and carriers compete in both departure times and fares. In the last stage, consumers with heterogeneous desired departure times decide whether or not to travel and if so, which facility they depart. The results confirm that without any differentiation, the aeronautical charges and fares are proportional to the facilities' and carriers' marginal costs. When an airport possesses a location advantage, it can set a higher aeronautical fee and its downstream carrier can charge a higher fare. We also find that duopolistic competition drives to identical departure times across carriers when their operational does not vary with the time of day, but generally leads to distinct service times when this cost depends on the time of the day. Differentiation in departure times allows the airports and their carriers to compete in an additional dimension that can reduce or strengthen location advantage. Minimizing the social costs requires a captive market that corresponds to the third of the total market, and differentiated departure times if the time costs are ignored.

time.

Chapter 1

Effects of Corruption on Efficiency of the European Airports

Abstract

The effect of corruption on airport productive efficiency is analyzed using an unbalanced panel data of major European airports from 2003 to 2009. We first compute the residual (or net) variable factor productivity using the multilateral index number method and then apply robust cluster random effects model in order to evaluate the importance of corruption. We find strong evidence that corruption has negative impacts on airport operating efficiency; and the effects depend on the ownership form of the airport. The results suggest that airports under mixed public-private ownership with private majority achieve lower levels of efficiency when located in more corrupt countries. They even operate less efficiently than fully and/or majority government owned airports in high corruption environment. We control for economic regulation, competition level and other airports' characteristics. Our empirical results survive several robustness checks including different control variables, three alternative corruption measures: International Country Risk Guide (ICRG) corruption index, Corruption Perception Index (CPI) and Control of Corruption Index (CCI). The empirical findings have important policy implications for management and ownership structuring of airports operating in countries that suffer from higher levels of corruption.

Keywords: Corruption effect; European airport operating efficiency; Residual (or net) variable factor productivity; Ownership form; Random effects model

1.1 Introduction

This paper investigates the relationship between airport efficiency and corruption in Europe. The determinants of airport efficiency have been largely analyzed in the literature. Studies found that ownership forms (Oum et al., 2006; Assaf and Gillen, 2012; Adler and Liebert, 2014), the level of competition (Chi-Lok and Zhang, 2009; Malighetti et al., 2009), economic regulation (Assaf and Gillen, 2012; Adler and Liebert, 2014) and institutional arrangements (Oum et al., 2008), among others, affect the performance and productivity of airports. The impacts of corruption on airport cost efficiency have received limited attention.

To our knowledge, the study by Yan and Oum (2014) appears to be the only one that investigates the effects of corruption on productivity and input allocation of airports. Using the case of major commercial US airports, their findings reveal that corruption negatively influences airport productivity: in more corrupt environments airports become less productive and tend to use more contracting-out to replace in-house labor. Nonetheless, their empirical analyses are limited to the US airports, which have limited forms of governance. US airports are owned and operated either by a branch of government (mostly municipal or metropolitan government) or through an airport or port authority set up by government. In this study, we extend the analysis of Yan and Oum (2014) to include different forms of airport management and ownership, including mixed public-private ownership with private minority, mixed public-private ownership with private majority and fully private ownership.

In recent years, the private-sector participation in airport management and/or ownership has become a worldwide trend. Starting from the seven major airports in UK including Heathrow, Gatwick and Stansted airports in 1987, many airports in Europe are fully or partially privatized and/or in the process of being privatized.[1] The main goal of airport privatization is to allow for easier access to private sector financing and investment, and to improve operating efficiency (Oum et al., 2006). We argue that privatized airports operating in corrupt environments may not achieve higher levels of efficiency because the incentives for managers to pursue efficiency goals are lower. Furthermore, private sector managers have more autonomy to change the allocation of inputs compared with bureaucrats, then they may focus on deriving personal benefits.

Our research is motivated by the literature on the effects of corruption on firm performance, and the empirical findings of Yan and Oum (2014)[2] and Dal Bó and Rossi (2007)[3] on the negative correlation between corrupt environments and firm productivity. Corruption, which is defined as the misuse of public resources for private gains (Svensson, 2005) is a major source of economic inefficiency, as it diverts scarce resources from their most productive use. Furthermore, corruption is found to divert firms' managerial efforts from productive activities to rent-seeking activities including political connection building (Fisman and Svensson, 2007; Svensson, 2003; Clarke and Xu, 2004; Dal Bó and Rossi, 2007). This study attempts to

[1]For example, majority stakes in Copenhagen Kastrup, Vienna International, and Rome's Leonardo Da Vinci Airports have been sold to private owners.

[2]Yan and Oum (2014) argue that in corrupt environments, bureaucrats have no strong incentives to pursue mandated tasks, leading to a loss of productivity for publicly owned airports.

[3]Dal Bó and Rossi (2007) argue that corrupt countries are strongly associated with more inefficient firms (public and private) in the sense that firms employ more inputs to produce a given level of output.

contribute to both the literature on the influence of corruption on economic performance at the micro level and the literature on the efficiency of airports.

We use airports located in Europe to investigate our research question. The corruption levels of European organizations are relatively lower compared with the rest of the world; however evidence shows that corruption remains a major concern in the European countries. Empirical findings of Hessami (2014) suggest that corruption in the broad sense of use of government office for private benefit is an issue in OECD countries and is not limited to low-income countries. Furthermore, the OECD (2014) reports that bribes are not just a problem for developing world: bribes are being paid to officials from countries at all stages of economic development. The report also reveals that bribes are usually paid to win public contracts from western organizations and most bribe payers and takers are from wealthy countries.

The airport industry in Europe is not free from corruption scandals; for instance, the New York Times reported that a $183 million airport project in Spain has become a symbol of the "wasteful spending that has sunk Spain deep into the recession and the banking crisis".[4] Corruption was also exposed in the reconstruction of Terminal 2 at Germany's Frankfurt Airport in 1996.[5] More recently in 2014, bribery scandals hit the airport of Berlin Brandenburg (BER); bribes were suspected to have been paid by firms wanting to secure airport contracts.[6]

We use an unbalanced panel data set consisting of 47 major airports from 27 European countries during the 2003-2009 period to empirically investigate the impacts of corruption on operating efficiency. Our main corruption measure is the country-level International Country Risk Guide (ICRG) corruption index.[7] The residual (or net) variable factor productivity purchased from the Air Transport Research Society (ATRS) is used as measure of airport operating efficiency. We find that corruption lowers airport managerial efficiency; and the impacts depend on the airport ownership form. Our results confirm the previous findings that privately owned airports, including majority and fully private ownership, are generally more efficient than majority and/or fully government owned airports. However, privately owned airports operate less efficiently than their publicly owned counterparts in high corruption environment. We control for the form of regulation prevalent across European airports, levels of competition, airport characteristics, and potential shocks that may affect airport efficiency during the 2003-2009 period. Our empirical results withstand several robustness checks including different control

[4]The management of the airport of Castellón has been questioned since the airport has not received a single scheduled flight since its inauguration in 2011. See *The New York Times* (July 19, 2012): "In Spain, a symbol of ruin at an airport to Nowhere"

[5]See *The Financial Times* (July 2, 1996): "German Airport Corruption Probe Deepens: Five Jailed and 20 Companies under Investigation" and Reuters Business Report (September 25, 1996): "German corruption wave prompts action", reported in Rose-Ackerman (1999).

[6]For more information, see The Local: Germany's news in English (May 28, 2014): "Bribery probe hits Berlin's scandal airport".

[7]Similar as in Dal Bó and Rossi (2007), we use the ICRG corruption index as our main measure of corruption. The index possesses the advantages of transitivity compared with other indices including World Bank corruption index and/or Transparency International corruption index.

variables, three alternative corruption measures: International Country Risk Guide (ICRG) corruption index, Corruption Perception Index (CPI) and Control of Corruption Index (CCI) and change in the ownership categories.

1.2 Literature Review

Corruption influences economic performance at both macro and micro levels. The impacts of corruption on economic performance at the macro level are considered in Shleifer and Vishny (1993); Mauro (1995); Ades and Di Tella (1999); Wei (2000); Habib and Zurawicki (2002); Sanyal and Samanta (2008); Halkos and Tzeremes (2010). These studies reveal that corruption negatively affects investment and economic growth.

With respect to the effect of corruption on firm-level performance, Murphy et al. (1990, 1993) show that corruption generates social losses because it props up inefficient firms and drives the allocation of talent, technology and capital away from the socially most productive uses. Dal Bó and Rossi (2007) investigate the role of corruption among the determinants of the efficiency of electricity distribution firms. Their theoretical model states that corruption increases the factor requirements of firms, as it diverts managerial effort away from factor coordination. They empirically find that more corruption in the country is strongly associated with more inefficient firms, and the magnitude of the effects of corruption is considerable. Fisman and Svensson (2007) empirically find that firm growth is negatively correlated to both rate of taxation and bribery. Their results reveal that corruption delays the development process to a much greater extent than taxation. Wren-Lewis (2013) confirms these findings, but argues that the participation of an independent regulatory agency reduces the correlation between corruption and efficiency.

For the aviation industry, Yan and Oum (2014) theoretically investigate the effects of local government corruption on the cost of providing public goods, and find that the impact of corruption is contingent on the governance structure and institutional arrangements of airports. Based on US commercial airports, they empirically confirm their theoretical predictions that corruption lowers airport productivity and increases the ratio of non-labor variable input to labor input of airports. The differences in the effects of corruption between airport authorities and airports managed by local government are due to the internal organization structure such as decision-making and managers' autonomy to allocate resources. As a result, governance restructuring, which consists of transferring airport management from a local government to an airport authority may not necessarily lead to efficiency gains in corrupt environments.

Yan and Oum (2014) limit their analysis to the US commercial airports. The US airports are subject to specific governance structure; they are mostly owned, managed and operated by local governments either as government branches or via airport authorities. Since the first privatization of British Airports Authority in 1987, airport governance restructuring has proliferated elsewhere in the world. The goal of our paper is to extend and confirm the findings of Yan and Oum (2014) to include other forms of ownership and governance. Airports in Europe are chosen to test the impact of corruption on efficiency of fully and partially privatized airports.

Literature on airport efficiency identifies three different performance and productivity analysis methods for airports. These approaches include productivity Index Number method, Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). The multilateral index number method, the consistency of which with neoclassical theory of the firm first established by Caves et al. (1982), uses total factor productivity (TFP) as measure of efficiency. TFP is defined as the ratio of output index to input index, and is easy to compute if firms use single inputs to provide single outputs. However, airports utilize multiple inputs such as labor, capital, and other resources to produce multiple services for both airlines and passengers. Similar as in Oum et al. (2006) and Obeng et al. (1992), the multilateral index number method proposed by Caves et al. (1982) can be used to aggregate inputs and outputs.[8] In the past, many studies including Hooper and Hensher (1997) and Nyshadham and Rao (2000) have used TFP approach to evaluate airport performance.

Data envelopment analysis (DEA) is a non-parametric frontier method firstly proposed by Charnes et al. (1978). Based on linear programming method, DEA evaluates efficiency scores for firms (or Decision Marking Units) relative to an efficiency frontier, which is formed by enveloping the data on the frontier. While DEA assumes the continuity and convexity of the production possibility set, it allows for using physical measures of capital inputs such as terminal size, number and/or length of runway as approximation of capital inputs.[9] Some applications of DEA to the aviation industry can be found in Gillen and Lall (1997); Adler and Berechman (2001); Martín-Cejas (2002); Abbott and Wu (2002); Pels et al. (2001, 2003); Barros and Sampaio (2004).

Stochastic Frontier Analysis (SFA) is a parametric approach that uses regression equation to assess efficiency. Firstly developed by Aigner et al. (1976) and Meeusen and Van den Broeck (1977), SFA explains output as a function of inputs and a stochastic disturbance, which consists of two parts: a stochastic inefficiency and a traditional "noise term". For the case of estimating production (cost) function the former is always negative (positive). Similar to DEA, SFA assumes the continuity and convexity of the production possibility set. SFA further assumes a particular form of inefficiency distribution and involves a specification of frontier function, which enables it to conduct hypothesis tests and distinguish the sources of efficiency growth. Tsionas (2003); Pestana Barros (2009); Marques and Barros (2010); Brissimis et al. (2010); Suzuki et al. (2010) are among the many SFA applications. Liebert and Niemeier

[8] TFP assumes that firms are under constant returns to scale and are allocatively efficient. However, TFP requires input and output prices and quantities that are not always available.

[9] One important drawback of DEA method is the lack of transitivity

(2010) provide an interesting review of all three approaches. The TFP approach is chosen for the purposes of this study.

1.3 Methodology

To investigate the effect of corruption on airport efficiency, a two-stage procedure is used. The first stage considers the multilateral index number approach to evaluate the residual (or net) variable factor productivity (rvfp) − our measure of airport operating efficiency. The second stage specifies a regression analysis that explains airport efficiency as a linear function of corruption index and a set of business environmental factors.

1.3.1 Residual (or net) variable factor productivity (rvfp)

The residual (or net) variable factor productivity (rvfp) computed by Air Transport Research Society (ATRS, 2011) is used as measure of airport true managerial efficiency. To obtain the residual (or net) variable factor productivity (rvfp), we first compute the variable factor productivity (vfp) index, which is defined as the ratio of aggregate outputs to aggregate inputs. Since airports utilize multiple inputs to produce multiple outputs, we apply the multilateral index number method, devised by Caves et al. (1982) to aggregate the inputs and outputs.

The number of aircraft movements (ATMs), passenger volumes and non-aeronautical revenues are considered to aggregate outputs.[10] It is noteworthy that demand for non-aeronautical services is closely related and complementary to that for aeronautical services (Oum et al., 2006). Moreover, the non-aeronautical revenues account for a large and increasing portion of airport revenues.[11] Thus, we need to include non-aeronautical revenues among aggregate outputs in order to circumvent serious bias in measuring airport operating efficiency.

With respect to inputs, airports utilize multiple resources including labor input, purchased goods and materials, and purchased services (outsourcing and contracting out) to produce multiple services for airlines and passengers. Labor input is defined as the full-time equivalent number of employees directly paid for by the airport operators. The outsourced services for goods, services, and materials purchased directly by an airport are combined with all other inputs to form a so-called "soft-cost input". We note that our efficiency measure does not consider capital inputs. It is almost impossible to assess capital inputs and expenditures accurately on a comparable basis. Besides, capital costs are usually quasi-fixed during a long-term period while the vfp accounts for a short and/or medium term period.

[10] Air cargo services are generally handled by airlines, third-party cargo handling companies and others, which lease space and facilities from airports. Air cargo services are not considered as a separate output in this research, as airports derive a very small percentage of their income from direct service related to air cargo

[11] On average, the non-aeronautical activities including concessions, car parking, and numerous other services account for about half of the total airport's revenue in our sample.

The residual (or net) variable factor productivity (rvfp) is obtained by using a regression analysis, which consists of removing the effects of factors that cannot be controlled by airport managers at least in the short to medium term from the vfp index. These factors include the percentage of international passengers, cargo share, capacity constraint, average aircraft size, airport size and different macroeconomic shocks. The residual of the variable factor productivity index is deemed as more accurate for this research.

1.3.2 Econometric model

In the econometric section, we estimate a model that explains airport efficiency, measured by the residual (or net) variable factor productivity ($rvfp$) as a linear function of a set of potential business environmental variables. These variables include the country-level corruption index of the airport (CI_{it}), the airport's ownership form ($\mathbf{OF}'_{it}$), an interaction between ownership and corruption, and a set of control variables (X_{it}). When the data structure is a sample of airports observed over several time periods (a panel dataset), the regression equation reads:

$$rvfp_{it} = \alpha + \lambda CI_{it} + \mathbf{OF}'_{it}\beta + (CI_{it} \times \mathbf{OF}'_{it})\gamma + \mathbf{X}'_{it}\delta + \varepsilon_{it} \quad (1.1)$$

where $rvfp_{it}$ represents the residual (or net) variable factor productivity of airport i at time t. CI_{it} corresponds to the country-level corruption index (CI) of airport i at time t and $\mathbf{OF}'_{it}$ the ownership form. We include an interaction between the corruption index and ownership form, ($CI_{it} \times \mathbf{OF}'_{it}$) to capture the effects of corruption under different types of ownership. $\mathbf{X}'_{it}$ denotes a set of control variables that potentially affect airport efficiency in addition to corruption, including the form of economic regulation that is prevalent across Europe, the level of competition across gateways and within the catchment area, whether the airport is used as airline hub and/or international gateway, whether the airport belongs to a group from a managerial perspective, and gross domestic product (GDP) per capita. Another set of controls including indicators of institutional quality variables, a proxy of openness to trade and a measure of the importance of government in the economy are added to test the robustness of our results.[12] ε_{it} refers to an independent and identically distributed error term over the airport i and time t dimensions; α is the regression's intercept. The parameters $\lambda, \beta, \gamma, \delta$ represent the marginal effects of the explanatory variables.

Given the panel structure of the equation, we estimate both pooled Ordinary Least Squares (OLS) and airport/time-specific random effects (RE) models. The pooled OLS model assumes common intercepts and slopes across airports and periods, and it produces consistent estimates when the data are poolable.[13] The random effects (RE) model assumes the intercept α as being a random component. When appropriate, the RE estimator is usually better at capturing the

[12] These variables are largely recognized in the literature as having a strong relationship with corruption.

[13] Checking the poolability assumption requires a sample size that allows running individual time-series regressions or cross-sectional yearly regressions, see Hsiao (1986, Chapter 2) . In our case, the lack of degrees of freedom prevented us to perform individual time-series regressions.

individual and time heterogeneity and it can strongly improve the fit as compared to the pooled OLS model. Our econometric analysis also applies statistical tests that check the violation of fundamental hypotheses of the standard regression model (heteroscedasticity, autocorrelation and cross-sectional dependencies), which alters inference. We apply the required corrections when needed. Other tests are also conducted to compare the competing models and select the most appropriate one from a statistical viewpoint.

1.4 Data description

We compile data from 47 airports located in 27 European countries during the 2003-2009 period. The airport data comes from various sources including the International Civil Aviation Organization (ICAO), Airport Council International (ACI), International Air Transport Association (IATA) and airport annual reports. Some of the data was obtained directly from the airports. Table 1.1 lists the airports included in the sample as well as the form of ownership that governs each airport during the 2003-2009 period.

Among the sample of 47 airports during the 2003-2009 period, 5 were fully private, 7 were owned and/or operated by mixed public-private enterprises with private majority, 9 were owned and/or operated by mixed public-private enterprises with government majority, and 21 were owned and/or operated or by 100% government (or public corporations). Five airports including Amsterdam Schipohl (AMS), Brussels (BRU), Rome Ciampino (CIA), Paris Charles de Gaulle (CDG) and Paris Orly (ORY) have experienced ownership and management restructuring during the period of concern. These airports were traditionally fully owned, managed and operated by governments. The majority of stakes of Rome Ciampino and Brussels airports were sold to private sector interests in 2004 and 2005, respectively. The management and ownership of Paris Charles de Gaulle, Paris Orly and Amsterdam Schiphol airports were transferred to mixed private-public enterprises with government majority in 2006, 2006 and 2008, respectively.

Table 1.1 – List of airports

Code	Airport	Country	Time Period	Ownership
AMS	Amsterdam Schiphol	Netherlands	2003-2007	100% government
			2008-2009	Mixed with govt majority
ARN	Stockholm Arlanda	Sweden	2003-2009	100% government
ATH	Athens	Greece	2004-2009	Mixed with govt majority
BCN	Barcelona El Prat	Spain	2003-2009	100% government
BHX	Birmingham	United Kingdom	2003-2009	Mixed with private majority
BRU	Brussels	Belgium	2003-2004	100% government
			2005-2009	Mixed with private majority
BTS	Bratislava Milan Rastislav Stafanik	Slovaki	2004-2009	100% government
BUD	Budapest Ferihegy	Hungary	2008-2009	Mixed with private majority
CDG	Paris Charles de Gaulle	France	2004-2005	100% government
			2006-2009	Mixed with govt majority
CGN	Cologne/Bonn Konrad Adenauer	Germany	2004-2009	100% government
CIA	Rome Ciampino	Italy	2003	100% government
			2004-2009	Mixed with private majority
CPH	Copenhagen Kastrup	Denmark	2003-2009	Mixed with private majority
DUB	Dublin	Ireland	2003-2009	100% government
DUS	Dlughafen Dusseldorf	Germany	2003-2009	Mixed with govt majority
EDI	Edinburgh	United Kingdom	2003-2009	Fully private
FCO	Rome Leonardo Da Vinci/Fiumicino	Italy	2003-2009	Mixed with private majority
FRA	Frankfurt Main	Germany	2003-2009	Mixed with govt majority
GVA	Geneva Cointrin	Switzerland	2003-2009	100% government
HAJ	Hannover-Langenhagen	Germany	2009	Mixed with govt majority
HAM	Hamburg	Germany	2003-2009	Mixed with govt majority
HEL	Helsinki Vantaa	Finland	2003-2009	100% government
IST	Istanbul Ataturk	Turkey	2009	Mixed with private majority
KEF	Keflavik	Iceland	2007, 2009	100% government
LGW	London Gatwick	United Kingdom	2003-2009	Fully private
LHR	Heathrow	United Kingdom	2003-2009	Fully private
LIS	Lisbon Portela	Portugal	2003-2009	100% government
LJU	Ljubljana	Slovenia	2007-2009	Mixed with govt majority
LTN	London Luton	United Kingdom	2009	Mixed with private majority
MAD	Madrid Barajas	Spain	2003-2009	100% government
MAN	Manchester	United Kingdom	2003-2009	100% government
MLA	Malta	Malta	2003-2009	Mixed with private majority
MUC	Munchen	Germany	2005-2009	100% government
NAP	Naples	Italy	2009	Mixed with private majority
NCE	Nice Cote d'Azur	France	2009	100% government
ORY	Paris Orly	France	2004-2005	100% government
			2006-2009	Mixed with govt majority
OSL	Oslo	Norway	2003-2009	100% government
PRG	Prague	Czech Republic	2003-2007	100% government
RIX	Riga	Latvia	2004-2009	100% government
SOF	Sofia	Bulgaria	2004-2009	100% government
STN	Stansted	United Kingdom	2003-2009	Fully private
SZG	Salzburg	Austria	2009	100% government
TLL	Tallinn	Estonia	2003, 2006-2009	100% government
TRN	Turin	Italy	2009	Mixed with govt majority
TXL	Berlin Tegel	Germany	2007-2009	100% government
VIE	Vienna	Austria	2003-2009	Mixed with govt majority
WAW	Warsaw Frederic Chopin	Poland	2003-2009	100% government
ZRH	Zurich	Switzerland	2003-2009	Mixed with govt majority

Note: "Mixed with govt majority" denotes "Mixed public-private with government majority" and "Mixed with private majority" denotes "Mixed public-private with private majority".

1.5 Description of variables

1.5.1 Variables in the efficiency analysis

Details on the variables used for the efficiency analysis are summarized in Table 1.2. The output variables include the number of aircraft movements (ATMs), passenger volumes and non-aeronautical revenues. As for input variables, labor input, purchased goods and materials and purchased services (outsourcing and contracting out) are considered.

Table 1.2 – Descriptive statistics of the variables used in the airport efficiency analysis

Variable	Observation	Mean	Standard Deviation	Min	Max
Output (thousands)	254	1.306	1.271	0.0539	5.813
Number of runways	254	2.25	0.949	1	5
% Non-aeronautical revenue	254	0.474	0.141	0.183	0.848
Number of employees	254	2897	4450.92	136	30437
Variable Factor Productivity (VFP)	254	1.120	0.419	0.335	2.472
% International Passengers	254	0.797	0.188	0.278	1
Cargo share	254	0.010	0.009	0.000	0.042
Aircraft size (thousands)	254	4.401	0.269	3.343	4.967
Low Cost Carriers (thousands)	254	0.319	0.467	0	1
Terminal size (square metres)	254	190620.6	199602.8	8000	1000000
Residual variable factor productivity (rvfp)	254	0.628	0.212	0.216	1.280

Source: ATRS global airport performance benchmarking reports (2003- 2009). Units of measurement are in brackets.

1.5.2 Variables in the econometric analysis

Measures of corruption

Corruption, our main variable of interest, is defined as the misuse of public office for private gain (Svensson, 2005). We consider three indices of corruption drawn from three different sources: the corruption index computed by International Country Risk Guide (ICRG), Corruption Perception Index (CPI) provided by Transparency International and the Control of Corruption Index (CCI) delivered by the World Bank.[14] All three indices are survey-based.

The ICRG corruption index captures the likelihood and the expectations that government officials will demand special payment in the form of "bribes connected with import and export licenses, exchange controls, tax assessment, police protection, or loans". Drawn from indicators assembled by panels of inte rnational experts, it evaluates corruption mainly within the political system. ICRG corruption index allows for comparison across countries and over time, therefore it is particularly well suited to our main objective. Besides, the ICRG corruption index is widely used in the economics literature (see for example, Knack and Keefer (1995),

[14] This analysis focuses on country-level corruption. The subjective indices, which are derived from fully convincing methodology, provide satisfactory country coverage during the 2003-2009 time period. In addition, the corruption perception surveys are relatively well suited to compare countries in terms of corruption because the sources all aim at measuring the degree of corruption, using identical methodology. Mauro (1995) and Lambsdorff (2006) discussed the validity and precision of subjective corruption indices.

Dal Bó and Rossi (2007)). The original index ranges between zero (highly corrupt) and six (highly clean); so a higher corruption index corresponds to a less corrupt country.

Both CPI and CCI are composite indices. While CPI looks at corruption in the public sector, CCI considers corruption in both public and private sectors. CPI corresponds to the average of ratings reported by a number of perception-based sources and business surveys[15] carried out by a variety of independent and reputable institutions. However, CCI is drawn from a large set of data sources including a diverse variety of survey institutes, think tanks, and non-governmental and international organizations. Contrary to ICRG corruption index, CCI and CPI lack "transitivity". Their country rankings can change substantially as one adds or drops one or more countries from the sample.[16] The original CPI scores countries on a scale from zero (highly corrupt) to ten (highly clean) while the original CCI scores range from -2.5 (highly clean) to 2.5 (highly corrupt). Since it is not meaningful to compare original scores generated by each source, the corruption scores are rescaled between 0 and 10 by setting the value for the most corrupt country at 10 and the least corrupt country at 0. Table 1.3 compares the three alternative corruption indices in 2009.

The country rankings and corruption scores are compared across the three sources. Regardless of the methodology used, Finland, Denmark, Sweden, the Netherlands and Iceland are the cleanest countries in our sample whereas Bulgaria, Greece, Italy, Turkey and Slovakia are the most corrupt countries. The country rankings in the top and bottom ranges of the scores are quite robust with respect to the methodology. By contrast, the country rankings in the middle ranges including Italy, Ireland and Poland rankings are more sensitive to the source used. Nonetheless, the three corruption indices are highly correlated with each other.[17] The correlation between CCI and CPI is the highest, indicating that both indices yield rather similar country rankings.

Ownership form

The applied literature has established the influence of the ownership form on airports' operating efficiency. We explore this finding for European airports by including the ownership form of airport i at time t in the model. We observe 4 types of ownership in our sample of airports including (1) fully private ownership (2) mixed public-private ownership with private majority (above 50%) (3) mixed public-private ownership with government majority (above 50%) (4) 100% government or public corporation ownership. However, due to the limited data, we

[15] The surveys include questions relative to the misuse of public power for private benefits such as bribery by public officials, kickbacks in public procurement, embezzlement of public funds.

[16] For more details on the methodology used by World Bank and Transparency International to compute CCI and CPI scores, readers can refer to http://www.worldbank.org and http://www.transparency.org. We note that Transparency International has improved its methodologies to compute CPI index since 2012 in order to allow for comparison over times.

[17] The correlation coefficients between ICRG index and CPI, ICRG index and CCI and CCI and CPI are 0.8803, 0.8875, 0.9662, respectively.

Table 1.3 – Corruption Indices of the sample of countries - 2009

Country	ICRG Corruption Index	Country	CPI	Country	CCI
Finland	0	Denmark	3.8	Denmark	0.15
Denmark	1.25	Sweden	3.9	Sweden	0.58
Iceland	1.25	Switzerland	4.1	Finland	0.58
Sweden	2.5	Finland	4.2	Netherlands	0.83
Netherlands	2.5	Netherlands	4.2	Iceland	0.97
Austria	2.5	Iceland	4.4	Switzerland	0.99
Norway	2.5	Norway	4.5	Norway	1.16
Germany	2.5	Germany	5.1	Austria	1.54
France	2.5	Ireland	5.1	Ireland	1.63
Belgium	2.5	Austria	5.2	Germany	1.71
Switzerland	3.75	United Kingdom	5.4	United Kingdom	2.03
United Kingdom	5	Belgium	6	Belgium	2.24
Portugal	5	France	6.2	France	2.31
Spain	5	Estonia	6.5	Portugal	3.00
Ireland	6.25	Slovenia	6.5	Slovenia	3.01
Malta	6.25	Spain	7	Spain	3.09
Estonia	7.5	Portugal	7.3	Estonia	3.25
Hungary	7.5	Malta	7.9	Latvia	3.29
Slovenia	7.5	Hungary	8	Malta	3.29
Poland	8.75	Poland	8.1	Poland	4.26
Italy	8.75	Latvia	8.6	Hungary	4.39
Slovakia	8.75	Slovakia	8.6	Slovakia	4.58
Turkey	8.75	Turkey	8.7	Turkey	4.94
Bulgaria	10	Italy	8.8	Greece	5.01
Greece	10	Bulgaria	9.3	Italy	5.14
Latvia	10	Greece	9.3	Bulgaria	5.54

Notes: ICRG Corruption Index is the International Country Risk Guide's corruption indicator (average over 12 months). CPI is the Corruption Perception Index computed Transparency International and CCI compute the Control of Corruption Index by the World Bank. ICRG, CPI and CCI scores are rescaled so that each index ranges between 0 and 10, with a higher score indicating higher corruption and a lower score indicating lower corruption.

combine fully private ownership and mixed public-private ownership with private majority.[18] Thus, we categorize ownership forms according to: (1) mixed public-private ownership with private majority (including fully private) (2) mixed public-private ownership with government majority (above 50%) (3) 100% government or public corporation ownership. Ownership forms are modelled with the help of dummy variables. We denote mixed public-private ownership with private majority as the reference category. We further enquire whether corruption has an effect that potentially depends on the ownership form by including interaction terms between corruption and ownership dummy variables.

[18]Seven of our sampled airports are owned and operated by mixed enterprises with private majority (50%) and five are fully privatized airports.

Economic regulation and competition

Previous research has found that competition and economic regulation, individually or jointly affect airport efficiency (Chi-Lok and Zhang, 2009; Malighetti et al., 2009; Scotti et al., 2012; Adler and Liebert, 2014). Regarding economic regulation, airports in Europe are traditionally subject to rate of return or cost-based regulation. More recently there has been a trend towards implementing a form of incentive regulation - the price-cap regulation- when airports are privatized or semi-privatized (Gillen and Niemeier, 2006). Both cost-based and price cap regulations can be set under a single or dual till regime.[19] Following Adler and Liebert (2014), we classify the forms of airport economic regulation according to (1) no ex-ante regulation (2) single-till cost-plus regulation (3) dual-till cost-plus regulation (4) single-till price-cap regulation (5) dual-till price-cap regulation (6) charges set by airports (single and dual till).

The proxy of airport competition is defined in line with Adler and Liebert (2014). The variable is based on the number of commercial airports with at least 150 000 passengers per annum within a catchment area of 100 km around the airport. Two levels of competition are considered: strong and weak. An airport is assumed to be facing weak competition at the regional level if there is no more than one additional airport within the catchment area, and strong competition if there are at least two additional airports within the catchment area. In addition, a hub airport that serves as a regional or international gateway is classified as facing strong competition, regardless of its local catchment area. Due to the lack of information, we are not able to account for different product diversification strategies such as low cost carrier traffic. As Adler and Liebert (2014) pointed out, this measure of competition only indicates an upper level of likely competition across airports.

Airport characteristics

We include a set of control variables that capture the major characteristics of our sample of airports. These variables consist of the status of the airport as a hub and/or international gateway[20], whether the airport belongs to a group from a managerial perspective, and the gross domestic product (GDP) per capita. The controls are included in the model with the help of dummy variables. GDP per capita would capture time and country-specific macroeconomic factors such as productivity shocks. Details on variables used in the econometric analysis are summarized in Table 1 in the Appendix A.

[19] Czerny (2006) discusses the key difference between single-till and dual-till regulation. He argues that with single-till the price-cap is set in anticipation of the revenues from aeronautical and commercial services. The dual-till approach, in contrast, tries to separate out the two airport business branches, particularly by attributing specified portions of airports' costs to aeronautical and commercial branches.

[20] Hub airports may possess advantages in terms of efficiency because of their size and location, therefore we include a dummy variable to capture the status of the airport as an international and/or regional hub.

1.6 Empirical results

The first part consists of a discussion on airport efficiency results. In the second part, we analyze the impacts of corruption and other factors on the airport operating efficiency.

1.6.1 Estimates from the efficiency analysis

This study uses the residual (or net) variable factor productivity as a measure of airport operating efficiency. Efficiency scores of the sample of airports are listed in Table 1.4.

The scores vary from 0.216 (the least efficient) to 1.28 (the most efficient). The average efficiency score goes from 0.616 in 2003 to 0.613 in 2009, with around 42% of all airports categorized as relatively efficient. Except for Brussels airport (BRU), none of the airports in the sample consistently improved their efficiency over time. Between 2003 and 2009, Brussels increased its score from 0.639 to 0.906. The private sector participation in the management and ownership of Brussels airport in 2005 may contribute to consistently maintain its improvement in terms of efficiency.

Amsterdam (AMS), Dublin (DUB), Stockholm (ARN) and Helsinki (HEL) airports enhanced their efficiencies between 2003 and 2004, but consistently exhibit an efficiency decrease between 2004 and 2009. By contrast, Paris Charles de Gaulle (CDG), Rome Fiumicino (FCO), Gatwick (LGW), Manchester (MAN), Paris Orly (ORY), Stansted (STN), Vienna (VIE) and Warsaw (WAW) airports appear to have relatively constant efficiency scores between 2003 and 2009. For some airports including Amsterdam, Paris Charles de Gaulle and Paris Orly, the minor participation of private sectors in the airport management and ownership does not necessarily lead to efficiency gains. Copenhagen airport (CPH) is found as the most efficient airport among the sample of European airports between 2003 and 2009, with an average operating efficiency of 1.007. The top performers during the 2003-2009 period include Istanbul (IST), Oslo (OSL), Barcelona (BCN) and Madrid (MAD), with average efficiency scores of 0.985, 0975, 0.936 and 0.924, respectively. The airports of Cologne-Bonn (CGN), Munich (MUC), Berlin (TXL), Bratislava (BTS), Riga (RIX) and Sofia (SOF), by contrast, appear to be the least relatively efficient airports in the sample, with average scores less than 0.4. Cologne-Bonn suffers from excess airside capacities despite the extensive cargo operations resulting from its position as the European hub for Germanwings, FedEx Express and UPS Airlines (Adler and Liebert, 2014).

1.6.2 Econometric results

Statistical tests show that the Random Effect (RE) model is the most appropriate, and its Pooled OLS counterpart delivers similar results without providing efficiency gains in the es-

Table 1.4 – Residual (or net) variable factor productivity (rvfp) efficiency scores

Airport	2003	2004	2005	2006	2007	2008	2009
AMS	0.763	0.921	0.827	0.758	0.743	0.720	0.651
ARN	0.789	0.984	0.641	0.643	0.694	0.509	0.426
ATH	-	1.244	0.715	0.774	0.719	0.769	1.059
BCN	0.828	1.051	0.959	0.924	1.101	1.032	0.655
BHX	0.948	0.655	0.713	0.668	0.643	0.646	0.675
BRU	0.639	0.670	0.783	0.790	0.803	0.888	0.906
BTS	-	0.329	0.402	0.341	0.309	0.359	0.391
BUD	-	-	-	-	-	0.578	0.457
CDG	-	0.735	0.720	0.694	0.834	0.769	0.709
CGN	-	0.284	0.297	0.309	0.284	0.306	0.328
CIA	0.932	0.779	0.794	0.802	0.849	0.684	0.691
CPH	0.872	0.931	0.817	1.280	1.128	0.984	1.040
DUB	0.497	0.855	0.793	0.745	0.746	0.696	0.618
DUS	0.573	0.506	0.433	0.395	0.402	0.402	0.406
EDI	0.486	0.582	0.560	0.544	0.668	0.851	0.750
FCO	0.630	0.583	0.547	0.663	0.712	0.607	0.626
FRA	0.393	0.496	0.471	0.421	0.450	0.398	0.352
GVA	0.715	0.749	0.783	0.847	0.824	0.944	0.903
HAJ	-	-	-	-	-	-	0.727
HAM	0.350	0.495	0.496	0.503	0.474	0.503	0.508
HEL	0.520	0.610	0.600	0.558	0.494	0.431	0.391
IST	-	-	-	-	-	-	0.985
KEF	-	-	-	-	0.326	-	0.627
LGW	0.565	0.639	0.596	0.492	0.635	0.562	0.518
LHR	0.548	0.612	0.550	0.390	0.519	0.419	0.416
LIS	0.569	0.596	0.700	0.741	0.726	0.966	0.663
LJU	-	-	-	-	0.540	0.611	0.657
LTN	-	-	-	-	-	-	0.658
MAD	0.772	0.980	0.936	0.889	1.116	1.073	0.704
MAG					0.541	0.544	0.477
MAN	0.511	0.746	0.518	0.512	0.577	0.515	0.511
MLA	0.443	0.505	0.557	0.536	0.514	0.561	0.587
MUC	-	-	0.339	0.345	0.324	0.330	0.310
NAP	-	-	-	-	-	-	0.654
NCE	-	-	-	-	-	-	0.849
ORY	-	0.445	0.365	0.419	0.547	0.502	0.473
OSL	0.760	0.709	0.963	1.067	1.059	1.150	1.116
PRG	0.432	0.425	0.822	0.511	0.490	-	-
RIX	-	0.216	0.325	0.388	0.432	0.382	0.462
SOF	-	0.322	0.375	-	-	0.422	0.401
STN	0.670	0.747	0.710	0.587	0.649	0.642	0.619
SZG	-	-	-	-	-	-	0.502
TLL	0.436	-	-	0.477	0.472	0.475	0.568
TRN	-	-	-	-	-	-	0.609
TXL	-	-	-	-	0.389	0.329	0.314
VIE	0.490	0.503	0.527	0.537	0.495	0.536	0.557
WAW	0.387	0.487	0.456	0.454	0.483	0.422	0.355
ZRH	0.732	0.784	0.786	0.891	0.858	0.892	0.961

Notes: "-" indicates that the rvfp score of the airport for that year is not available in the dataset.

timates.[21] We notice in Table 1.5 that the RE model explains a much higher share of the total variance of the dependent variable (R Squared) than the pooled OLS regression, and its Adjusted R Squared is much larger as well. Therefore, the RE model is superior in terms of within-sample goodness-of-fit. The Fisher tests accept the absence of time-fixed effects in both pooled OLS and RE models, indicating that no common significant shocks have affected the efficiency of European airports during the period of scrutiny.[22]

We report the estimation results from the pooled OLS model in column (2) of Table 1.5 and the ones from the RE model in column (3). The estimation results from the RE model are used as the basis for our analysis. Given that both models display strong heteroscedasticity and autocorrelation in the residuals, robust standard errors are stated in parenthesis.[23]

First, we notice that the partial effects of the main variables of interest - corruption, ownership and the interaction terms between corruption and ownership - are highly significant in the RE model and that the signs and magnitudes remain rather robust in the pooled OLS model. Given that the influence of corruption on airport operating efficiency depends on the ownership form, we ran a regression of rvfp on the corruption index, the ownership dummies and the business environmental factors without including the interaction terms in the regression. We found no significant effects of corruption on rvfp.[24] This stresses the importance of accounting for the interactions to uncover the effect of corruption on airport efficiency.

As shown in Table 1.5, the impact of corruption on airports' efficiency is negative, and its effect is significant at the 1% level in both RE and pooled OLS specifications. This result suggests that corruption has a negative impact on airport efficiency under mixed public-private ownership with private majority (the default ownership category). Privately owned airports located in less corrupt countries operate more efficiently than the ones situated in more corrupt countries. An increase in one point[25] in the corruption index decreases the residual (or net) variable factor productivity of 0.04 units. This negative influence of corruption on efficiency is consistent with previous literature in other sectors (see for example Dal Bó and Rossi (2007)). Indeed, corruption is found to lower productivity through a diversion of managerial efforts away from running productive activities. In a high corruption environment, airport managers would have more incentives to use bribes when they channel resources to establish lobbies and connections. Then, poor governance and culture of cronyism in highly corrupt countries spur managers of privately owned airports to focus less on airport productivity objectives, leading

[21] The Lagrangian Multiplier test for random effects displays a statistic of Fisher value of 161.32 and associated p-value of 0.000, indicating that Random effects model is preferred to Pooled OLS.

[22] The statistics of Fisher (and their associated p-value) for Pooled OLS and RE models are 1.58 (0.174) and 6.91(0.329), respectively indicating that we cannot reject the null hypothesis that year effects are insignificant.

[23] We employ cluster-robust standard errors as recommended by Wooldridge (2002).

[24] We do not report here the estimation results for the sake of parsimony.

[25] We need to be careful in the interpretation of these results. As pointed out by Mauro (1995), when using perception indexes, it is not clear if the difference between the corruption grade of one and two is the same as between 4 and 5.

eventually to lower airport efficiency.

The effects of corruption on mixed public-private ownership with government majority and 100% government ownership are obtained by summing the estimated coefficient of the corruption index to the estimated coefficients' vector of the interaction terms (i.e., $\lambda + \gamma$ if we refer to Equation 1.1). For each ownership category, the impact is significant if the sum is statistically different from zero. In the RE specification, mixed ownership with government majority displays a sum of 0.007, whereas fully public ownership exhibits a sum of -0.013. In both cases, the Fisher test concludes that the sum is not significantly different from zero at the required cutoffs.[26] Corruption has no effects on the efficiency of both publicly owned airports.

In a high corruption environment, privately owned airports appear to operate less efficiently than publicly owned airports. This finding lines up with the work of Yan and Oum (2014) with respect to the autonomy of airport managers in allocating inputs. Yan and Oum (2014) argue that local tax revenues can fund the operations of a government-owned airport, and that the funding source restricts the airport's flexibility to change inputs allocation.[27] By contrast, managers of privately owned airports have enough managerial autonomy to allocate inputs, so they can either pursue cost efficiency objectives or divert resources to their personal benefits. Therefore, managers of privately owned airports have more freedom to pursue personal goals via changing the allocation of inputs than those of publicly owned airports when corruption is high.

With respect to the ownership form, the estimation results reveal that privately owned airports generally provide higher efficiency scores than publicly owned airports. The effect of each ownership category in the absence of corruption (ICRG index =0) is derived from the estimated coefficient of the ownership dummy (i.e β if we refer to Equation 1.1). The coefficients for mixed public-private ownership with government majority and 100% government ownership are -0.332 and -0.254, respectively. The statistical tests confirm the negative and highly significant coefficients for both majority and fully public ownership. These results suggest that publicly owned airports are less efficient than privately owned airports in a highly clean environment, in line with the findings of Oum et al. (2006) and Oum et al. (2008). Allowing the private sectors to hold a majority stake in the airport management and ownership would improve operating efficiency in a low corruption society. As such, a change from 100% government ownership to mixed public-private ownership with private majority would lead to an efficiency gain of 0.274.[28]

[26] The Fisher statistics (and their p-values) for mixed ownership with government majority and 100% public ownership are 1.60 (0.206) and 0.58 (0.446), respectively. In both cases, the null hypothesis cannot be rejected, suggesting that the sum of the coefficients is equal to zero. Corruption has no effects on efficiency of both types of ownership.

[27] Yan and Oum (2014) state that bureaucrats treat inputs as exogenous for the US commercial airports.

[28] The efficiency gain from privatization is obtained by using a regression of rvfp on ownership form dummies

The level of local and gateway competition appears to have no specific impact on airport efficiency, in line with Adler and Liebert (2014). This result may be explained by the approach used to define the level of competition. Chi-Lok and Zhang (2009) stressed that airports serve many different markets including long and short distance, transshipment, and origin-destination markets. However, we are not able to consider these different markets due to the lack of information. We thus may have ignored product diversification strategies.

The coefficients of the form of regulation dummies vary across models but are not always statistically significant. In the pooled OLS specification, airports subject to cost-plus regulation with single till appear to be more statistically efficient than unregulated airports, while the ones subject to incentive regulation with dual till seem to be statistically less efficient. The RE model delivers different estimation results - none of the dummies are statistically significant - indicating that there is no difference between regulated and unregulated airports in terms of operating efficiency. Though some studies including Assaf and Gillen (2012), Adler and Liebert (2014) have emphasized the importance of accounting for the interaction between ownership, regulation and competition to explain airport operating efficiency, our study is limited to the analysis of the effects of corruption. Thus, we may have ignored the interaction between ownership, competition and regulation.[29]

The status as hub and/or international gateway of the airport is not statistically significant in both Pooled OLS and RE models. This provides some indication that most of the hubs in our sample do not possess size and location advantages. We also find no significant impact of multi-airport management on airport efficiency, suggesting that airports included in our sample may not exploit economies of scale and learning effects when they operate with multiple units in the same region. Our findings do not support the argument by Malighetti et al. (2009).

At each stage of the estimation, we include time effects in the model, but the time effects were formally rejected in all cases. We note that the residual (or net) variable factor productivity already accounts for time effects.[30] Therefore, different shocks that potentially affect airport efficiency including the 9/11 terrorist attacks or the 2008 financial crisis should be captured by the rvfp index.[31] The coefficient of GDP per capita is positive and always statistically significant at the 10% level, suggesting that airports operating in more developed countries are more efficient in general.

and other explanatory variables, and setting the "100% government' ownership as the reference category. Thus, the effect of a change in the ownership from 100% government to mixed public-private ownership with private majority on rvfp is explained by the estimated coefficient of the mixed ownership with private majority.

[29] This study focuses on the effects of corruption on airport operating efficiency. Competition, regulation and ownership variables are included in the model as control variables.

[30] In computing the rvfp index, we exclude factors that are beyond managerial control including year dummies.

[31] As result of the terror attacks, security requirements were legally altered in Europe, requiring substantial investments on the part of the airports. As for the financial crisis in 2008, it provoked large drops in demands.

Table 1.5 – Estimation results using pooled OLS and Random Effects (RE) models

Dependent variable: residual (or net) variable factor productivity (rvfp)	Pooled OLS	Random Effects (RE)
Corruption Index (ICRG Index)	−0.046***	−0.041***
	(0.017)	(0.018)
Ownership form	Base: Mixed ownership with private majority	
Government majority (above 50%)	−0.318***	−0.332***
	(0.116)	(0.098)
Public corporation (100% government)	−0.230**	−0.254**
	(0.111)	(0.101)
Ownership form*Corruption Index (ICRG Index)	Base: Mixed ownership with private majority * ICRG Index	
Government majority* ICRG Index	0.064***	0.048**
	(0.023)	(0.019)
Public corporation* ICRG Index	0.015	0.028
	(0.018)	(0.020)
Regulation	Base: No ex-ante regulation	
Cost-plus, single till	0.188**	0.136
	(0.080)	(0.092)
Cost-plus, dual till	−0.093	−0.003
	(0.084)	(0.079)
Incentive, single till	−0.040	−0.043
	(0.057)	(0.060)
Incentive, dual till	−0.128*	−0.097
	(0.069)	(0.069)
Charges set by airports (single & dual till)	0.130	0.076
	(0.080)	(0.089)
Competition	Base: Weak competition	
Strong	−0.177***	−0.097
	(0.050)	(0.060)
Status as a hub and/or international gateway	0.082	0.039
	(0.052)	(0.060)
Airport group management dummy	0.064	0.045
	(0.054)	(0.051)
GDP per capita	0.002**	0.002*
	(0.001)	(0.001)
Intercept	0.865***	0.823***
	(0.111)	(0.128)
R-Square	0.384	0.820
Adjusted R-Square	0.345	0.772
Number of observation	254	254

Notes: "* * *", "**", "*" denote statistical significance at the 1%, 5%, 10% levels, respectively. Robust standard error associated to each coefficient is stated in parenthesis. We dropped "mixed public-private ownership with private majority (including fully private)" dummy, "the interaction between mixed public-private ownership with private majority and corruption index", "no ex-ante regulation dummy" and "weak competition dummy" in all regressions to avoid multicollinearity.

1.7 Robustness checks

1.7.1 Using additional sets of control variables

In order to ensure the robustness of our results, we extend the controls in the $\mathbf{X}_{it}$ matrix of our equation (Eq. 1.1) to add country-specific institutional quality variables. This model is dubbed model II in Table 1.6. Lambsdorff (2003) emphasizes that corruption includes many different types of behavior, and decomposing it into governance-related subcomponents can identify the channels through which it affects productivity. Mauro (1995) argues that the efficiency of institutions is relevant for any firm operating in the country of interest, since they are assessed independently of macroeconomic variables. Therefore, we include government stability, quality of bureaucracy, internal and external conflict and law and order as indicators of institutional quality variables.[32] In model III of Table 1.6, another set of controls is added to model II: a proxy of openness to trade (share of imports in GDP) and a measure of the importance of government in the economy (share of central government revenues in GDP). The latter regressors are largely recognized in the literature as having a strong relationship with corruption.[33] Table 1.6 shows the estimation results using random effects specification. Robust standard errors are in parenthesis.[34]

The former results remain valid whatever the control variables, and in almost all extended models, the corruption impact on airport efficiency remains negative and significant at the 1% significance level. The negative coefficients of mixed public-private ownership with government majority and 100% government ownership confirm that privately owned airports are the most efficient in the absence of corruption. The interaction term between corruption index and mixed ownership with government majority keeps its positive and significant impact at the 5% level in both extended models. However, the statistical tests indicate that the overall effects of corruption on publicly owned airports including 100% and majority government owned airports remain insignificant.

The effects of the form of regulation, competition level, hub status and airport group management dummies remain statistically insignificant. GDP per capita does not appear to have significant impacts. When we include openness to trade and the share of government revenue to the model, the picture does not significantly change. We apply statistic tests to verify

[32]We follow the definitions proposed by ICRG to specify the institutional quality variables. Bureaucratic quality signals the independence of administration from political pressure, the use of established mechanisms for recruiting and training, and the strength and expertise of government services. Government stability defines the government's ability to carry out its declared program(s) and its ability to stay in office. Law evaluates the strength and impartiality of the legal system while the Order scores the popular observance of the law. Ethnic tension considers the degree of tension within a country attributable to racial, nationality, or language divisions. Internal conflict evaluates political violence in the country and its actual or potential impact on governance whereas external conflict scores the risk to the incumbent government from foreign action, ranging from non-violent external pressure to violent external pressure.

[33]See for example Mauro (1995), Dal Bó and Rossi (2007)

[34]Since all models display strong heteroscedasticity and autocorrelation in the residuals, we employ cluster-robust standard errors as recommended by Wooldridge (2002).

Table 1.6 – Estimation results using additional control variables

Dependent variable: residual (or net) variable factor productivity (rvfp)	Model II	Model III
Corruption Index (ICRG Index)	-0.052^{***}	-0.053^{***}
	(0.019)	(0.020)
Ownership form	Base: Mixed with private majority	
Government majority (above 50%)	-0.279^{***}	-0.291^{***}
	(0.099)	(0.097)
Public corporation (100% government)	-0.222^{**}	-0.214^{**}
	(0.101)	(0.102)
Ownership form*ICRG Index	Base: Mixed with private majority * ICRG Index	
Government majority* ICRG Index	0.041^{**}	0.046^{**}
	(0.019)	(0.019)
Public corporation* ICRG Index	0.026	0.025
	(0.018)	(0.019)
Regulation	Base: No ex-ante regulation	
Cost-plus, single till	0.099	0.128
	(0.100)	(0.101)
Cost-plus, dual till	−0.042	−0.030
	(0.088)	(0.085)
Incentive, single till	−0.084	−0.048
	(0.074)	(0.070)
Incentive, dual till	-0.135^{*}	−0.117
	(0.076)	(0.075)
Charges set by airports (single & dual till)	−0.024	0.036
	(0.106)	(0.094)
Competition	Base: Weak competition	
Strong	-0.150^{**}	-0.126^{*}
	(0.074)	(0.073)
Status as a hub and/or international gateway	0.091	0.060
	(0.065)	(0.064)
Airport group management dummy	0.025	0.021
	(0.062)	(0.062)
GDP per capita	0.002	0.002
	(0.001)	(0.001)
Institutional quality variables		
Quality of Bureaucracy	0.008	0.008
	(0.009)	(0.008)
Law and Order	0.016	0.013
	(0.022)	(0.022)
Ethnic tension	−0.003	−0.005
	(0.010)	(0.010)
Internal conflict	0.009	0.011
	(0.010)	(0.011)
External conflict	0.009	0.012
	(0.011)	(0.010)
Government Stability	0.003	0.003
	(0.005)	(0.005)
Openness to trade	-	−0.002
		(0.001)
Share of central government revenues	-	0.005
		(0.005)
Intercept	0.699^{***}	0.792^{***}
	(0.225)	(0.139)
Number of observations	252	254

Notes: "$***$", "$**$", "$*$" denote statistical significance at the 1%, 5%, 10% levels, respectively. Robust standard error associated to each coefficient is stated in parenthesis. We dropped "mixed public-private ownership with private majority (including fully private)" dummy, "the interaction between mixed public-private ownership with private majority and corruption index", "no ex-ante regulation dummy" and "weak competition dummy" in all regressions to avoid multicollinearity.

whether the overall impacts of the institutional variables, openness to trade and the share of central government revenues are significant, and the results show that these additional factors do not have significant effects.[35] To sum up, our econometric results seem very robust across models.

1.7.2 Using alternative corruption indices

The use of alternative measures of corruption allows to check on the robustness of our results and to make sure that the latter are not driven by the use of a particular index. We then consider two other corruption measures including Corruption Perception Index (CPI) of Transparency International and Control of Corruption Index of World Bank. Both are composite indices, which have the advantages to admit the biases of specific indices to cancel each other out, thereby determining an average opinion of corruption (Méon and Weill, 2010). Using the parsimonious specification from the RE estimator, Table 1.7 confirms that the previous main results are robust to other measures of corruption.[36]

1.7.3 Using different categories of ownership

We want to test if our results are robust to the change in the ownership categories. For this purpose, we separate fully private ownership from mixed public-private ownership with private majority. Four types of ownership are then considered: (1) 100% government (or public corporation), (2) mixed public-private ownership with government majority (above 50%), (3) mixed public-private ownership with private majority (above 50%) and (4) fully private. The 100% government ownership is used as the reference category. The estimation results using the RE specifications are reported in Table 1.8, with robust standard errors in parenthesis.

As stated in Table 1.8, the coefficient of corruption index is negative but not statistically significant at the required levels, which suggests that corruption has no effects on fully government-owned airports (the reference category). This confirms our previous findings. With respect to the impact of corruption on rvfp in privately owned airports, our previous results hold only for mixed public-private ownership with private majority. The coefficients of both corruption index and interaction terms, as well as the statistic of Fisher confirm the negative relationship between rvfp and corruption for this ownership category. However, we find no significant effects for the other forms of ownership including fully private ownership. This result may be explained by the limitation of data on fully private airports included in our sample.

[35]We test the null hypotheses that (a) the joint effects of the institutional quality variables are null and (b) the joint effects of openness to trade and share of central government revenues are null. Chi-squared displays statistics (and its p-value) of 6.10 (0.41) and 2.37 (0.3063), respectively, suggesting that the null hypotheses cannot be rejected.

[36]The Fisher tests confirm that the coefficients of both interaction terms in each model are null, indicating that corruption has no effects on efficiency of publicly owned airports.

Table 1.7 – Estimation results using alternative corruption indices

Explanatory variable	Using CPI Index	Using CCI Index
Corruption Index	-0.044^{*}	-0.080^{***}
	(0.024)	(0.028)
Ownership form	Base: Mixed with private majority	
Government majority (above 50%)	-0.495^{**}	-0.266^{**}
	(0.235)	(0.119)
Public corporation (100% government)	-0.258^{*}	-0.273^{***}
	(0.176)	(0.103)
Ownership form*Corruption Index (CI)	Base: Mixed with private majority * CI	
Government majority*Corruption Index	0.072^{*}	0.071
	(0.039)	(0.044)
Public corporation*Corruption Index	0.026	0.062^{*}
	(0.027)	(0.032)
Regulation	Base: No ex-ante regulation	
Cost-plus, single till	0.142	0.159
	(0.098)	(0.100)
Cost-plus, dual till	−0.003	0.031
	(0.096)	(0.096)
Incentive, single till	−0.052	−0.051
	(0.094)	(0.095)
Incentive, dual till	−0.083	−0.093
	(0.098)	(0.099)
Charges set by airports (single & dual till)	0.051	0.117
	(0.121)	(0.124)
Competition	Base: Weak competition	
Strong	−0.088	−0.107
	(0.072)	(0.072)
Status as a hub and/or international gateway	0.037	0.040
	(0.076)	(0.077)
Airport group management dummy	0.042	0.053
	(0.072)	(0.073)
GDP per capita	0.002**	0.003**
	(0.001)	(0.001)
Intercept	0.866^{***}	0.793^{***}
	(0.173)	(0.123)
Number of observations	253	254

Notes: "***", "**", "*" denote statistical significance at the 1%, 5%, 10% levels, respectively. Robust standard error associated to each coefficient is stated in parenthesis. We dropped "100% government (or public corporation) ownership" dummy variable, "the interaction between 100% government ownership dummy and corruption index", "no ex-ante regulation dummy" and "weak competition dummy" in all regressions to avoid multicollinearity problem.

Table 1.8 – Estimation results using different ownership categories

Dependent variable: residual (or net) variable factor productivity (rvfp)	Coefficient
Corruption Index (ICRG Index)	-0.013
	(0.010)
Ownership form	Base: 100% government (public corporation)
Government majority	-0.075
	(0.076)
Private Majority	0.364***
	(0.102)
Fully Private	0.016
	(0.235)
Ownership form*Corruption Index (ICRG Index)	Base: 100% government *ICRG Index
Government majority *ICRG Index	0.020
	(0.015)
Private majority* ICRG Index	-0.041**
	(0.020)
Fully Private* ICRG Index	0.007
	(0.053)
Form of regulation	Base: No ex-ante regulation
Cost-plus, single till	0.123
	(0.095)
Cost-plus, dual till	-0.015
	(0.080)
Incentive, single till	-0.032
	(0.060)
Incentive, dual till	-0.112
	(0.068)
Charges set by airports (single & dual till)	0.076
	(0.097)
Competition	Base: Weak competition
Strong	-0.083
	(0.063)
Status as a hub and/or international gateway	0.018
	(0.066)
Airport group management dummy	0.059
	(0.052)
GDP per capita	0.002
	(0.001)
Intercept	0.592***
	(0.095)
Number of observation	254

Notes: "***", "**", "*" denote statistical significance at the 1%, 5%, 10% levels, respectively. Robust standard error associated to each coefficient is stated in parenthesis. We dropped "100% government (or public corporation) ownership" dummy variable, "the interaction between 100% government ownership dummy and corruption index", "no ex-ante regulation dummy" and "weak competition dummy" in all regressions to avoid multicollinearity problem.

The positive and statistically significant coefficient for mixed public-private ownership with private majority is consistent with our previous finding. Again, privatized airports exhibit higher efficiency scores than government owned airports in the absence of corruption. However, no significant difference is found between fully private, mixed public-private ownership with government majority and fully public ownership, in terms operating efficiency.

1.7.4 Treating outliers

Given the characteristics of our dataset, we would expect important outliers for some of the countries included in the sample. To address this potential issue, we drop from the sample: (1) extreme values of airport efficiency (rvfp), (2) airports that provide the largest values of rvfp, (3) airports that display the smallest values of rvfp and (4) airports that display the smallest and largest values of rvfp. Table 1.9 compares the estimation results according to each specification using RE model, with robust standard error in parenthesis.

Our results are robust to whatever the set of sample. The coefficient of corruption index remains negative and statistically significant at least at the 10% level in each specification. Corruption negatively affects efficiency of privately owned airports. Except for the last sample in which we drop the smallest and largest airports, in the absence of corruption the publicly owned airports including 100% government ownership and mixed public-private ownership with government majority appear less efficient than privately owned airports. However, the coefficients of the corruption index, the interaction terms as well as the Fisher tests confirm that in high corruption environment the mixed public-private ownership with private majority are the least efficient.

Table 1.9 – Estimation results using different set of sample

Dependent variable: rvfp	Full sample	Drop			
		the extreme values	the largest (1)	the smallest (2)	(1) and (2)
Corruption Index (ICRG Index)	-0.041^{***}	-0.037^{**}	-0.036^{**}	-0.037^{**}	-0.031^{*}
	(0.018)	(0.017)	(0.018)	(0.017)	(0.016)
Ownership form	Base: Mixed ownership with private majority				
Govt maj. (> 50%)	-0.332^{***}	-0.312^{***}	-0.270^{***}	-0.299^{***}	-0.232^{**}
	(0.098)	(0.094)	(0.104)	(0.099)	(0.105)
100% govt	-0.254^{**}	-0.249^{**}	-0.228^{**}	-0.195^{**}	-0.160^{**}
	(0.101)	(0.100)	(0.111)	(0.098)	(0.114)
Ownership form*ICRG Index	Base: Mixed ownership with private majority*ICRG Index				
Govt maj.* ICRG Index	$0.048*^{**}$	0.045^{**}	0.043^{**}	0.043^{**}	0.037^{**}
	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)
100% govt* ICRG Index	0.028	0.027	0.027	0.022	0.021
	(0.020)	(0.019)	(0.019)	(0.019)	(0.018)
Regulation	Base: No ex-ante regulation				
Cost-plus, single till	0.136	0.110	0.008	0.135^{*}	0.013
	(0.092)	(0.085)	(0.094)	(0.077)	(0.077)
Cost-plus, dual till	−0.003	−0.015	−0.014	0.028	0.016
	(0.079)	(0.074)	(0.084)	(0.070)	(0.078)
Incentive, single till	−0.043	−0.051	−0.045	−0.082	−0.083
	(0.060)	(0.059)	(0.058)	(0.055)	(0.054)
Incentive, dual till	−0.097	−0.106	-0.119^{*}	−0.093	-0.118^{*}
	(0.069)	(0.068)	(0.072)	(0.068)	(0.070)
Charges set by airports (single & dual till)	0.076	0.072	0.084	0.028	0.024
	(0.089)	(0.086)	(0.091)	(0.078)	(0.076)
Competition	Base: Weak competition				
Strong	−0.097	−0.068	−0.045	−0.073	−0.030
	(0.060)	(0.054)	(0.061)	(0.058)	(0.059)
Status as a hub and/or international gateway	0.039	0.028	0.008	0.035	−0.003
	(0.060)	(0.059)	(0.064)	(0.061)	(0.063)
Airport group management dummy	0.045	0.046	0.035	0.013	−0.006
	(0.051)	(0.048)	(0.049)	(0.046)	(0.043)
GDP per capita	0.002*	0.002	0.001	0.003**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	0.823^{***}	0.818^{***}	0.807^{***}	0.832^{***}	0.825^{***}
	(0.128)	(0.128)	(0.143)	(0.127)	(0.139)
Number of observations	254	234	225	228	199

Notes: "***", "**", "*" denote statistical significance at the 1%, 5%, 10% levels, respectively. Robust standard error associated to each coefficient is stated in parenthesis. We dropped "mixed public-private ownership with private majority (including fully private)" dummy, "the interaction between mixed public-private ownership with private majority and corruption index", "no ex-ante regulation dummy" and "weak competition dummy" in all regressions to avoid multicollinearity.

1.8 Conclusion of Essay 1

While a number of studies have analyzed the determinants of airport efficiency, the role of corruption has attracted limited attention. The aim of this research is to investigate the effects of corruption on operating efficiency of 47 major European airports from 2003 to 2009, using a two-stage approach. In the first stage, the multilateral index number method is applied to compute our efficiency measure, the residual (or net) variable factor productivity (rvfp) index. The same index method is used by Air Transport Research Society (ATRS, 2011) to assess and compare managerial efficiency of airports worldwide. In the second stage, the effect of corruption on the airport efficiency is assessed using robust cluster random effects model. We use the corruption index from International Country Risk Guide (ICRG) as our main measure of corruption. The estimation results are consistent across the pooled Ordinary Least Squares (OLS) and random effects (RE) models but the latter provides better fit of the data.

We find strong evidence that corruption has negative impacts on airport's operating efficiency, and the impacts depend on the airport's ownership form. Airports owned and operated by mixed public-private enterprises with private majority (including 100% private) are expected to be the most efficient in a society where corruption is low. However, they exhibit lower levels of efficiency compared with airports operated by mixed public-private enterprises with government majority and fully government owned airports in highly corrupt countries. These results reflect the differences in autonomy of airport managers when they allocate and channel resources. Accordingly, managers of privately owned airports have more freedom to allocate resources than bureaucrats. We argue that poor governance and culture of cronyism in highly corrupt countries would provide incentives for private sector managers to focus heavily on rent seeking instead of focusing on airport productivity objectives, and eventually lead to lower airport efficiency. Also, there is more room for corruption to creep in because the majority of privatized firms avoid regular audits that the government owned enterprises are usually subject to.

Our empirical findings survive several robustness checks. To deal with potential omitted variable issues, we control for the form of regulation prevalent across European airports, competition level within the catchment area and across gateways, airport characteristics, including airport status as a hub and/or international gateway, whether the airport management belongs to a group from a managerial perspective and GDP per capita. We extend the set of controls to include country-specific institutional quality indicators and variables that vary across countries and over time such as a measure of openness to trade (share of imports in GDP) and a measure of the importance of government in the economy (share of central government revenues in GDP). The main results hold despite using two additional alternative measures of corruption: Corruption Perception index (cpi) established by Transparency International and Control of Corruption index (cci) provided by the World Bank.

Findings from this paper have important policy implications for government and airport managers. Our empirical findings suggest that high corruption in the country might be a hindrance to airport efficiency. Thus, governments who want to transfer airport management and ownership to private sectors may want consider the levels of corruption in the country and allocate adequate resources to reduce corruption.

The corruption levels of European countries are relatively lower compared with many parts of the world. Nonetheless, corruption has become a major concern since the number of officials and state-owned companies from European countries involved in bribery cases and other corruption acts has been increasing. This research, which is limited to Europe, can be extended to airports in other regions including Asia, Oceania and more specifically developing countries and highly corrupted regions. Major air infrastructures in developing countries are funded by the World Bank and/or funding agencies. If corruption not only causes misuse of resources but also impacts on airport operating efficiency, the recipient countries may not be able to pay back the loans. As such, the infrastructure projects lenders may want to retain a certain percentage of their loans, and use it for the country to set up clean project bidding and tendering processes with proper checks and balances, to educate and train officials and employees, and auditing during the project implementation period as well as ex-post auditing.

Furthermore, we use a specific airport efficiency index namely the residual (net) variable factor productivity index, which accounts for the short and medium term airport operating efficiency and does not consider capital investment. Future research is advised to consider alternative measures of efficiency that include capital investment.

Chapter 2

Flexible Estimation of an Airport Choice Model: The Case of Quebec Airports

Abstract

This paper explores the determinants of passengers' choice between a primary hub and a secondary airport in Quebec. Among the most popular models, we explore fixed- and random-coefficients logistic models along with two flexible alternatives including an additive logistic model and a kernel-based conditional density with continuous and discrete variables. Using an original dataset from the 2010 Airport Service Quality survey conducted in Quebec airports, we show that flight frequency, access time and access mode to airports, among others, are the main factors of airports' choice across all specifications. Airfare, the reason for travel, flight destination and departure times also appear to have significant impacts. While the logistic models have strong theoretical foundations based on the random utility models, the recent kernel-based tests reject these specifications, which stresses that the linear random utility model may not capture well the underlying relationships that are present in the data. In terms of within sample performance (pseudo-R^2 and classification ratios), the flexible estimators dominate the two other conventional logistic regressions. We use the nonparametric kernel estimators to capture non linearities and interactions effects between selected explanatory variables without imposing shape constraints on the conditional probability.

Keywords: Airport choice; Random Utility Models; Specification tests, Flexible Estimators.

2.1 Introduction

Discrete choice models are fundamental tools to explore travellers' choices in transportation economics. They have strong foundation in the theory of utility maximization and allow to predict the probability that a traveller chooses an alternative among a set of alternatives. Discrete response models belong to the family of random utility models, which treat utilities as random variables to reflect the lack of information regarding the characteristics of the alternatives and/or travellers from the observer viewpoint (Manski, 1977). When the choice set of individuals consists of two alternatives, binomial models are mostly applied. When more than two alternatives are considered, their multinomial counterpart appears to be the most popular choice. In both cases, the indirect utility of travellers is specified as function of two *additive* terms: a deterministic part and a stochastic error term that possesses a predetermined distribution. Assuming that the utility function is linear in the choice attributes, the empirical researchers can link the econometric model to the economic theory of random utility model.

In the last decades, misspecification of discrete response models has attracted the attention of researchers. Misspecification arises when either the indirect utility function is not correctly specified or the distribution of the error term is not appropriate. From an econometric viewpoint, misspecification leads to erroneous predictions and incorrect inference about the most relevant determinants of the choice probability. Several technics have been proposed to test the correct specification of discrete response models and a whole range of flexible semi-parametric and nonparametric estimators for multinomial responses have been developed to avoid misspecification. However, specification tests and flexible estimators have been rarely applied to investigate airport choice models.

This paper explores different specifications to identify the main determinants of passengers' choice when two alternative airports are considered by travellers: a regional versus a hub airport. Almost all empirical applications on airport choice use logistic models to analyze travellers' bevahiour (see for example Harvey, 1987; Pels et al., 2001, 2003; Ishii et al., 2009). In this application, we estimate two standard logistic models, namely the fixed- and variable-coefficients estimators. The goal of the latter specification is to allow heterogeneous individual preferences. Then, we investigate the flexible logistic model that belongs to the family of the generalized additive models (GAM hereafter) to introduce more flexibility in the relationship between the choice probability and the continuous explanatory variables (access time, flight frequencies and airfares). Using the kernel based nonparametric specification tests for conditional densities performed by Fan et al. (2006) and Li and Racine (2013), we investigate whether the parametric and semi-parametric models are correctly specified. Nonparametric estimators have emerged as a powerful tool to relax functional shapes in conditional probabilities with continuous and discrete explanatory variables. In addition, the kernel estimator allows to explore the interaction effects of the variables without shape constraints.

The study uses an original database that captures the choice made by air travellers departing from one of the two main airports of Quebec province in 2010. Quebec hosts two major airports: the medium-size Quebec City Jean-Lesage international Airport (YQB) and the airline-hub Montreal Pierre-Elliott-Trudeau international Airport (YUL). According to the authority of Quebec airport, the annual total passengers of YQB is about 1.6 million; and every year, approximately 1.4 million travellers from Quebec city decide to drive about 3 hours to take advantage of services offered at YUL, instead of using their local airport.

Identifying the factors that determine passengers' choice and evaluating passengers' sensitivity to these factors have important implications for local authorities and managers of YQB, which aim at reducing the leakage rate and at making investment decisions on infrastructures based on reliable empirical evidence.[1]

Our main results suggest that flight frequency, access time and access mode to airports, flight destination and departure time are the main determinants of airport choice. Flight frequency has a positive effect on the choice probability while access time to airport and airline' ticket price display a negative impact. The choice is also linked to flight and travellers' characteristics, such as flight destination, reason of flight, gender and age. Indeed, we find that the local airport attracts more passengers on domestic flights than transborder and international destinations. We also stress the significant impact of departure times on travellers's choice.

The signs of the coefficients do not change with the flexible random-coefficients logit and Generalized Additive Model (GAM) estimators but the magnitude and significance may vary. Though the parametric and semiparametric models have strong theoretical foundation, the formal specification tests appear to reject these specifications. We then conclude that the linear random utility model may not capture well individuals' behaviour. However, the marginal effects of the random utility models seem to be reasonably close to the more flexible estimates. Nonparametric estimators dominate their (semi) parametric counterparts in terms of within predictions (classification ratios and pseudo-R^2). Moreover, nonparametric estimators provide attractive tools to explore the interaction effects of access time and airfare according to the flight destination and purpose without shape constraints.

The remainder of the paper is organized as follows. Section 2.2 summarizes the literature on airport choice studies. We also present the most popular semiparametric and nonparametric specifications used to estimate discrete choice models. Section 2.3 describes the models and specification tests being used in this analysis. Section 2.4 introduces the data. Section 2.5 reports the estimation results from the parametric, semi-parametric and fully nonparametric models along with the results of the specification tests. We compare goodness-of-fit of the selected models in Section 2.6 and Section 2.7 proposes concluding remarks.

[1] Besides, evidence shows that YQB has spent over 550 million dollars on infrastructure investment these past 15 years, with 277 million dollars to increase the terminal size in 2016 (Source: *Le Journal de Québec*, August 3, 2016.)

2.2 Literature Review

The literature on aviation have widely used discrete choice models to analyze passenger's behavior in choosing between two or several nearby competing airports. In this literature review, we first concentrate on parametric logistic models with linear indexes, which are the most popular models. Then, we turn to the flexible estimators that include Generalized Additive Models (GAM), the single-index model of Klein and Spady (1993) and kernel estimators.

2.2.1 Logistic models with linear indexes

Logistic models have been used by most of the airport choice studies to analyze travellers' behavior in selecting between multiple airports. Harvey (1987) presented the initial study of airport choice within a formal individual choice framework. He applied *a multinomial logit model* to identify the factors influencing passengers' choice between three airport alternatives in the region of San Francisco Bay area. Windle and Dresner (1995) extended the analysis by considering the effects of passengers' experience with one or more airports. Focusing on the region of Baltimore area, they found that passengers with good experiences at an airport continue to use the same airport in the future. Başar and Bhat (2004) further explored the choice process of passengers in the San Francisco Bay area. They argue that different travellers may not consider all the available airports when making their choice. Instead, they may select and form a subset of airport alternatives in which they establish their choice. Therefore, they use *a probabilistic choice set multinomial logit model* to capture this passenger behavior. According to these authors, the probabilistic logit model allows the choice set to be constructed by travellers and provides a more accurate prediction of the choice process. All these studies agree that access time and flight frequency are the main determinants of airport choice in a multi-airport region.

In recent years, correlation between airport, airline and access-mode choices has been explored. Air travellers may choose departure airports simultaneously with airlines and/or access modes, when flying to a particular destination. Researchers have developed discrete choice models that account for these simultaneous choices. The most popular are: the nested logit and cross-nested logit models. Pels et al. (2001) used the *nested logit* specification to model the joint airport-airline choice of passengers departing a flight at one of the airports in the San Francisco Bay area. Pels et al. (2003) evaluated airport and access-mode choices of passengers and their relationship, by specifying a *two-level nested logit* with access mode choice at the lower level and airport choice at the top level.[2] Both studies found that access time, access cost, airfare, flight frequency, flight-time, airport delay, the availability of particular airport-airline combinations, and early arrival times strongly influence the choice probabilities.

[2]Their model allows to capture the fact that a passenger may buy a ticket at the airport and has to choose in advance what airport is preferred and how to get there, or a ticket is bought in advance, but this choice also depends on access mode.

Refined versions of the nested multinomial logit models have been proposed. Suzuki (2007) postulated that travellers may first screen airlines at each airport to reduce the number of airline choice alternatives per airport, and then evaluate all the remaining combination of airport-airline alternatives by using the utility-maximization rule. To capture this choice-making process, he estimated *a two-step nested logit model* using data on air travellers in the central Iowa; and found that a traveller tends to choose the closest airport along with the airline that offers lower fares and frequent services to the destination. Hess and Polak (2006) proposed *a cross-nested logit model* to account for correlation between travellers' departure airport, airline and access-mode choices and their interactions in the London area. Their results reveal significant influences on passenger behaviour of access time, access cost, flight-frequency and flight-time. The two-step nested logit and cross-nested logit models also appear to outperform the conventional multinomial and nested logit models.[3] Pels et al. (2009) focused on competition between full-service and low-cost airlines serving adjacent airports in the Greater London area, with a particular interest in estimating own- and cross-price elasticities with respect to airfares. They compared *nested logit*, *cross-nested logit* and *mixed multinomial logit models* to capture three key dimensions of passenger choice including air fare, surface-access costs and flight frequency; and obtained statistically significant estimates of price elasticities, which appeared to be on the low side. Ishii et al. (2009) studied the trade-off across airline and airport characteristics for passengers departing from airports in San Francisco Bay area, using *mixed multinomial logit* and *weighted conditional logit models*. The weighted conditional logit allows to incorporate the effect of airport dominance and travel delay in a multinomial logit specification while explicitly controlling for the airline offerings and observable airport characteristics at competing airports. They found that both mixed multinomial and weighted conditional logit models yield similar results, suggesting that access time, airport delay, flight frequency, the availability of particular airport-airline combinations, and early arrival times strongly affect choice probabilities. More recently, de Luca (2012) investigated the effects of type of flight connection, trip duration and departure date on airport choice in Italian multi-airport region with three airports. He considered *multinomial logit, mixed multinomial logit and cross-nested logit models* to account for correlation structures among perceived utilities (geographical, operating airlines, airport type) and heteroscedasticity.

While the aforementioned studies have examined travellers' choice and airport competition in a multi-airport region, only few analyses were devoted to airport choice in small cities and communities. Innes and Doucet (1990) evaluated the importance of proximity and level-of-service on decision of the residents of New Brunswick in Canada in choosing between three airports. Based on *a binomial logistic model*, they computed the probability of choosing the

[3] Suzuki (2007) argued that the two-step nested logit specification outperforms the conventional multinomial and nested logit models because it allows to distinguish between the set of all available choice alternatives and the subset of the screened alternatives. Hess and Polak (2006) also showed that the cross-nested logit leads to important gains in model performance and accuracy compared with the nested logit model, which in turn outperforms the multinomial logit model.

more distant airport; and found that the type of aircraft, flying-time difference and availability of direct flight significantly impact the airport choice. Zhang and Xie (2005) identified the factors that influence the use of nearby airports in small communities served by the Golden Triangle Regional Airport (GTR) and three major nearby airports via *a multinomial logit*. Their results revealed that ticket price, distance to the airport, past experience and flight schedule are the main drivers of airport choice. Lian and Rønnevik (2011) analyzed airport leakage from regional airports to main airports in Norway.[4] Using *a logistic regression*, they estimated the probability that travellers choose the main airport rather than the closest regional airport; and showed that difference in airfares and long travel time linked to indirect services at the regional airports are the main drivers of traffic leakage.

All the above logit models belong to the family of additive random utility maximization models (ARUM) and are based on a stochastic utility function, which is linear in parameters and in attributes. Many applications to airport choice models have argued that linear specification may not be appropriate for attributes that display decreasing or increasing marginal returns. As a result, non-linear transformation of some attributes such as frequency and access time has been explored. For example, Harvey (1987) represented responses to flight frequency and travel time as non linear; and found that both access time and flight frequency have non linear effects on airport utility.[5] Pels et al. (2001, 2009) included flight frequency in logarithmic form to justify its decreasing marginal utility. Başar and Bhat (2004) also tried several nonlinear forms for capturing the effect of access time and flight frequency, but concluded that the simple linear functional form performed better than the more complex functional forms. Hess and Polak (2006) demonstrated that a log-transform for flight frequency, flight-time, in-vehicle access-time and access-cost leads to important gains in model performance. de Luca (2012) considered a logarithmic form of flight frequency and Box-cox transformation of access time; and showed that non-linear transformation of access time and frequency improved model goodness-of-fit.

2.2.2 Semiparametric and nonparametric models

We have shown that discrete choice models are the most commonly used estimators of airport choice. A wide variety of flexible estimation of a binary outcome model has also been developed in the last decades to circumvent inconsistency issues and erroneous predictions resulting from misspecification of distribution of the error term and of the linear index. Nevertheless, applications to airport choice models are still very limited.

The most well-known estimator is Manski (1975)'*robust maximum score estimators* (MS model).

[4] According to Fuellhart (2007), "leakage" occurs when travellers avoid using the local airport in their regions and use other out-of-region airports to take advantage of lower fares and more convenient airline services

[5] Direct flight was included in the form of parabolic variable to capture the decreasing headway advantage afforded by each additional flight.

Contrary to the discrete choice models, which require the assumption that the disturbances belong to a family of logistic distributions, the maximum score method requires only independence of the stochastic terms and the condition that each stochastic term has zero median for consistency. It offers a certain amount of proven robustness against distributional misspecification, in particular in the presence of heteroscedastic errors.[6] Since the objective function of the maximum score estimator is a step function, Horowitz (1992) proposed *a smoothed maximum score estimator* (SMS model) to permit the score function to become continuous and differentiable. Cosslett (1983) developed *a consistent distribution-free estimator* for binary choice by directly applying the maximum likelihood principle.[7] Klein and Spady (1993) proposed *a semiparametric estimation* method (KS model) that makes no assumption concerning the functional form of the choice probability function. Instead, they assumed that the probability depends on a parametrically specified index function, which allows arbitrary heteroscedasticity and then used a kernel to get a flexible cumulative distribution.

A different class of semiparametric specification relaxes the assumption on the linearity (in parameters) of the utility function, but postulates a certain parametric distribution for the stochastic term. For a binary response, the most popular model is the Hastie and Tibshirani (1986)' *Generalized Additive Model* (GAM model), which allows to estimate an additive nonparametric function when the random component is assumed to be logistically distributed. In particular, the utility function is specified as a sum of one-dimensional flexible functions of relevant explanatory variables. Abe (1999) extended the methodology proposed by Hastie and Tibshirani (1986) to multinomial logit models of discrete choice.

Horowitz (1993) applied several parametric and semiparametric models to examine the binary choice between automobile and transit for the work trip. He compared estimation results, statistical inferences and predictions from *probit with fixed and random coefficients*[8], *KS model* and Manski's *MS* and *SMS* estimators. He showed that different estimation methods yield very different estimates of parameters. The specification test results indicate that the random-coefficients probit and smoothed maximum score for arbitrarily heteroskedastic models provide a more accurate description of the data than do the fixed-coefficient probit and KS models. He also demonstrated that differences among the predicted probabilities are large and can even exceed 50% depending the models and the values of the explanatory variables. Fosgerau (2006) contrasted various nonparametric and semiparametric methods to estimate the distribution of the value of travel time savings. He estimated the parameters of a linear index binary choice model using the estimator of Klein and Spady (1993) without assuming a

[6] Manski (1975) showed that the estimator is computationally tractable but the root mean square errors are sometimes considerably larger than those of the logit estimator.

[7] Nevertheless, the asymptotic distribution of the maximimum score and distribution-free maximum likelihood estimators are unknown and need to be estimated in order to make predictions of choice probabilities.

[8] The probit model specifies a cumulative normal distribution function for the error term and the coefficients associated with attributes can be fixed or randomly independently distributed (normally or log-normally).

distribution for the error terms. He also tested a range of parametric distributions[9] against the nonparametric alternative using the specification test developed by Zheng (1996); and found that Gamma, Triangular, Johnson S_B and Beta distributions would predict probability choices well. Based on a stated choice experiment, he showed that the mean value of travel time savings is extremely dependent on the choice of parametric distribution. Fosgerau (2007) attempted to identify a specification for the willingness to pay for travel time changes using nonparametric technics. He found that the classical formulation of the binary logit model is not consistent with the data since marginal utilities of both time and cost are constant. As a result, he proposed to formulate the model to allow the willingness to pay to be the only source of randomness and applied a semi-parametric model with weak assumptions on the stochastic terms, which gives a good representation of the data.

In this paper, we focus on travellers' choice between a regional airport and the closest airline-hub in the province of Quebec in Canada. We first use a binomial logit with fixed coefficients and then explore individual heterogeneity using a random-coefficients model. Next, we relax the usual linear-in-parameters utility assumption of the logit to explore nonlinear relationships of the most relevant explanatory variables, using a Generalized Additive Model (GAM). We also apply the estimator of Klein and Spady (1993), which relaxes the assumption on the distribution of the error term but keeps the linear structure of the utility. To avoid misspecification problems, we formally test the parametric and semi-parametric models using the kernel based nonparametric specification tests proposed by Fan et al. (2006) and Li and Racine (2013). We show the results of the nonparametric kernel estimation along with related plots that enable us to communicate graphically the interaction effects of the most relevant variables of the model. Finally, we compare the predictions of all the selected models using the conventional $Pseudo - R^2$ and the classification ratios. Indeed, local authorities or airport managers can use this study to make important decisions regarding infrastructure investment and regional development.

2.3 Methodology

This section focuses on binary response models that we will use in our application. We first characterize the binary response model and then describe the estimation that we employ in the empirical section.

2.3.1 General framework

Consider a binary variable denoted $y \in \{0, 1\}$ and a vector of observable exogenous variables $\mathbf{X} \in \mathbb{R}^k$ where k is the number of variables. Following Matzkin (1992), the binary outcome

[9] Eight different distributions are tested including normal, gamma, uniform, triangular and two versions of beta and Johnson S_B distributions.

model is defined by the following equation:

$$y = I[h(\mathbf{X}) - \varepsilon \geq 0] \tag{2.1}$$

where $h_{\mathbb{R}^k \to \mathbb{R}}$ represents a single or multiple index mapping; ε is an unobservable random variable with a cumulative distribution F and $I[A]$ is an indicator that takes value 1 if A is true and 0 otherwise, where $A = h(\mathbf{X}) - \varepsilon \geq 0$. When we observe $\mathbf{X}$, the probability that A is true can be derived directly from Equation 2.1, which is:

$$P(y = 1|\mathbf{X}) = P[h(\mathbf{X}) \geq \varepsilon] \equiv F[h(\mathbf{X})] = p(\mathbf{X}) \tag{2.2}$$

The observed frequency $p(X_i)$ is the most we can get from the data (y_i, X_i) at each value of X_i on $\mathbb{R}$. We need identifying assumptions to recover structural parameters related to function h and F and to disentangle economic effects from $p(\mathbf{X})$. The random utility choice models provide such assumptions. Matzkin (2007) discussed about identification issues in discrete choice models and provided conditions under which such models are identified.

2.3.2 Additive Random Utility Models (ARUM) for airport choice

Consider two alternative departing airports $j = \{0, 1\}$ in the choice set of individual i, $i = \{1, ..., N\}$ where N represents the number of individuals who decide to travel. The individual chooses airport j if her indirect utility denoted by $u(\mathbf{x_{ij}}, \boldsymbol{\theta})$ is higher at this airport than elsewhere. The vector $\mathbf{x_{ij}}$ includes explanatory variables that vary across alternatives (for example airfares, flight frequency, access time and access costs), and that are specific to individuals such as socio-economics variables (age, gender, etc) while $\boldsymbol{\theta}$ denotes a vector of parameters.

The Additive Random Utility Models (ARUM) posit that the indirect utility can be decomposed into two additive terms: a deterministic part denoted by $v(\mathbf{x_{ij}}, \boldsymbol{\theta})$ and a stochastic error term $\boldsymbol{\varepsilon_{ij}}$. Therefore, we can write the indirect utility of individual i as follows :

$$u(\mathbf{x_{ij}}, \boldsymbol{\theta}) = v(\mathbf{x_{ij}}, \boldsymbol{\theta}) + \boldsymbol{\varepsilon_{ij}}, \quad j = 0, 1 \tag{2.3}$$

Term $\boldsymbol{\varepsilon}_{ij}$ captures the effects of unobserved variables on the indirect utility and $v(\mathbf{x}_{ij}, \boldsymbol{\theta})$ indicates the deterministic part of the utility function. The deterministic part is assumed to be linear in the parameters while the error term $\boldsymbol{\varepsilon_{ij}}$ may have a parametric and symmetric distribution (see McFadden (1974)). When we assume that the vector $\mathbf{x_{ij}}$ is composed of variables $\mathbf{w_{ij}}$ that vary across alternatives such as airfares, flight frequency, access time and access costs, and variables $\mathbf{z_i}$ that are specific to individuals such as income, age, gender, and other socio-economics variables, such that $\mathbf{x_{ij}} = (\mathbf{w_{ij}}, \mathbf{z_i})$, the indirect utility of individual i at facility j can be expressed as follows:

$$u_{ij}(\mathbf{w_{ij}}, \mathbf{z}_i, \boldsymbol{\theta}) = \alpha_{ij} + \phi\ \mathbf{w_{ij}} + \delta_{ij}\mathbf{z}_i + \boldsymbol{\varepsilon_{ij}} \tag{2.4}$$

where $\boldsymbol{\theta} = (\alpha_{ij}, \phi, \delta_{ij})$ is a vector of parameters; α_{ij} represents the constant term; ϕ and δ_{ij} are the parameters associated with variables $\mathbf{w_{ij}}$ and $\mathbf{z_i}$, respectively. Based on (2.4), the probability that traveller i chooses alternative 1 over alternative 0 is given by:

$$\begin{aligned} P(y=1|\mathbf{w},\mathbf{z}) &= P[u_{i1}(\mathbf{w}_{i1},\mathbf{z}_i,\boldsymbol{\theta}) \geq u_{i0}(\mathbf{w}_{i0},\mathbf{z}_i,\boldsymbol{\theta})] && (2.5)\\ &= P[(\alpha_{i1}-\alpha_{i0}) + \phi(w_{i1}-w_{i0}) + (\delta_{i1}-\delta_{i0})z_i \geq \varepsilon_{i0}-\varepsilon_{i1}] && (2.6)\\ &= P[\Delta\alpha + \phi\mathbf{W} + \Delta\delta\ \mathbf{Z} \geq \boldsymbol{\varepsilon}] && (2.7)\end{aligned}$$

with $\Delta\alpha = \alpha_{i1} - \alpha_{i0}$, $\Delta\delta = \delta_{i1} - \delta_{i0}$, $\mathbf{W} = w_{i1} - w_{i0}$ and $\boldsymbol{\varepsilon} = \varepsilon_{i0} - \varepsilon_{i1}$.

Let's denote $\boldsymbol{\beta} = (\Delta\alpha, \phi, \Delta\delta)$ the vector of parameters to be estimated and $\mathbf{X} = (\mathbf{W}, \mathbf{Z})$ the vector of explanatory variables. Hence, the choice probability in (2.7) becomes:

$$P(y=1|\mathbf{X}) = F_{\boldsymbol{\varepsilon}}[\mathbf{X}'\boldsymbol{\beta}] \tag{2.8}$$

where $F_{\boldsymbol{\varepsilon}}$ is the cumulative distribution function of the error term $\boldsymbol{\varepsilon} = \varepsilon_{i0} - \varepsilon_{i1}$. At this stage, we can establish a link between the choice probabilities in (2.8) and (2.2) and conclude that the two expressions are equivalent with $h(\mathbf{X}) = \mathbf{X}'\boldsymbol{\beta}$ and $F = F_{\boldsymbol{\varepsilon}}$.

To obtain the choice probability in (2.8), we need to specify or estimate the functional form of the cumulative distribution $F_{\boldsymbol{\varepsilon}}$. When $\varepsilon_{ij},\ i = \{1, ..., N\},\ j = 0, 1$ is independent and identically distributed (i.i.d.) and follows the Extreme Value type I distribution, the error term $\boldsymbol{\varepsilon} = \varepsilon_{i0} - \varepsilon_{i1}$ follows a logistic distribution. When ε_{ij} is i.i.d normally distributed, $\boldsymbol{\varepsilon}$ follows a probit distribution. Notice that a logistic or normal distribution is function of a vector of parameters that characterize the probability distribution.

Among the available technics, the maximum likelihood method is the most standard procedure to estimate the parameters. The method consists of maximizing the log-likelihood function $L(\boldsymbol{\beta})$ with respect to parameter $\boldsymbol{\beta}$, such that

$$L(\boldsymbol{\beta}) = \log[\prod_n p(\mathbf{X}_i)] = \sum_n y_n \log F_\varepsilon(\mathbf{X}'\boldsymbol{\beta}) + (1-y_n) \log [1 - F_\varepsilon(\mathbf{X}'\boldsymbol{\beta})] \tag{2.9}$$

where $F_{\boldsymbol{\varepsilon}}$ is the logistic or normal cumulative distribution function for the error term $\boldsymbol{\varepsilon}$.

If we assume that $\boldsymbol{\varepsilon}$ is logistically distributed and the parameters to be estimated are constant, we estimate a **fixed-coefficients logit model**. **The random-coefficients model** consists of keeping $F_{\boldsymbol{\varepsilon}}$ as logistic to allow for individual heterogeneity in the coefficients. The probability of choosing alternative 1 is similar to (2.8), except that the vector of parameters $\boldsymbol{\beta}$ is independently and identically normally distributed with mean $\bar{\boldsymbol{\beta}}$ and a variance covariance matrix $\boldsymbol{\Sigma}_\beta$. Then, we have

$$P(y=1|\mathbf{X}) = \frac{1}{1+\exp(\mathbf{X}'\boldsymbol{\beta})} \quad \text{where} \quad \boldsymbol{\beta} \sim \text{ an iid } N(\bar{\boldsymbol{\beta}}, \boldsymbol{\Sigma}_{\boldsymbol{\beta}}) \tag{2.10}$$

where $\bar{\boldsymbol{\beta}}$ and $\boldsymbol{\Sigma}$ represent the mean and variance covariance matrix of $\boldsymbol{\beta}$.

In what follows, we denote $\eta(\mathbf{X})$ a predictor index, such that

$$\eta(\mathbf{X}) = \mathbf{X}'\boldsymbol{\beta} = \sum_p \beta_p X_p \tag{2.11}$$

where p is the number of explanatory variables of the model. Thus, the predictor index for the logit models are linear in parameters of explanatory variables.

A more flexible additive estimation of the choice probability in (2.8) can be obtained by using **Generalized Additive Models (GAM)**, which are nonlinear extension of the generalized linear models. Hastie and Tibshirani (1986) and Abe (1999) have been the first to formally link this estimator to the ARUM framework. GAM relax the linear relationship between the predictors to a sum of one-dimensional nonparametric functions of the explanatory variables so that the predictor index takes a form $\eta(\mathbf{X})$, with

$$\eta(\mathbf{X}) = \sum_p f_p(X_p) \tag{2.12}$$

where f_p denotes a nonparametric function related to the p^{th} explanatory variable. The nonparametric partial-utility function $f_p(X_p)$ for the p^{th} variable can be specified as a smoothing cubic spline. Poirier (1973) provides details regarding piecewise regression using cubic splines. It is worth to mention that the GAM specification still maintains the logistic framework because the model has the additive-in-covariates form. In addition, the separability structure permits a subset of covariates to be specified nonparametrically. Therefore, the choice probability in (2.10) is expressed as follows:

$$P(y = 1|\mathbf{X}) = \frac{1}{1 + \exp[-\eta(\mathbf{X})]} \tag{2.13}$$

In nonparametric methods, the likelihood is maximized when the estimated function interpolates the observed values of a response variable. Such a nonparametric function would be too wiggly and rough, however. A smoother function can be obtained by maximizing a conditional likelihood that penalizes the curvature of the estimated function characterized by a quadratic form of the second derivative (Abe, 1999).

2.3.3 Semiparametric models

The semiparametric model relaxes the shape of the distribution $F_{\boldsymbol{\varepsilon}}$, preserving the linearity of the index $h(\mathbf{X}) = \mathbf{X}'\boldsymbol{\beta}$. A kernel estimator (described later in this section) is usually used to estimate $F_{\boldsymbol{\varepsilon}}$. In other words, the semiparametric approach uses the parametric model with a flexible function. Using the flexible estimate of $F_{\boldsymbol{\varepsilon}}$, the choice probability in Equation (2.8) becomes:

$$P(y = 1|\mathbf{X}) = \hat{F}_{\varepsilon}\left(\mathbf{X}'\boldsymbol{\beta}\right) \tag{2.14}$$

where $\hat{F}_{\boldsymbol{\varepsilon}}$ is the nonparametric estimate of $F_{\boldsymbol{\varepsilon}}$.

Klein and Spady (1993) provide one of the most popular semiparametric single index estimators. One can use a local constant (lc) regression to estimate the function $F_{\boldsymbol{\varepsilon}}$. Technically, the lc method consists of estimating $F_{\boldsymbol{\varepsilon}}$ at any point X_0 of $\mathbf{X}$ by forming a weighted average of y_n in a small neighbourhood of x_0. The neighbourhood is defined by a bandwidth that determines the size of the neighbourhood over which to average; and the weighted average is given by a kernel function[10]. Several technics are available for selecting the optimal bandwidths (the Newton-Raphson method NR, least square cross validation LSCV, maximum likelihood cross-validation MLCV) while the kernel has been shown to have little impact on the estimator. The estimate of F_ε is the weighted average of y_n around X_0 and corresponds to

$$\hat{F}_\varepsilon(X_0) = \frac{\sum_n y_n \; K_h\left(\frac{X_n - X_0}{h}\right)}{\sum_n K_h\left(\frac{X_n - X_0}{h}\right)} \tag{2.15}$$

where K denotes the Kernel function and h the associated bandwidth. The desired probability can estimated with the maximum likelihood methods by substituting the cumulative distribution function F_ε of the log-likelihood function in (2.9) by its local constant estimate $\hat{F}_\varepsilon$.[11]

2.3.4 Nonparametric models

Fully nonparametric estimators are not subject to misspecification bias and capture the interaction between the discrete and continuous explanatory variables. The estimator, however, amounts to estimating directly the conditional probability $P(y = 1|\mathbf{X})$, ignoring the structure of the index in the ARUM, i.e, $h(\mathbf{X})$. While the method remains robust, the structural parameters are subsumed in the estimates. The nonparametric estimators evaluate directly the conditional density function $p(y|\mathbf{X})$ using the estimates of the joint and marginal probabilities denoted by $p(y, \mathbf{X})$ and $p(\mathbf{X})$, respectively.

By definition, the probability that a variable y takes a specific value condition on values of $\mathbf{X}$ is the joint probability conditional on the realization $\mathbf{x}$ divided by the marginal probability. Following this rule, the probability of choosing alternative 1 is

$$P(y = 1|\mathbf{X} = \mathbf{x}) = p(y|\mathbf{x}) = \frac{p(y, \mathbf{X} = \mathbf{x})}{p(\mathbf{X} = \mathbf{x})} = \frac{\hat{p}(y, \mathbf{X} = \mathbf{x})}{\hat{p}(\mathbf{X} = \mathbf{x})} \tag{2.16}$$

where $p(y, \mathbf{X})$ and $p(\mathbf{X})$ denote the joint and marginal probabilities and $\hat{p}(y, \mathbf{X})$ and $\hat{p}(\mathbf{X})$ their estimates. The nonparametric estimators evaluate the conditional density $p(y|\mathbf{X})$ and the joint and marginal probabilities with product kernels (for more details, see Li and Racine

[10] A kernel is a function used to weight observations at the neighbourhood of the support x.

[11] Researches usually choose standard optimization method to maximize the new likelihood function.

(2003)) given by

$$\hat{p}(y, \mathbf{X} = \mathbf{x}) = n^{-1} \sum_{i=1}^{n} \prod_{j=1}^{p} W(X_{ij}^c, X_j^c) \prod_{k=1}^{q} l(X_{ik}^d, X_k^d) \prod_{h=1}^{r} \tilde{l}(X_{o,ih}^d, X_{o,h}^d) \times l(y_i, y), \quad (2.17)$$

$$\hat{p}(\mathbf{X} = \mathbf{x}) = n^{-1} \sum_{i=1}^{n} \prod_{j=1}^{p} W(X_{ij}^c, X_j^c) \prod_{k=1}^{q} l(X_{ik}^d, X_k^d) \prod_{h=1}^{r} \tilde{l}(X_{o,ih}^d, X_{o,h}^d) \quad (2.18)$$

where y is the independent discrete variable; X^c, X_o^d and X^d are the continuous, discrete ordered and unordered regressors, respectively. $W(.)$, $l(.)$ and $\tilde{l}(.)$ represent, respectively, the continuous, unordered and ordered kernel functions used to estimate the density functions. $W(.)$, $l(.)$ and $\tilde{l}(.)$ can be computed by

$$W(X_{ij}^c, X_j^c) = \frac{1}{b_j} K\left(\frac{X_{ij}^c - X_j^c}{b_j}\right) \quad \text{for the continuous regressor,} \quad (2.19)$$

$$l(X_{ik}^d, X_k^d) = \begin{cases} 1 - \lambda_k & \text{if } X_{ik}^d = X_k^d \\ \frac{\lambda_j}{c_j - 1} & \text{otherwise} \end{cases} \quad \text{for the discrete unordered factor,} \quad (2.20)$$

$$\tilde{l}(X_{o,ih}^d, X_{o,h}^d) = \begin{cases} 1 & \text{if } X_{o,ih}^d = X_{o,h}^d \\ \gamma_h^{|X_{o,ih}^d - X_{o,h}^d|} & \text{otherwise} \end{cases} \quad \text{for the discrete ordered factor,} \quad (2.21)$$

where $K(.)$ is the Gaussian Kernel or the normal density function; b_j, λ_k, λ_j and γ_h are parameters that can be estimated by minimizing some loss function or by using a rule-of-thumb. The techniques for bandwidth selection in kernel density estimation include several rules-of-thumb (e.g. Silverman, Scott), the Maximum Likelihood Cross Validation and Least Square Cross Validation. In this analysis, we explore several methods, including reasonably large bandwidths to get smooth patterns.

2.3.5 Specification tests

The objective of the tests is to ensure that the parametric and semiparametric models are correctly specified. In this section, we describe the specification tests for binary outcome models developed by Fan et al. (2006) and Li and Racine (2013). The idea is to test whether the conditional density function of y given $\mathbf{x}$ denoted by $p(y|\mathbf{x})$ belongs to a particular parametric family.[12] Denoting $f(y|\mathbf{x}, \theta)$ a parametric conditional density function with θ being an unknown $(k \times 1)$ dimensional parameter vector, the null and alternative hypotheses to be tested, H_0 and H_1, are given by

- $H_0 : Pr[\ p(y_i|x_i) = f(y_i|x_i, \theta_0)\ ] = 1$ for some $\theta_0 \in \Theta$ where Θ is a compact set in $\mathbb{R}^k$;

[12] The data consist of $\{y_i, x_i\}_{i=1}^n$, an i.i.d. sample drawn from the joint density function $p(y, \mathbf{X})$.

- $H_1 : Pr[\ p(y_i|x_i) = f(y_i|x_i, \theta_0)\ ] < 1 \quad \text{for all } \theta \in \Theta$

The procedure of test is simple. For example, assume that the logistic model is the correct specification. The non-rejection of the null-hypothesis suggests that the conditional probability derived from the logistic model, $f(y_i|x_i, \theta_0)$ should be equal to the conditional density computed from the data $p(y_i|x_i)$, with probability of 1 for many values of paramaters θ_0 (in this case, θ_0 represents the estimate of parameters from the logistic model). The conditional probability $p(y|\mathbf{x})$ is estimated using nonparametric estimators with product kernels as described in Section 2.3.4. Fan et al. (2006) and Li and Racine (2013) proposed a statistic as a basis for a consistent test for H_0, which is based on the linearized version of the Kullback-Leibler information criterion between two conditional distribution functions $p(y|\mathbf{x})$ and $f(y|\mathbf{x}, \theta_0)$. The statistic of the test, denoted T_n is the expected value of the difference between the true and estimated conditional density functions, given by

$$T_n \quad = \quad E\left[\frac{p(y_i, x_i) - f(y_i|x_i, \theta_0)\ p(x_i)}{f(y_i|x_i, \theta_0)}\right] \tag{2.22}$$

Under the null hypothesis H_0, the statistic T_n, assumed to be positive, follows a normal distribution with mean 0 and variance 1: $T_n \to N(0, 1)$. The test suggests that the equality between $p(y|\mathbf{x})$ and $f(y|\mathbf{x}, \boldsymbol{\theta_0})$ holds almost everywhere if and only if H_0 is true.

Fan et al. (2006) and Li and Racine (2013) considered both continuous and discrete explanatory variables and allowed the dependent variable y to be either continuous or discrete. While Fan et al. (2006) developed a nonsmoothing test for correct specification of parametric conditional distributions, Li and Racine (2013) performed a smooth version of the test.[13] By *smoothing* the discrete components of $\mathbf{x}$ and y, the split of the sample into discrete subsets ("cells") is avoided. Furthermore, efficiency gains can be obtained in finite-sample settings when information from nearby cells is borrowed.

2.4 Data

The empirical exercice relies on data from the 2010 Airport Service Quality (ASQ) Passenger Survey carried out by Airport Council International (ACI) on airport sites between January 1st and December, 31 of 2010. This survey was conducted at Canadian airports, including Quebec City Jean Lesage International (YQB) and the metropolitan airline hub Montreal-Trudeau (YUL) airports. Both airports are located in the province of Quebec and are roughly 3 hours away from each other by car, according to Google Map. Each observation contains information on the characteristics of the trip (flight destination, departure time, trip purpose, selected airline, past flight experience of the traveller and access mode used to reach the

[13] Li and Racine (2013) argue that the smoothed statistic displays improved finite-sample power over the nonsmoothed one.

airport) as well as socioeconomic characteristics of the traveller (age, gender, nationality, residency or ZIP code).

Additional information was added to the data set. First, daily flight frequency by origin-destination for the applicable period was obtained from Transport Canada. Thus, for each observation in our database, we matched the number of available flights with the selected airport (YQB/YUL), flight destination and departure date. For example, on January 18^{th}, YUL offered 29 flights to Toronto Pearson international airport (YYZ), 8 flights to Newark Liberty international airport (EWR) and 5 flights to Cancun international airport (CUN) while YQB provided 8 flights to YYZ, 4 flights to EWR and 2 flights to CUN. Second, we computed the access time to the facilities by using passengerSeptembers' and airports' zip codes along with the information on the transportation mode used to reach the airport. Google Map provides an estimate of travel time in minutes from one point to another per transportation mode (private car, train, bus, walk).[14] Information on the fares paid by each passenger was not available, neither in the original data set nor from the airlines we contacted. Data on ticket prices are always difficult to obtain. This is why many researchers don't use it or rather rely on proxies in their analysis. For this research, we constructed a proxy variable, which corresponds to the airfare displayed on the airlines' websites during a particular period of 2011 (from September, 10th to September, 17th). We collected these prices matching the characteristics of each flight in our database (origin, destination, trip purpose, departure time, departure date, airline, travellers' age category and gender) at both airports.[15] When multiple choices were available for the same flight characteristics (several flights were equally valid candidates), we averaged the airfare. We are aware that this measure is prone to measurement error. Passengers may have bought their tickets through specialized search engines and not directly on airlines' website, the fares vary significantly depending on the day of purchase, potential sales, etc. Recognizing fully the limits of our exercice, we propose estimates with and without this proxy.

It is also important to note that the data set was adjusted to allow for competition between YUL and YQB airports. First, we restrict our sample to travellers, who reside in Quebec's province. Second, we only consider routes that are served by both airports in the applicable date. We then exclude observations with destinations that are served by only one of the two airports during the same period. For example, on May 15^{th} 2010, we observe that YUL offered one flight to Brussels airport (BRU). However, the same destination was not served by YQB this day. This observation is not taken into account in this analysis. We agree that after dropping these observations, our sample is largely reduced, but this selection method allows us to disentangle the demand effects from the supply ones. Third, all passengers waiting for

[14]We are aware that our measure of access time is imperfect and excludes the cost of congestion, which may be quite relevant to reach both airports.

[15]Some airlines' websites do ask for the age of the traveller or the purpose of the trip before showing their fares.

their connecting flights at YUL or YQB are dropped from the data base. Therefore, we focus our analysis on travellers, who depart their initial flight at YUL or YQB. Nevertheless, we cannot observe whether the destination is served by a direct or connecting flight. Finally, observations with missing critical items are dropped from the data base. Table 2.1 lists the variables that we retain for the estimation.

Table 2.1 – Variables used in the choice models

Variable	Description
Dependent variable	
Airport choice	Binary variable equals to 1 if YQB is chosen and 0 if YUL is chosen.
Explanatory continuous variables	
Airfare diff. (in $)	Proxy of the ticket price paid by the traveller for a specific destination,
Access time diff. (in minutes)	Travel time from the individual's location to the airport, according to the transportation mode used,
Flight frequency diff. (per destination per day)	Total number of daily flights per destination at the airport, from January 1^{st} to December, 30^{st} in 2010,
Explanatory discrete variables	Categories
Access mode	Private (private and rental cars, taxi and limo), Public (bus, train, subway) and Others (bicycle, walk or dropped by a friend),
Departure time	$[6-8)$, $[8-10)$,$[10-12)$, $[12-14)$, $[14-16)$, $[16-18)$, $[18-20)$ and > 20 $p.m$,
Flight destination	Domestic, Transborder and International,
Flight purpose	Business and Leisure,
Flight experience	$[1-5]$, $[6-10]$ and > 10,
Gender	Male and Female,
Age category	$[16-25]$, $[26-44]$, $[45-64]$ and ≥ 65.

Note: Continuous variables are expressed in difference between YQB and YUL airports ($x_{\text{YQB}} - x_{\text{YUL}}$). The flight experience is the number of trips undertaken by the traveller during the past 12 months.

Table 2.1 shows all the variables considered in the empirical analysis, classified into continuous and discrete variables.[16] The continuous variables include airfare, access time and flight frequency. As for the discrete variables, we distinguish between the flight characteristics such as access mode, departure time, flight destination, flight purpose and the travellers' characteristics such as travellers' flight experience over the past 12 months at the departure airport, gender and age. The original access modes' categories (private car, bus and shuttle, taxi and limo, train and subway, rental car, others) to the airport are grouped into three categories:

[16] In the fully nonparametric approach, these variables are treated with specific bandwidths. Since it is well-known that kernel estimation suffers from a dimensionality curse related to the number of explanatory continuous variables, this classification outlines that we do not have that many continuous predictors.

private mode (car, rental car, taxi and limo), public mode (bus, train and subway) and other transportation modes.[17] Departure time, originally divided into 17 categories varying from 6 *a.m* to 23 *p.m* is grouped into 8 categories including $[6-8)$, $[8-10)$,$[10-12)$, $[12-14)$, $[14-16)$, $[16-18)$, $[18-20)$ and > 20 *p.m.* Flight destination is classified into three categories: domestic, transborder and international while flight purpose includes business and leisure. Flight experience corresponds to the number of trips undertaken by the traveller during the past 12 months and is categorized into 3 classes: $[1-5]$, $[6-10]$ and 10+. Gender is divided into two categories: male and female. Finally, the age category ranges from 16 to more than 65 years old but we merged all these categories in 4 broader classes: $[16-25]$, $[26-44]$, $[45-64]$, and 65+.

The final data set includes 834 observations and represents passengers who departed either YQB or YUL airports. As we do not observe the full itinerary of the travellers, we assume that all individuals who depart a flight at YQB (YUL) chose Quebec (Montreal) as a departure airport.[18]

Of the total travellers, about 60.4% chose YQB and 39.6% selected YUL. These statistics may be explained by the fact that about 71% of the total travellers in our sample are located in Quebec City, 16% are situated in Montreal City and 13% are residents of cities that lie between Montreal and Quebec such as Drummondville, Trois-Rivières and Sherbrooke. Besides, we only consider flight destinations that are available at both airports in the applicable date, which excludes a number of travellers that choose YUL because of the non-availability of the routes at YQB. Based on our sample, the leakage rate[19] at Quebec city is about 18.6% and this proportion is much higher (approximately 87%) at the cities lying between Quebec and Montreal. However, we do not observe any travellers living in Montreal that depart flights from YQB. Table 2.2 shows some interesting descriptive statistics.

[17] Other transportation modes include bicycle, walk or travellers dropped off by friends or family at the airport.

[18] For travellers who departed a flight at YQB but transited at YUL, their choices are categorized as YQB airport. It can be expected that those individuals may choose YUL instead of YQB but decide to reach YUL by plane instead of using other access modes. Unfortunately, we do not observe the detailed itinerary of all travellers included in our sample so that we can identify these travellers. To reduce potential biases, one may include a variable that captures whether a direct flight is offered by the airline for the observed Origin-Destination, or include dummies that control for all destinations that are potentially affected by this issue.

[19] In our analysis, we define the leakage rate at a particular city as the proportion of travellers from that city, who choose YUL instead of YQB.

Table 2.2 – Descriptive Statistics

Variable	Category	Frequency	Percentage
Dependent variable			
Airport choice	YQB	504	60.4%
	YUL	330	39.6%
Explanatory continuous variables	Mean (in absolute value)	Std. deviation	[min; max]
Airfare diff. (in $)	9.30	45.42	$[-150; 172]$
Access time diff. (in minutes)	51.02	208	$[-676; 750]$
Flight frequency diff. (per destination per day)	11	8	$[-24; 5]$
Explanatory discrete variables	Category	Frequency	Percentage
Access mode	Private	450	54%
	Public	170	20 %
	Others	214	26 %
Departure time	$[6-8)$	107	13%
	$[8-10)$	146	18%
	$[10-12)$	83	10%
	$[12-14)$	76	9%
	$[14-16)$	107	13%
	$[16-18)$	145	17%
	$[18-20)$	93	11%
	> 20	77	9%
Flight destination	Domestic	490	59%
	Transborder	173	21%
	International	171	20%
Flight purpose	Business	330	40%
	Leisure	504	60%
Flight experience	$[1-5]$	560	67%
	$[6-10]$	166	13%
	> 10	108	20%
Gender	Male	415	49%
	Female	419	51%
Age category	$[16-25]$	72	9%
	$[26-44]$	321	38%
	$[45-64]$	368	44%
	≥ 65	73	9%

Note: Continuous variables are expressed in difference between YQB and YUL.

As shown in Table 2.2, the difference in flight ticket prices at the two airports ranges from −150$ to 172$ for all flight categories. For domestic flights, the average price differs by about 20$, against 5$ and 1$ for transborder and international flights, respectively. As for the access time difference, its average value corresponds to about 51 minutes. The difference in daily flight frequency at the airports is large, with about 11 flights per destination per day, on average. This difference is especially apparent when it comes to domestic flights, with an average difference of 15 flights per day. It can even reach a maximum of 24 flights per day during peak season. For transborder and international flights, the average gaps are approximately 6 and 3 flights per day, respectively.

Regarding the transportation modes used to reach the airports, private and rental cars are the most used access modes (58%). However, public transportation is less popular (20%), especially at YQB where only 12% of the total travellers use public transport to access the airport. 26% of the total passengers travelled by other transportation modes (by bicycle, walk or dropped by a friend). The proportion of domestic flights in our sample is larger (59%) than transborder and international flights (21% and 20%, respectively). Finally, of the total passengers, 330 travel for business reason while 504 are for leisure purpose. Other interesting statistics about travellers' characteristics are displayed in Table 2.2.

2.5 Empirical results

The empirical models estimate the probability of choosing the regional airport (YQB) rather than the airline-hub (YUL), so we take the perspective of the secondary facility. Hence, $\hat{P}(y = 1)$ is $\hat{P}(y = YQB)$. Moreover, we do not report the results of the Klein and Spady estimator, as the model is difficult to estimate with this large subset of discrete explanatory variables. In this section, we first focus on the fixed- and variable- coefficients logistic models. Then, we explore the additive logistic model (splines or GAM estimator hereafter) and test all the logistic specifications. Finally, we turn to the kernel estimates and compare conditional probabilities of the models.

2.5.1 Fixed- and random- coefficients logistic models

We estimate two versions of each model: one with airfares and another one without this variable, as including our proxy for airfares among the explanatory variables may result in biased estimates of all marginal effects.[20] Columns 2 and 3 of Table 2.3 shows the estimates obtained when airfares are dropped in the fixed-, respectively random-, coefficients logits while columns 4 and 5 provide the estimates when the airfare variable is included. All computations are done with the *R* software and the *mlogit* package. The reported standard deviations are their robust version.

[20]As pointed out in the data section, our proxy for airfares is measured with errors, and its correlation with other explanatory variables may biased estimates.

Table 2.3 – Estimation results of the fixed- and random-coefficients logistic model

Dependent: $Pr(y = YQB)$	**Airfare Excluded**		**Airfare Included**	
Explanatory variable	Fixed coeff.	Random coeff.	Fixed coeff.	Random coeff.
Airfare diff	-	-	-0.005^{*}	-0.024^{***}
	-	-	(0.003)	$(0.000)^{***}$
Access time diff.	-0.011^{***}	-0.029^{**}	-0.011^{***}	-0.107^{***}
	(0.001)	$(0.010)^{**}$	(0.001)	$(0.002)^{***}$
Flight frequency diff.	0.051^{**}	0.115^{*}	0.047^{**}	0.765^{***}
	(0.027)	$(0.065)^{**}$	(0.027)	$(0.164)^{***}$
Access mode	Base: Private transportation			
Public transportation	-0.877^{**}	-1.155	-0.824^{**}	-4.928
	(0.303)	(0.852)	(0.305)	(5.465)
Other modes	1.150^{**}	3.430^{**}	1.173^{**}	38.071^{***}
	(0.304)	(1.518)	(0.307)	(0.818)
Flight destination	Base: Domestic			
Transborder	-1.390^{**}	-2.220^{**}	-1.224^{**}	-9.018^{*}
	(0.399)	(1.007)	(0.396)	(5.324)
International	-2.228^{***}	-5.160^{**}	-2.333^{***}	-33.424^{***}
	(0.462)	(1.879)	(0.468)	(1.603)
Flight reason	Base: Leisure			
Business	-0.629^{**}	-1.467	-0.653^{**}	-11.873^{**}
	(0.308)	0.883	(0.306)	(5.479)
Departure time	Base: $> 20.00\ p.m$			
$[6.00 - 8.00)$	1.672^{**}	35.132^{***}	1.724^{**}	4.828^{*}
	(0.480)	(2.552)	(0.484)	(0.980)
$[8.00 - 10.00)$	0.568	1.046	0.556	8.397^{**}
	(0.409)	(1.602)	(0.415)	(3.119)
$[10.00 - 12.00)$	1.097^{*}	2.874	1.051^{*}	13.275^{*}
	(0.529)	(1.934)	(0.523)	(7.151)
$[12.00 - 14.00)$	1.098^{*}	1.784	1.019^{*}	15.551^{*}
	(0.534)	(1.814)	(0.519)	(8.340)
$[14.00 - 16.00)$	1.634^{**}	3.398^{*}	1.583^{**}	28.757^{***}
	(0.504)	(1.946)	(0.511)	(1.308)
$[16.00 - 18.00)$	1.250^{**}	3.504^{*}	1.220^{**}	19.614^{***}
	(0.418)	(1.958)	(0.428)	(1.314)
$[18.00 - 20.00)$	2.014^{***}	4.961^{**}	2.019^{***}	36.955^{***}
	(0.497)	(2.444)	(0.520)	(7.495)
Flight experience	Base: $[1 - 5]$ years			
$[6 - 10]$	0.289	0.736	0.295	-1.164
	(0.419)	(0.945)	(0.426)	(7.784)
> 10	0.043	0.350	0.060	-0.745
	(0.347)	(0.837)	(0.344)	(6.148)
Gender	Base: Male			
Female	-0.420^{*}	-0.517^{*}	-0.452^{*}	-2.231^{**}
	(0.241)	(0.726)	(0.241)	(1.015)
Age category	Base: ≥ 65 years old			
$[16 - 25]$	1.398^{**}	3.649^{*}	1.456^{**}	14.616^{**}
	(0.660)	(2.116)	(0.651)	(6.798)
$[26 - 44]$	0.574	1.233	0.665	7.273
	(0.521)	(1.206)	(0.522)	(6.728)
$[45 - 64]$	1.000^{**}	2.523^{*}	1.101^{**}	11.339^{*}
	(0.529)	(1.383)	(0.539)	(6.565)
(Intercept)	0.081	-0.889	0.092	-7.857
	(0.787)	(2.009)	(0.788)	(7.044)
Number of observation	834	834	834	834
Log-likelihood	-252.1	-235.93	-250.45	-345.23
Pseudo-R^2	0.5497	0.5786	0.5526	0.3833

"***", "**" and "*" denote statistical significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in brackets.

Recall that the random-coefficients logistic model provides a simple way to generalize the fixed-coefficient logistic model, by accounting for the possibility that travellers may display heterogeneous valuation of the characteristics retained to model airport choice. It allows some parameters of the logit to be randomly distributed according to a density function. In this analysis, we assume that the coefficients of access time, flight frequency and airfare are normally distributed with mean $\bar{\boldsymbol{\beta}}$ and variance-covariance matrix $\boldsymbol{\Sigma}_{\boldsymbol{\beta}}$. However, we treat the coefficients of the discrete predictors as fixed.

Comparing roughly the estimates with and without airfares in Table 2.3, we notice that including airfares among the predictors has little impact on the signs and significance levels of the coefficients of the other predictors but the magnitude of the impacts may vary. Thus, we focus on the model *without airfares* and we stress the main differences with the estimates with airfares when relevant. Moreover, while the fixed-coefficients model with airfares appears to fit better the data than the random-coefficients model, the reverse holds when airfares are excluded.[21] Note also that most random coefficients have the same signs as the fixed ones, but, again, the magnitude of some of the random-coefficients appears to be quite large, particularly in the model that includes airfares.

Let's first focus on the airfare variable. In the random-coefficients model with airfares, the standard deviation of the airfare variable is significant at the 0.1% level, suggesting heterogeneity in individuals' valuation of airfares. The impact of airfare on the likelihood of choosing the secondary airport (YQB) is negative and statistically significant, at the 10% level in the fixed- and at the 1% level in the random-coefficients model. This suggests that demand for YQB is a decreasing function of the difference in airlines' ticket price between YQB and YUL and that fares are important even when all predictors are simultaneously considered. This result is in line with the economic theory and corroborates the findings of Zhang and Xie (2005); Suzuki (2007); Ishii et al. (2009); de Luca (2012). Some researchers including Harvey (1987); Pels et al. (2003); Başar and Bhat (2004), however, found no significant effects of airfare on travellers' choice when accounting for flight and passengers' characteristics. Their findings may be explained by the use a proxy variable to measure the actual airfare paid by travellers, as we do. Proxies can be more or less accurate and bias the estimates in an unpredictable manner.

Travellers' accessibility to the facilities is particularly relevant in theoretical models of facility choice. Transportation costs play an important role in spatial models. Two explanatory variables capture this aspect in our empirical models: access time and access mode. The coefficient of access time is negative and strongly significant, as expected, suggesting that the probability of choosing YQB increases when the access time difference between YQB and YUL decreases. Thus, the attractiveness of the regional facility is decreasing in access time. We also find that the probability of choosing YQB is linked to the access mode. More precisely, the coefficient for public transportation dummy is negative and significant at the 1% level, indicating that travellers using private mode of transportation to go to the departure airport

[21] A closer look at the within-sample predictive performance of the models is proposed at the end of this section.

are more likely to choose the regional facility than passengers using public transportation. This finding does not come as a surprise as YQB airport does not appear to have frequent buses to reach the facility. In this particular case, this aspect seems to be quite important.

Another particularly relevant aspect in airport choice is flight frequencies. Competition in flight frequencies across airports has received enormous attention in transportation economics (Brueckner and Flores-Fillol, 2007; Brueckner, 2010). One would expect that larger frequencies at a facility offer the travellers a wider choice in terms of departure times, total travel time, routes (in case of connecting flights) and qualitative characteristics of the flight. In our estimations, the flight frequency variable appears to have the expected positive and significant impact on the choice probability of the secondary airport. This implies that an increase in the number of daily flights per destination at YQB airport would improve its chance to be chosen by travellers. These results are in line with the empirical airport choice literature (see for example Harvey (1987); Windle and Dresner (1995); Başar and Bhat (2004); Pels et al. (2003); Ishii et al. (2009)). Note that, in the random-coefficients models, the standard deviations of access time and flight frequency are statistically significant at least at the 5% significance level, suggesting that the two coefficients vary across individuals.

We now focus on narrower flight characteristics, such as flight destination, flight purpose and the time of departure. One may expect that the secondary facility is more attractive for domestic flights as the number of international flights offered is in general limited. A secondary facility may also be more attractive for business travellers if the primary rival facility is congested. Therefore, which of the two passengers types is the most likely to choose YQB is an open question. Regarding departure times, early services would typically capture the demand of travellers located closer to the secondary airport while late services may allow potential travellers located farther away to take advantage of competitive fares.

Turning to the empirical results, we find that travellers are more likely to use YQB for domestic flights rather than for transborder or international flights, as suggested by the negative and significant coefficients of the transborder and international dummies. The purpose of the flight also appears to have a significant impact on the choice probability. Leisure travellers are more likely to depart YQB than business passengers over destinations available at both airports. The airport choice also appears to be strongly associated with the departure time of the flights, which is in line with Zhang and Xie (2005) and Ishii et al. (2009). The coefficients of the departure time dummies are positive and, almost in all cases, significant at least at the 10% level. Departure times between $[6-8]$, $[14-16]$ and $[18-20]$ are those which affect the most strongly and positively the likelihood of choosing the secondary facility. This implies that travellers are more likely to choose YQB when the flight is scheduled within these intervals rather than late at night (> 20 $p.m$), which is the baseline case.

Frequent flyers, i.e., passengers travelling more than 6 times a year, appear to favour none of the facilities. Regarding the impact of the travellers' characteristics, gender and age appear to be relevant predictors of the airport choice, both in the fixed- and random- coefficients models. YQB attracts more men than women while travellers between $[16-25]$ and $[46-64]$ years old are more likely to choose YQB rather than YUL, as compared to the ≥ 65 year-old category.

In logistic models, the coefficients related to the utility index capture the effect of each explanatory variable on the utility while the marginal effects give the change in probability due to a unit change in the explanatory variables at a particular value.[22] To be able to compare the parametric results with the nonparametric estimates, we compute the marginal effects at the mean of the explanatory continuous variables and for the following levels of the categorical variables: domestic flight, private mode of transportation, leisure, male, age category superior than 65 year-old, departure time > 20.00 $p.m$ and flight experience within the $[1-5]$ year interval. Table 2.4 gives the marginal effects based for the model that includes airfares.

Table 2.4 – Average marginal effects from the fixed-coefficients logit

Explanatory variable	Marginal effects
Airfare diff.	-0.001
Access time diff.	-0.001
Flight frequency diff.	0.004
Access mode	Base: Private transportation
Public transportation	-0.069
Other modes	0.099
Departure time	Base: > 20.00 $p.m$
$[6.00-8.00)$	0.141
$[8.00-10)$	0.047
$[10.00-12.00)$	0.088
$[12.00-14.00)$	0.086
$[14.00-16.00)$	0.133
$[16.00-18.00)$	0.107
$[18.00-20.00)$	0.170
Flight destination	Base: Domestic
Transborder	-0.103
International	-0.196
Flight purpose	Base: Leisure
Business	-0.055
Flight experience	Base: $[1-5]$ years
$[6-10]$	0.025
> 10	0.005
Gender	Base: Male
Female	-0.038
Age category	Base: ≥ 65 years old
$[16-25]$	0.123
$[26-44]$	0.056
$[45-64]$	0.093
Number of observation	834

Table 2.4 shows negative marginal effects for airfares and access time, which indicates that if the difference in access time/ airfares is reduced by *one minute*/1\$, then the probability of choosing the regional facility would increase by about 0.001. This implies that a decrease of *one hour* in ground travel time would increase the choice probability by about 6%. We obtain

[22]The marginal effect with respect to a change in a continuous regressor x_j, evaluated at the mean of the variables ($x = \bar{x}$) and is given by : $F(\bar{x}'\hat{\beta})[1 - F(\bar{x}'\hat{\beta})]\ \hat{\beta}_j$ where $F(.)$ is the cumulative distribution function of the error term.

the same effects if the difference in ticket price at the airports decreases by about 60$. The marginal impact of flight frequency is positive and suggests that an additional daily flight at the regional facility would increase its probability to be chosen by travellers by 0.4%.

Regarding the discrete explanatory variables, the marginal effect for public mode of transportation shows how the probability of choosing YQB changes if travellers switch from private cars to public transport to reach the regional facility. In our estimation, the probability would decrease by about 7%. The marginal effects of departure times are all positive, indicating that scheduling a flight earlier than 20.00 p.m would increase the chance of the regional airport to be chosen. The marginal effects associated with each departure time dummy are given in Table 2.4. Switching from domestic to transborder and international flights also penalize the regional facility, with changes in probability about −10.3% and −19.6%, respectively. The marginal impacts linked to other explanatory variables are displayed in Table 2.4.

We now interpret the within-sample predictive performance of the models, based on two indicators: the pseudo-R^2 or McFadden's R^2 and the classification ratios. A pseudo-R^2 close to 1 can be interpreted as a good performance of the model. As for the classification ratios, they give the percentage of predicted which match the actual choice made by the individual. A ratio close to 1 suggests that the model correctly predicts most individual choices observed in the sample.

The fixed-effect coefficients logistic model displays a pseudo-R^2 of 0.5526 when airfare is included and 0.5497 if excluded. Setting the classification cut-off to 0.5 (assuming that all probabilities superior to (inferior to) 0.5 denote individuals likely to depart YQB (YUL)) the percentage of correctly specified values is about 87.29%. Specifically, the model misclassifies 106 observations, 40 values are classified as 1 while the correct classification should be 0, and 66 observations are misclassified as 0 while they should be classified as 1. The overall classification ratio is 86.91%.

However, the random-coefficient specification gives a better representation of the data than the fixed-coefficients model only if we exclude the airfare variable, as its pseudo-R^2 is larger than its fixed-coefficients counterpart only when airfares are excluded. Thus, we focus on the estimation results from the random-coefficients logit without airfares. In Table 2.5, we conduct Likelihood Ratio (LR) and Wald tests to investigate if the random-coefficients specification provides better fit than its fixed-coefficients counterpart. Both statistical tests reject the null hypothesis of absence of individual heterogeneity. Therefore, we conclude that the random-coefficients logistic model (without airfares) is the most appropriate.

Table 2.5 – Likelihood Ratio and Wald tests: Fixed v.s Random-Coefficients logit

H_0: No random effects

Likelihood Ratio test	LogLik	Statistic of the test χ^2 (p-value)
Fixed coeff.	-252.10	
Random coeff.	-235.93	32.346 (p-value=0.000)***
Wald test		6.548 (p-value = 0.038)

The chi-squared distribution is evaluated at two degrees of freedom. "***", "**" and "*" denote statistical significance at the 1%, 5% and 10% levels, respectively.

2.5.2 Flexible logit model

We now focus on the additive logistic model under the assumption that the discrete predictors do not interact with the continuous explanatory variables. Therefore, this model focuses on the flexibility of the continuous regressors. Table 2.6 provides the estimation results for the continuous variables using GAM.

Table 2.6 – Estimates of the continuous variables from Generalized Additive Models

	Airfare Excluded			**Airfare Included**		
Continuous variable	edf	Ref. df	χ^2 (p-value)	edf	Ref. df	χ^2 (p-value)
Airfare diff.	-	-	-	2.123	2.684	12.03 (0.007**)
Access time diff	8.178	8.325	41.47 (0.000***)	8.380	8.615	41.37 (0.000***)
Flight frequency diff.	8.139	8.669	33.65 (0.000***)	8.213	8.700	35.84 (0.000***)

We use cubic splines and the automated method for choosing the knots of the basis. "***", "**" and "*" denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.6 reports statistics regarding the estimated degrees of freedom for the spline bases (edf), the reference degrees of freedom used for the tests (Ref. df), the Chi-squared empirical statistic and its associated p-value. All continuous variables appear to be statistically significant, suggesting that introducing nonlinearities in the relationships significantly improves the model. Note that the model displays a $pseudo-R^2$ of 0.756, which is higher than the pseudo-R^2 of the logistic models. Thus, this estimator dominates the linear logistics specifications in terms of within-sample fit performance. To have a sense of the non-linearities captured in this model, we plot the partial effects related to the explanatory continuous predictors when we display the nonparamatric fits (see later). Regarding the coefficients obtained for the discrete variables, they are given in Table 2.7.

Similarly to the random-coefficients logistic model, the effects of the public and private transportation modes are not statistically different, the coefficients of transborder, international and business dummies keep their negative and statistically significant effects and gender plays no role. Moreover, the signs and significance levels of the departure time coefficients are similar to the random-parameters' results, but their magnitudes differ. Regarding the differences with the random-coefficients model, flight experience within $[6-10]$ becomes statistically sig-

Table 2.7 – Estimates of the discrete explanatory variables of Generalized Additive Models

	Airfare Excluded	**Airfare Included**
Explanatory variable	coefficient	coefficient
Access mode	Base: Private transportation	
Public transportation	-0.786^{*}	-0.718
	(0.443)	(0.454)
Other modes	1.427^{***}	1.370^{***}
	(0.395)	(0.399)
Departure time	Base: > 20.00 $p.m$	
[6.00 − 8.00)	1.950^{**}	1.992^{**}
	(0.772)	(1.992)
[8.00 − 10)	-0.250	-0.443
	(0.859)	(-0.443)
[10.00 − 12.00)	1.117	1.000
	(0.769)	(1.000)
[12.00 − 14.00)	1.570^{**}	1.387^{*}
	(0.790)	(1.386)
[14.00 − 16.00)	1.350^{*}	1.378^{*}
	(0.789)	(1.378)
[16.00 − 18.00)	1.690^{**}	1.644^{**}
	(0.731)	(1.644)
[18.00 − 20.00)	2.552^{***}	2.575^{**}
	(0.771)	(2.575)
Flight destination	Base: Domestic	
Transborder	-2.872^{***}	-3.258^{***}
	(0.741)	(0.721)
International	-3.731^{***}	-3.953^{***}
	(0.936)	(0.951)
Flight purpose	Base: Leisure	
Business	-1.261^{**}	-1.354^{***}
	(0.388)	(0.393)
Flight experience	Base: [1 − 5] years	
[6 − 10]	0.147	-0.704^{*}
	(0.493)	(0.428)
> 10	-0.583	0.133
	(0.415)	(0.489)
Gender	Base: Male	
Female	-0.479	-0.610^{*}
	(0.339)	(0.346)
Age category	Base: ≥ 65 years old	
[16 − 25]	1.077	1.308^{*}
	(0.759)	(0.793)
[26 − 44]	-0.142	0.103
	(0.595)	(0.660)
[45 − 64]	0.723	1.038
	(0.568)	(0.632)
Number of observation	834	834
Adjusted-R^2	0.743	0.756

"***", "**" and "*" denote statistical significance at the 1%, 5% and 10% levels, respectively.

nificant at the 10% level and the age category [46 − 65] years old does not influence anymore the choice of the regional facility.

2.5.3 Specification tests

The nonparametric specification tests proposed by Fan et al. (2006) and Li and Racine (2013), described in Section 2.3 are used to determine whether the parametric and semi-parametric models are correctly specified. We focus on the flexible conditional probabilities of the models *without airfares*.[23] The null hypothesis to be tested states that the conditional density function of the binary outcome y given covariates $\mathbf{x}$ is compatible with the postulated ARUM (logit with fixed or random-coefficients, GAM or single-index family). Two different versions of the tests are applied: the unsmoothed specification test developed by Fan et al. (2006) and the smoothed version performed by Li and Racine (2013). Note that we use the large sample version of the test.

The choice of the bandwidths of the kernel estimator are crucial for the specification tests. We used the *oversmoothed and adhoc* bandwidths reported in Table 2.9 from the next section. This choice may be surprising. Note that all specification tests reported below do *reject* the null of correct specification for the fixed- and random-coefficients and the additive logistic models when optimal data-driven bandwidths are used. However, the conditional probabilities resulting from these kernel estimates are very *undersmoothed*, defeating the purpose of having a fully flexible density as benchmark to be compared meaningfully with the logistic models. Thus, we elected to report the results of the *oversmoothed* flexible kernel estimator, which does provide a meaningful alternative to the logistic models. This is discussed more carefully in the kernel estimator section.

Table 2.8 presents the statistics of the test denoted T_n and associated $p-value$.

Table 2.8 – Results of the nonparametric specification tests

Model	T_n Smoothed (p-value)	T_n Unsmoothed (p-value)	Decision
Fixed-coeff. Logit	21.41(0.00)	28.55(0.00)	H_0 rejected
Random-coeff. Logit	16.05(0.00)	21.39(0.00)	H_0 rejected
GAM	12.05(0.00)	16.23(0.00)	H_0 rejected

In its asymptotic version, the statistic T_n follows normal distribution with mean 0 and standard deviation equals to 1. Columns 2 and 3 of Table 2.8, respectively, show the values of T_n with associated $p-value$ in brackets using the smoothed and unsmoothed versions of the test. As shown in Column 4 of Table 2.8, the null hypothesis H_0 is rejected in all cases, suggesting that the logit with fixed and random coefficients and the semi-parametric single-index models are misspecified. Although the parametric specifications have strong theoretical foundation, a more flexible model is likely to provide a better representation of the relationships between the observed choices and its predictors. We now exploit the kernel estimations of the conditional probability to explore the shapes of the partial relationship and interactions.

2.5.4 Nonparametric results

The kernel estimator provides a flexible way to describe the relationship between the conditional choice probability and its predictors. In this setting, we use partial plots to visualize

[23] The bandwidths of the models with airfares are given in the Appendix.

the marginal effects over the support of the explanatory variables, but also to explore selected interactions between the continuous regressor access time and some trip characteristics. But first, let's discuss about our choice of bandwidth, which is an important question when using nonparametric methods.

Tables 2.9 compares the three most popular bandwidth selection methods for kernel (conditional) densities, i.e., Silverman's rule of thumb with unsmoothed discrete regressors (NR), Maximum Likelihood Cross Validation (MLCV) and Least Square Cross Validation (LSCV) in models without airfare and when airfare is included. In moderate size samples, different methods may yield very different bandwidth values. The NR and MLCV methods appear to provide reasonable bandwidths for the continuous predictors given the measurement units and variability of the data while the LSCV technic seems to undersmooth quite heavily the continuous predictors. The inclusion of airfare in the model also influences the size of bandwidth. Indeed, including airfare decreases in general the bandwidth of flight frequency and almost all the discrete explanatory variables, but increases largely that of access time. To get smoothed plots, we use reasonable (oversmoothed) values of bandwidth, which are adjusted such that the conditional probability is smooth enough when visualized. This indeed amounts to smooth a density sufficiently to avoid wiggly patterns.

As outlined by Li and Racine (2007), the LSCV method has the ability to detect the relevant conditioning variables. If the LSCV bandwidth of the explanatory variable (discrete or continuous) reaches its upper bound, the test suggests that the variable is irrelevant for explaining the conditional probability. We then compare the LSCV bandwidth of each explanatory variable with their upper bounds given in the second column of Table 2.9; and conclude that, except for flight experience, all the explanatory variables appear to be relevant.

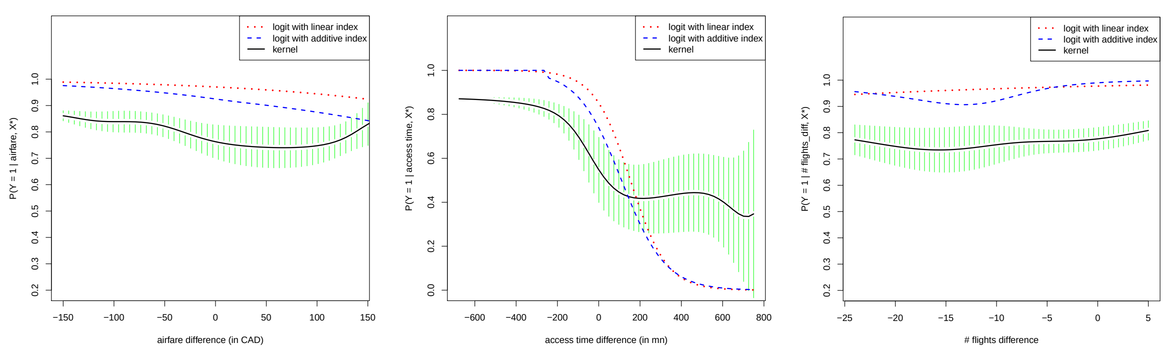
We now explore the marginal effects over the support of the continuous and discrete explanatory variables via the partial plots. Figure 2.1 compares the marginal effects of airfare, access time and flight frequency derived from the conventional logit with linear index, the flexible logit with additive index and the kernel estimators.

Table 2.9 – Bandwidths for the kernel estimator

		Airfare Excluded				**Airfare Included**			
		Bandwidths							
	Bounds	Methodology				Methodology			
	[min; max]	oversm.	NR	MLCV	LSCV	oversm.	NR	MLCV	LSCV
Explained Variable									
Airport choice	[0,0.5]	0.00	0.00	0.01	0.19	0.05	0.00	0.14	0.05
Explanatory Variables									
Airfare	$[-\infty, \infty]$	-	-	-	-	15	7.21	8.76	0.96
Flight frequency	$[-\infty, \infty]$	3	2.70	2.00	0.48	3	3.17	0.56	0.35
Access time	$[-\infty, \infty]$	120	71.76	11.61	0.34	120	84.22	97.80	4.70
Access mode	[0,2/3]	0.06	0.00	0.08	0.14	0.06	0.00	0.30	0.37
Departure time	[0,1]	0.10	0.00	0.81	0.02	0.10	0.00	0.45	0.42
Flight destination	[0,2/3]	0.06	0.00	0.19	0.01	0.06	0.00	0.00	0.66
Flight purpose	[0,1/2]	0.05	0.00	0.19	0.01	0.05	0.00	0.26	0.01
Gender	[0,1/2]	0.05	0.00	0.38	0.02	0.05	0.00	0.34	0.50
Age category	[0,1]	0.10	0.00	0.53	0.00	0.10	0.00	0.20	0.75
Flight experience	[0,1]	0.10	0.00	0.35	0.99	0.10	0.00	1.00	0.15
Log Likelihood		-74.38	-16.72	-64.99	-18.42	-61.70	-10.57	-37.8	-44.18
McFadden et al. stat		98.9%	99.5%	97.6%	99.9%	99.5%	99.6%	99.5%	99.8
Observations			834					834	

Note: Term "oversm." denotes "oversmoothed". "NR", "MLCV" and "LSCV" denote bandwidths computed with the following methods: Silverman's rule of thumb, Maximum Likelihood Cross Validation and Least Squares Cross Validation, respectively. "McFadden et al. stat."designates McFadden, Puig et Kerschner performance measure.

Figure 2.1 – Partial regression plots of the continuous explanatory variables

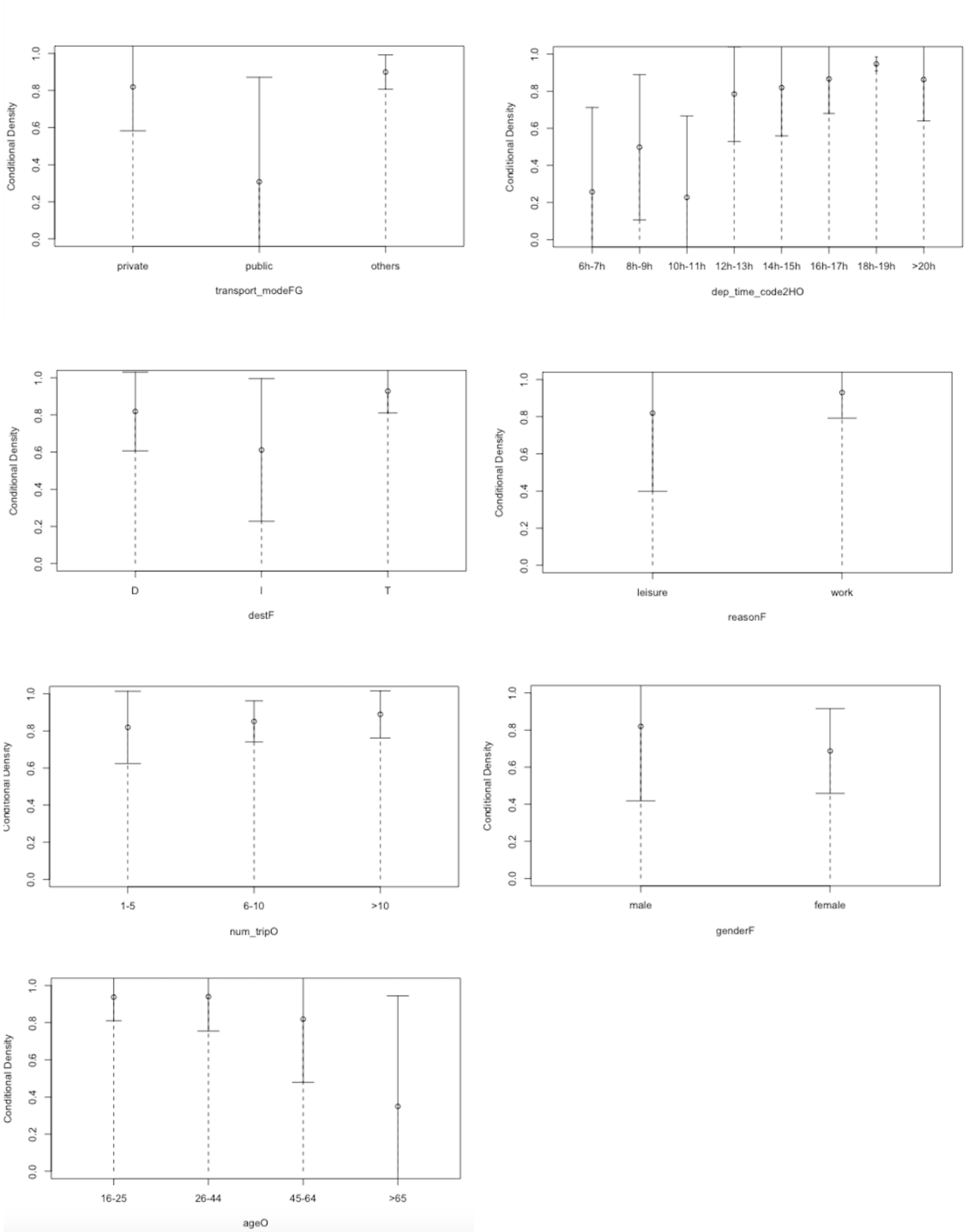


We see in Figure 2.1 that the impacts of each continuous variable are similar across models, but differ in terms of magnitude. Airfare and access time differences display negative impacts whereas flight frequency exhibits a positive effect. We also observe that there is no significant difference between the marginal effects from logit with linear index and GAM, contrary to their counterpart kernel estimator, which displays much lower values. The pattern difference is especially apparent for the access time variable, in particular, when the difference in access time exceeds 200 minutes. Of course, having used oversmoothed bandwidths, the probabilities computed by the kernel estimator can be biased. Whether this bias is worse than imposing a parametric shape, even if the logistic model is consistent with the economic theory, is a matter of debate from a statistical standpoint. More importantly, all models capture the same patterns for the continuous predictors. Thus, misspecification may rather be linked to the interaction effects, which will be explored for selected variables below.

The marginal effects of the discrete explanatory variables on the conditional probability are given in Figure 2.2. In each subfigure, the "dot" corresponds to the conditional choice probability of each category of discrete variable and the vertical line that encompasses it is the associated variability bound of the estimate, computed by pairwise bootstrap.

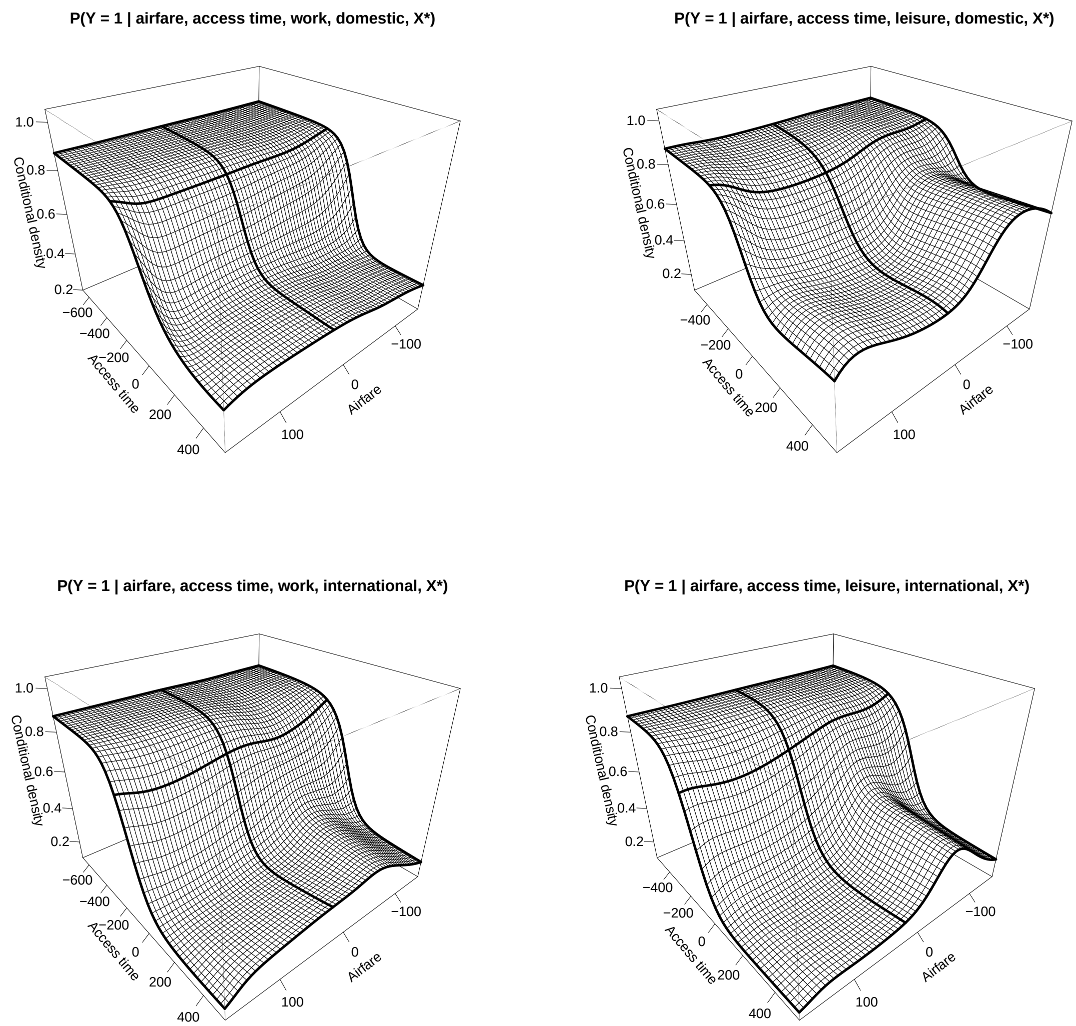
The marginal effects of transportation mode, flight experience, gender and age category are similar across the logit and kernel estimation. Therefore, the interpretation given Section 2.5.1 also applies. However, the kernel estimator provides different marginal impacts for departure time, flight destination and flight purpose. Regarding the impacts of departure time, the conditional choice probability when the flight is scheduled later than 18.00 *p.m* appears to be higher than when the flight is set earlier than 18.00 *p.m.* This contrasts the previous results and, instead, suggests that travellers are more likely to choose YQB when the flight is scheduled later than 18.00 *p.m*, rather than earlier. As for the flight destination, while the logit models suggest that travellers are more likely to use YQB for domestic flights rather than for transborder flights, the kernel estimator produces the opposite result. Finally, in the kernel estimation, business travellers appear to be more attracted to YQB than leisure passengers, which is the reverse of what we found when we use the parametric models.

Figure 2.2 – Partial regression plots of the discrete explanatory variables



The main advantage of nonparametric kernel estimation also stems from the plotting devices that enable us to uncover interaction effects without shape constraints. Figure 2.3 shows the interaction effects of airfare and access time according to flight purpose and flight destination, keeping the other predictors at their median.

Figure 2.3 – Interaction effects of airfare and access time according to flight purpose (leisure/business) and flight destination (domestic/international) using nonparametric Kernel estimator



The top plots of Figure 2.3 show how the impact of the airfare and access time variables on the choice of YQB is affected by the reason of flight for domestic routes. We notice that travellers for work purpose are more sensitive to the access time whatever the level of airfare difference between the two facilities. Leisure travellers are also sensitive to access time when the airfare difference is positive.[24] However, when the airfare difference is negative i.e. when the regional facility is more competitive in airfares, those who travel for leisure purpose become less sensitive to access time.

We also notice that travellers flying for a leisure purpose are more sensitive to the airfare difference when the access time is less favorable for YQB (access time difference above 0) while work travellers are quite insensitive to airfare differences whatever the difference in access time to the regional facility. Thus, access time seems to be very crucial for those travelling for work purpose.

The bottom plots explore the same question as above but for international flights. In this case, the patterns are quite similar across work and leisure travellers. The probability of choosing YQB is almost null when the access time difference between YQB and YUL exceeds 4 hours and when the flight is over $100 more expensive at YQB, even with the oversmoothed kernel estimate. The sensitivity to access time is clearly stronger for international flights than domestic flights for both categories of travellers, whatever the airfare difference. Airfares differences play no role when YQB is way closer to the place where the traveller resides in terms of access time. We also notice that more expensive flights at YQB decrease the probability of choosing YQB, particularly when the regional facility has a location disadvantage.

Thus, we conclude that, despite the adhoc way we choose the bandwidths of the kernel estimates, they uncover meaningful and interesting features hidden in the data, that we may want to confirm with the parametric models. This is developed in the next section.

Another aspect that is worth analyzing is how well the oversmoothed kernel estimator performs in terms of in-sample fit.[25]

2.6 Comparison of model goodness-of-fit

This section summarizes and compares the performance of the models selected in this analysis. As before, we use the statistic of pseudo-R^2 and the classification ratios to compare the fixed- and random-coefficient logit with the more flexible additive logit and the oversmoothed nonparametric kernel estimation. Table 2.10 summarizes the $pseudo - R^2$ statistics derived from each specification.

Table 2.10 – Statistics of Pseudo-R^2

Specification	Fixed-coeff. logit	Random-coeff. logit	GAM	Kernel estimator
$Pseudo - R^2$	0.55	0.58	0.77	0.99

[24] Note that a positive airfare difference indicates that YUL displays lower airfares than YQB, then is more competitive in prices.

[25] Testing the predictive performance of the kernel estimator with hold-out data would be more appropriate but this is left for future research.

We see from Table 2.10 that the more flexible model (non parametric kernel estimation) displays the highest value of $pseudo-R^2$ and the more restricted specification (fixed-coefficient logit) shows the lowest statistic (0.5526). Thus, a more flexible estimation is preferable.
The classification ratios also provide interesting information allowing to compare the goodness-of-fit of the models. However, this measure is sensitive to the cut-off used to classify the travellers. Researchers often use a cut-off point equal to 0.5, so all predicted probabilities superior (inferior) to 0.5 are classified into 1 (0).[26] Below, we explore the robustness of this cut-off point. Table 2.11 reports this exploratory analysis for all the selected models.

Table 2.11 – Classification table for different cut-offs

Model | Cut-off	0.5	0.6	0.7	0.8	0.9	0.95
Fixed-coeff. logit						
Correct classification of $P(y=1)$	86.91%	84.52%	83.14%	79.17%	72.62%	59.72%
Overall Classification	87.29%	87.29%	87.05%	85.97%	82.73%	75.42%
Random-coeff. logit						
Correct classification of $P(y=1)$	86.11%	84.32%	82.74%	79.96%	70.83%	57.14%
Overall Classification	56.95%	57.67%	59.59%	63.42%	68.35%	65.23%
Generalized Additive Model (GAM)						
Correct classification of $P(y=1)$	88.69%	87.89%	87.30%	86.91%	86.31%	86.11%
Overall Classification	91.84%	91.61%	91.37%	91.13%	91.01%	91.01%
Kernel estimator						
Correct classification of $P(y=1)$	99.52%	99.02%	98.36%	97.18%	96.98%	96.70%
Overall Classification	100.00%	100.00%	99.27%	98.85%	98.12%	97.32%

Two classification ratios are presented: the correct classification of probability equals to 1 and the overall classification that accounts for both probabilities $Prob(y=1)$ and $Prob(y=0)$. In all cases the kernel estimator dominates its parametric and Generalized Additive Model (GAM) counterparts in terms of both classification ratios. GAM outperforms its fixed- and random-coefficient logit counterparts for all cut-off levels. Note that the fixed-coefficient logit always displays higher classification ratios than its random-coefficient counterpart for all threshold levels, except for the case where the cut-off is set at 0.8. We conclude that increasing the flexibility of the model leads to gains in terms of within goodness-of-fit.

2.7 Conclusion of Essay 2

This paper investigates the main determinants of travellers' choice between a regional airport and the closest airline-hub in the province of Quebec in Canada. We compare the estimates from the conventional fixed- and random-coefficients binary logit model with those from more flexible specifications, including Generalized Additive model (GAM), Klein and Spady and nonparametric Kernel estimators; and conclude that more flexible specification provides better

[26]For example, if the model predicts a probability of 0.65 for the first observation, it would be classified into category 1. Then, we compare this predicted probability with the actual value of y and conclude whether the observation is correctly specified or not.

predictions within sample. The signs and significances of the marginal effects, however, do not significantly change though their magnitudes may vary. The empirical exercise is conducted on data from the 2010 Airport Service Quality (ASQ) Passenger Survey carried out by Airport Council International (ACI) on airport sites between January 1st and December, 31.

Access time and access mode to airport, flight frequency, airfare, flight destination and departure times appear to be the main factors of regional facility choice. travellers' characteristics such as gender and age category also influence the probability of choosing a regional airport. Airfare and access time to airport display negative effects while flight frequency exhibits a positive impact. Moreover, travellers are more likely to choose the regional facility for domestic flights, and when the flight is scheduled either very early in the morning (between 6.00 $a.m$ and 8.00 $a.m$) or in the afternoon rather than late in the night ($> 20.p.m$). Business travellers are more concerned about access time than airfare, while leisure travellers are facing trade-off between airfare and access time. As our measure of airfare may bias our estimates, we run models without this variable; and find no change in the signs and significances of the effects of the explanatory variables.

According to the kernel based nonparametric specification tests, the parametric and semi-parametric models appear to be misspecified. Though these models have strong theoretical foundation, the nonparametric kernel estimator gives a better representation of the relationship between our predictors and the conditional choice probability. In addition, the plots of the nonparametric estimates allow to uncover interesting characteristics of the travellers that are relevant for decisions makers and for understanding traveller choices.

This study is limited to the choice between the two main airports in the province of Quebec. Future work may consider to increase the number of available airports and formally define each airport' catchment area. Among the available parametric and semi-parametric models, our application only focuses on fixed- and random-coefficients logit and GAM estimators. Researchers may consider alternative methods of estimation. Finally, the proxy of airfare used in this research may not be the best proxy for this variable. A more accurate proxy of airfare should be considered.

Chapter 3

When Hotelling meets Vickrey Spatial differentiation and service timing in the airline industry

Abstract

This essay analyzes rivalry between transport facilities in a model that includes two sources of horizontal differentiation: geographical location and time scheduling. We explore how both sources influence facilities' charges and the price of the service offered by downstream carriers in a sequential game with simultaneous choices at each stage. To derive facility demands, we use an approach that combines both Hotelling and Vickrey frameworks. Travellers' cost includes fare, transportation cost to the facility and a schedule delay cost, which captures the monetary cost of departing earlier or later than desired. One carrier operates at each facility and schedules a single departure time. We first consider that departure times are exogenously set and carriers compete in prices. We then analyse departure times and price competition where departure times are chosen before fares. We show that duopolistic competition drives to identical departure times across carriers when their operational cost does not vary with the time of day, but generally leads to distinct service times when this cost depends on the time of the day. We also find that when a facility possesses a location advantage, it can set a higher fee and its downstream carrier can charge a higher fare. Differentiation in departure times allows the facilities and their carriers to compete in an additional differentiation dimension that can reduce or strengthen the location advantage.

Keywords: Facility Competition, Horizontal Differentiation, Time Scheduling, Airlines and Airports.

3.1 Introduction

Since the deregulation of the airline market in the US and Europe, rivalry between airports and their carriers has intensified. Travellers located in populous regions have often the opportunity to choose between multiple airports to fly toward the same destination. While a large theoretical literature is devoted to analyzing rivalry in prices and service frequency across facilities, a fundamental aspect of the air travel market has received less attention: scheduling competition. Airlines obviously compete in price as well as departure times in a market.[1] In addition, the timing of the services offered is of great concern not only for carriers but also for travellers. For carriers, time scheduling is an additional differentiation dimension that can be strategic for competition. For travellers, they incur "schedule delay costs" for not consuming the service at the preferred time. Transportation authorities would gain in having a better understanding on how scheduling plays in deregulated markets.

This paper proposes a facility-carrier model to study how facility charges, carrier fares and departure times are set in a duopoly where geography gives more market power to one of the facilities and its carrier. Hotelling (1929) has been widely used in industrial organization to study horizontal product differentiation and spatial competition between firms. Therefore, the Hotelling framework allows to study the impact on competition of spatial asymmetry in the geographical location. Departure times competition can be also analyzed in the light of Hotelling model where time scheduling can be interpreted as location on a time line. Alongside, since Vickrey (1969), time costs have become fundamental components for modelling firms' and consumers' timing decisions. Consumers' value of time and schedule delays, defined as the difference between the preferred and the actual departure/arrival/total time, are widely used to model congestible infrastructures. The costs related to the timing of the service is also central in carriers' planning. In this paper, we attempt to bring Hotelling (1929) and Vickrey (1969) frameworks together, by incorporating spatial differentiation and service timing in the same model to analyze pricing and scheduling decisions of rival facilities and their carriers.

Research explicitly recognizes that the airline market operates under different forms of imperfect competition and that pricing the access to the facilities (through a congestion toll or slot management) is an efficient way to address congestion.[2] de Palma and Leruth (1989) and De Borger and Van Dender (2006) investigate the capacity and price decisions of congestible facilities selling perfect substitutes in duopolistic markets by using sequential capacity-price games. Van Dender (2005) explores how duopolistic providers of perfect substitutes with fixed capacities set prices when access to each facility is subject to road congestion. While the aforementioned studies assume that facilities provide services directly to consumers, Basso

[1] Borenstein and Netz (1999) provides empirical evidence of departure time competition in the US airline industry.

[2] See Zhang and Czerny (2012) for an interpretative review of literature on recent research on both subjects or Brueckner (2009) for a non-technical overview on airport congestion.

and Zhang (2007) analyze rivalry between congestible facilities in 'a vertical structure'. They consider facilities as input providers (upstream firms) that reach final consumers only through carriers (downstream firms). In their setup, carriers may possess market power in the output market, and the characteristics of this market affect the pricing and capacity decisions of facilities. They show that duopoly facilities have lower fees than the monopolist but lower frequencies (service quality), depending on the timing of the fee-capacity game. They also compare service frequency between the monopoly and the social planner and show that the competitiveness of carriers' market is crucial.[3]

Since the seminal work of Vickrey (1969), consumers' value of time has become under more intense scrutiny in theoretical and applied work in transportation economics. Related to air travel, the pioneering papers are Douglas and Miller (1974) and Panzar (1979). Panzar proposes a spatial model with free entry in which two profit-maximizing airlines operate each a single flight and consumers' generalized costs depend on fares, flight frequency and schedule delay costs.[4] The analysis focuses on fares and frequency equilibria but ignores competition in departure times. A few papers explicitly incorporate departure times into the analysis. Encaoua et al. (1996) are the first to consider a time-then-fare game in an airport network involving two direct and one indirect connection between three cities. Assuming uniform desired departure times for the travellers over the time of day, various Nash equilibria in fares and departure times are characterized and minimal differentiation in scheduling is established in selected configurations. Lindsey and Tomaszewska (1999) also consider a sequential model where multiple service times are chosen before fares on a city pair route served by two airlines. A multinomial random utility model captures the utility of travellers across alternatives and travellers' schedule delay costs are assumed quadratic. Predatory behaviours, in which an airline attempts to hurt (potential) rivals, are also investigated. They show that predatory fare cutting is less effective than predatory scheduling but the outcome depends on the prey's scheduling response. Their results rely on numerical methods and equilibria depend on the chosen parameters. More recently, van der Weijde et al. (2014) analyze scheduling decisions of two duopolistic travel operators using a horizontal differentiation model with price-sensitive demands and asymmetric (piecewise linear) schedule delay costs. Departure times are treated as locations on the schedule line and each operator schedules a single time of departure. A thorough analysis of time-fare games with (separated and) covered markets is proposed. Assuming uniform desired times for consumers, they show that the simultaneous game has no equilibrium. Only if one operator sets its fare and departure time before the other can an equilibrium exist. The time-then-fare game also has a stable equilibrium in fares and times, and results in services scheduled closer than socially optimal but not necessarily in minimal differentiation. As the authors state, one drawback of their analysis is that most equilibrium

[3]Researches on airports' congestion within a vertical structure include Brueckner (2002) and Pels and Verhoef (2004), Verhoef (2010).

[4]Schedule delay costs designate the monetary costs associated to departing or arriving earlier/later than desired.

expressions have no intuitive interpretation.[5]

A number of researchers have evaluated empirically passengers' value of time in air transportation, relative to other characteristics of the trip. Pels et al. (2000, 2003); Adler et al. (2005); Brey and Walker (2011) confirm that travel demand is linked to the timing of the service (arrival or departure time) or to total travel time, in addition to the cost/time to access the departure facility and to other characteristics of the trip. The principle of minimal differentiation[6] in departure times has also been empirically tested in air travel on the US and Norwegian markets. Borenstein and Netz (1999) compare the average distance in departures times for flights scheduled before (year 1975) and after (year 1986) the deregulation of the US airlines market across the busiest 200 US domestic routes. They conclude to less differentiation in the year after deregulation. Salvanes et al. (2005) conduct a similar study on the Norwegian market before and after the 1994 deregulation. They find evidence of clustering in departure times after deregulation, which is stronger on duopolistic routes. Overall, applied research suggests that carriers operating in deregulated markets exacerbate fares competition in place of schedule differentiation.

Our work is in the vein of the spatial approaches. It borrows 'the vertical structure' proposed by Basso and Zhang (2007) in a spatial setting but drops its congestion components to incorporate scheduling decisions in the spirit of van der Weijde et al. (2014). Another distinguishing feature of our model is that it posits the existence of a spatial asymmetry in the location of facilities. Transportation costs toward competing facilities, say, primary and secondary airports located in a common metropolitan area, typically result in a geographic advantage for the primary airport and its carriers. More passengers going to a facility with fixed capacity may induce congestion for consuming the final service, which can be managed by giving incentives to the service providers to schedule their service at specific times (such as peak and off-peak charges or slots allocation).[7] Clearly, carriers are not always free to locate their departure times over the time schedule because scheduling a service is a complex process that entails costs. Scheduling a (transport) service early or late in the day can be more costly in terms of logistics, and may depend upon carriers' business model. Our framework allows these potentially differentiated time costs to affect downstream carriers' decisions. In addition,

[5] To circumvent the intractability of the spatial approaches in dealing with the timing of the service in theoretical models, Brueckner and Flores-Fillol (2007) and Brueckner (2010) propose to consider that individuals care for overall flight frequency rather than individual departure times. Higher frequencies are valued by passengers since they imply a broader range in choice of departure times. Thus, schedule delay costs are inversely related to frequencies. The authors propose to study time scheduling through frequency competition.

[6] See de Palma et al. (1985) for a theoretical discussion of the minimum differentiation principle under heterogeneity in consumers' tastes. This work also considers a model with two types of horizontal differentiation: along a line and along a circle. The cylinder model was studied by Ben-Akiva et al. (1989).

[7] Worldwide airports are classified by the International Air Transport Association (IATA) into three categories. Level 1 and 2 airports, also called *non-coordinated and schedule facilitated airports*, designate facilities where capacity adequately meets demand and slots are freely set by airlines. Level 3 airports also called *fully coordinated* airports, are those where demand exceeds capacity and the slot allocation is resolved through the IATA Scheduling Process.

while previous research relies on uniform distribution of travellers' desired departure times, our setup remains agnostic on the shape of this distribution.

To keep the analysis tractable, we assume that only one carrier serves each facility at a single time.[8] Revenues of facilities are derived directly from aeronautical activites (landing fees, terminal rentals, cargo and hangar rentals) and from rights granted to external firms to provide commercial services (retailing, advertising, car parking, car rentals, banking, terminal concessions) onsite to travellers.[9] We find that ignoring the location advantage of the primary airport and differences in departure times across carriers, airports' fees depend upon their own commercial revenues and those of their rival, and upon carriers' marginal operational costs. Duopolistic competition where departure times are chosen before fares drives to identical departure times across carriers when their time cost does not vary with the time of day, but generally leads to differentiated ones when this cost depends upon the time of departure. When a facility possesses a location advantage, it can set a higher fee and its downstream carrier can charge a higher fare. Differentiation in departure times allows the facility and its carrier to compete in an additional differentiation dimension that can reduce or strengthen the location advantage. Socially optimal service times can be achieved by setting increasing scheduling costs in the time of day at one facility and decreasing ones at the other one.

The essay is organized as follows. In Section 3.2, we present the model setup. Section 3.2.1 characterizes the consumers' problem. Section 3.2.2 analyzes the competition between the downstream carriers when departure times are exogenously set and when they are used as strategic variables. Section 3.2.3 examines the rivalry between the airports. We analyze the social cost minimization problem in Section 3.2.4. The last two sections present the results of our simulations and concluding remarks.

3.2 The Model

In a linear city of length one, potential consumers are uniformly distributed with a density of one consumer per unit of length. Two facilities ($i = 0, 1$) serve the city and a single operator at each facility schedules a homogeneous service at time T_i during its facility's operational hours. The opening and closing times of the facilities, denoted $\underline{T}, \overline{T} \in [0, 24]$, are exogenously set, equal across facilities and such that $\underline{T} < \overline{T}$.[10] Facility 0 is located at point h, with $h \in [0, 1[$, and facility 1 is situated at the end of the city at point 1. The location of the facilities are given and segment $[0, h]$ represents an asymmetric demand that gives facility 0 and its carrier

[8] van der Weijde et al. (2014) also posit that each operator schedule a single service.

[9] The importance of non-aeronautical revenues (or concessions) in airport profitability and pricing have been studied by Zhang and Zhang (1997, 2003) and Oum et al. (2004). See Zhang and Czerny (2012) for a recent discussion on how concession revenues affect private and public airport behaviours.

[10] Opening and closing hours of the facilities play no major role in our analysis, but they are included to identify where they could affect our setup.

a location advantage.[11] In what follows, we will mainly think of the service as being a trip or flight, carriers as carriers, consumers as travellers and facilities as airports.

The interactions between the airports and their downstream carriers in the vertical structure are represented by a three-stage game. In the first stage, two profit-maximizing airports simultaneously set the aeronautical fees they charge to their carriers and announce the available departure times. In the second stage, two cases are analyzed: (i) the departure times are exogenously set and carriers compete in fares only, (ii) carriers compete in both departure times and fares where departure times are chosen before fares. In the final stage, final consumers decide whether to fly or not and if so, which airport they depart. As usual in this framework, the game is solved backward, so we start by characterizing consumers' problem, then analyze competition between downstream carriers and finally proceed with rivalry between airports.

3.2.1 Consumers' problem

Consumers have unit demands for the service, which depend upon the fare $\widehat{p}_i$ at each facility, a transportation cost toward the facilities and a schedule delay cost that captures the monetary value of the inconvenience caused by departing earlier or later than desired. We assume that consumers' desired departure time, denoted t, are heterogeneous and distributed according to a strictly positive density $\rho(t)$ over a $[0, 24]$ interval. The delivery time of the service (or departure time) is given to consumers, and can differ across facilities. The total cost or 'full fare' of the service for a potential consumer located at $x \in [0, 1]$, consuming at facility i and with preferred time t, is given by

$$\widehat{p}_i + \widehat{C}(T_i, t) + \frac{\theta}{2} d_i^2(x),$$

where $\widehat{p}_i \geq 0$ is the (equilibrium) fare at facility i, $\theta/2 > 0$ is the transportation cost per unit of squared distance, denoted $d_i^2(x)$, between consumer's location at x and facilities' location. From consumers' perspective, a quadratic transportation cost is justified when the marginal disutility to access the transport facility increases with the distance. This cost is also quite common to model firms that locate apart from a rival that provides a homogeneous good. [12] Thus, we follow this literature. Term $\widehat{C}(T_i, t)$ is the schedule delay cost function that we assume piecewise linear

$$\widehat{C}(T_i, t) = \widehat{\beta}(t - T_i)\mathbf{1}_{t \geq T_i} + \widehat{\gamma}(T_i - t)\mathbf{1}_{t < T_i}, \tag{3.1}$$

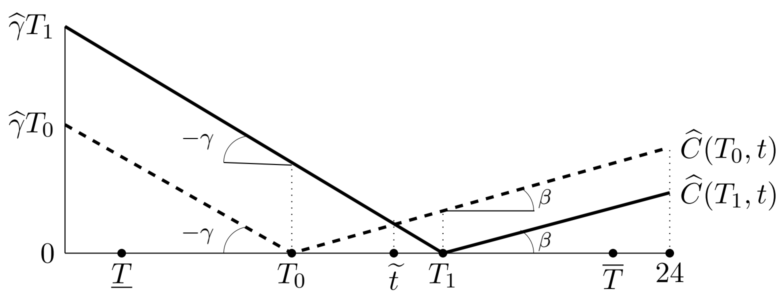
and where $\widehat{\beta} > 0$ represents the unit cost of departing earlier than desired, $\widehat{\gamma} > 0$ is its late counterpart and function $\mathbf{1}_A$ is an indicator function that equals 1 if condition A is satisfied

[11] By location advantage, we mean that, all other characteristics of the service being equal, positive (and symmetric) transportation costs towards the facilities result in a larger demand (for the operator located) at facility 0.

[12] In the Hotelling framework where location is chosen before prices, quadratic transportation costs guarantee continuous demands and concave profits in prices at every location $x \in [0, 1]$, see d'Aspremont et al. (1979).

and 0 otherwise. We posit that departing early is less costly than departing late, so that $\widehat{\beta} < \widehat{\gamma}$.[13] By construction, carrier 0 schedules the first service i.e., $T_0 \leq T_1$.[14] Thus, consumers can be classified into three desired times' categories: those with $t < T_0$ who prefer to depart earlier than the earliest service offered in the city, those with $t \in [T_0, T_1]$ who may incur early or late schedule delay depending on the chosen facility, and travellers with $t > T_1$ who prefer to depart later than the latest service offered.

Figure 3.1 – Consumer's schedule delay cost and the time line



Under the above assumptions, Figure 3.1 shows the schedule delay costs faced by consumers who compare the travel service offered at both facilities. A traveller with desired departure time $t = 0$ incurs the largest schedule delay cost at the facility offering the latest travel service (facility 1). If the preferred departure time is at the other extremity of the time schedule ($t = 24$) the largest delay cost arises from the facility offering the earliest service (facility 0). The schedule delay cost is null when consumer's desired departure time matches the time scheduled at one of the facilities ($T_i = t$), and equal across facilities when consumer's desired time corresponds to the cost-weighted average $\widetilde{t} = \frac{\widehat{\beta}T_0 + \widehat{\gamma}T_1}{\widehat{\beta} + \widehat{\gamma}}$.

The net benefit of traveling for a consumer with preferred time t, located at $x \in [0, 1]$, and departing facility 0 is given by:

$$\widehat{U}_0 = \widehat{U} - \widehat{p}_0 - \widehat{C}(T_0, t) - \frac{\theta}{2}(x - h)^2, \tag{3.2}$$

where $\widehat{U}$ represents the gross benefit of the trip in monetary units and $\widehat{p}_0 + \widehat{C}(T_0, t)$ will be referred to as the 'service cost' at facility 0, i.e., traveller's cost abstracting from the transportation cost to the departure facility. Similarly, if the traveller goes to facility 1, her net utility U_1 is:

$$\widehat{U}_1 = \widehat{U} - \widehat{p}_1 - \widehat{C}(T_1, t) - \frac{\theta}{2}(1 - x)^2. \tag{3.3}$$

[13] Small (1982) finds that this assumption is valid for work trips and arrival times. The evidence for air travel is more mixed, see Lijesen (2006); Warburg et al. (2006); Brey and Walker (2011) or Koster et al. (2014). In the Simulation section, we explore other configurations i.e. $\widehat{\beta} = \widehat{\gamma}$ and $\widehat{\beta} > \widehat{\gamma}$.

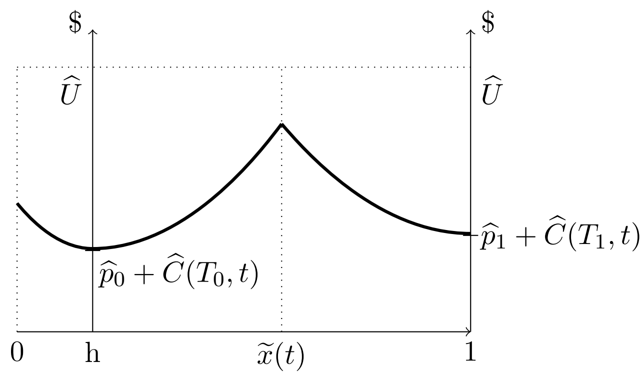
[14] The reverse case $T_0 \geq T_1$ is equally valid. All our results are symmetric to those obtained under our maintained hypotheses, and they are reported in Appendix B. 2. We will refer to the 'symmetric case' when necessary along the paper.

We assume that consumers' preferences for departure times are independent of their location in the city.[15] If everyone travels and both facilities receive consumers, the indifferent consumer $\widetilde{x}(t)$ is determined by equalizing U_0 with U_1, hence:

$$\widetilde{x}(t) = \frac{\widehat{p}_1 + \widehat{C}(T_1,t)}{\theta(1-h)} - \frac{\widehat{p}_0 + \widehat{C}(T_0,t)}{\theta(1-h)} + \frac{1+h}{2}. \tag{3.4}$$

The number of consumers going to facility 0 (rather than 1) decreases in its own service cost $\widehat{p}_0 + \widehat{C}_0$ and increases in the service cost at the rival facility $\widehat{p}_1 + \widehat{C}_1$. Further, facility 0 benefits from a larger market when the transportation cost of going from facility 0 to 1 for the consumer located at h offsets the difference in service costs between these facilities i.e. if $\frac{\theta}{2}(1-h)^2 > (\widehat{p}_0 + \widehat{C}_0) - (\widehat{p}_1 + \widehat{C}_1)$. Figure 3.2 provides a representation of the indifferent consumer along with its full fare on the geographic line.

Figure 3.2 – Indifferent consumer along the geographic line



For all consumers located in the $[0,1]$ geographical space to travel, the gross benefit (in monetary units) derived from the service offered at both facilities needs to compensate the full fare of a consumer with extreme departure time preferences ($t = 0$ or $t = 24$), i.e.

$$2\widehat{U} > \widehat{p}_0 + \widehat{p}_1 + \frac{\theta}{2}\left[(x-h)^2 + (1-x)^2\right] + \text{Max}[\ \widehat{\gamma}(T_1+T_0), -\widehat{\beta}(T_1+T_0) + 48\widehat{\beta}\ ]. \tag{3.5}$$

Moreover, to ensure that everyone consumes and a strictly positive fraction of consumers depart each facility whatever their desired departure time t, it would suffice that the consumer located at $x = 0$ (resp. $x = 1$) with desired departure time $t = T_1$ (resp. $t = T_0$) chooses facility 0 (resp. facility 1). The necessary and sufficient conditions for the market coverage

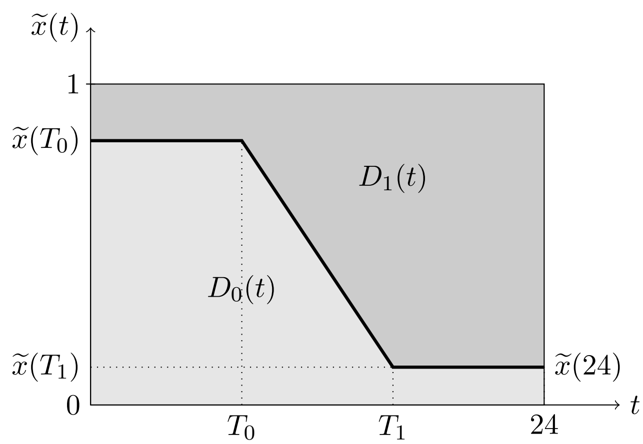
[15] Based on empirical evidence, travel time preferences in air travel are mostly affected by party size and time zone change, so independent of travellers' location, see Brey and Walker (2011). The consumers' preferences for departure times t and geographical location x may also be correlated. We could further address this potential correlation by considering a joint distribution of these preferences, denoted $f(x,t)$, in the analysis.

are:[16]

$$
\begin{aligned}
-\frac{\theta}{2}(1-h^2) < \widehat{p}_1 - \widehat{p}_0 + \widehat{\gamma}(T_1 - T_0) < \frac{\theta}{2}(1-h)^2 \\
-\frac{\theta}{2}(1-h^2) < \widehat{p}_1 - \widehat{p}_0 - \widehat{\beta}(T_1 - T_0) < \frac{\theta}{2}(1-h)^2.
\end{aligned}
\tag{3.6}
$$

The first equation of (3.6) states that the service cost at facility 0 should not be too large to allow travellers located at $x = 0$ with desired time T_1 (or later) to depart facility 0, while the second equation requires the transportation cost from facility 0 to facility 1 to be large enough to allow those located at $x = 1$ with desired time T_0 (or earlier) to depart facility 1. Both conditions (3.5) and (3.6) are maintained hereafter.[17] Figure 3.3 shows the indifferent consumer for varying levels of t and establishes the link between the geographic and time lines.

Figure 3.3 – Indifferent consumer along the time line



When the indifferent consumer prefers departing very early i.e. $t = 0$, $\widetilde{x}(t)$ becomes $\widetilde{x}(0)$ and is located close to 1 on the geographic line. Aggregating the (unit) individual demands over the relevant geographic segments results in a larger demand, $D(0) = \widetilde{x}(T_0)$, for the facility offering the earliest service. Reversely, the demand for the facility offering the latest service, $D_1(0) = 1 - \widetilde{x}(T_0)$, is smaller but positive under the maintained assumptions. Similarly, when the indifferent consumer desires departing late, i.e. $t = 24$, $\widetilde{x}(t)$ becomes $\widetilde{x}(24)$ and is located close to zero on the geographic line. The facility that offers the latest service receives a larger demand, $D_1(24) = 1 - \widetilde{x}(T_1)$, while facility 0 receives $D_0(24) = \widetilde{x}(T_1)$. Applying the same reasoning over the $[0, 24]$ time schedule, we get the shaded areas $D_0(t)$ and $D_1(t)$.[18]

Given a density $\rho(t) > 0$ of desired times, let m_ℓ, m_c and m_r designate the shares of consumers with preferred time within, respectively, $t \in [0, T_0]$, $t \in]T_0, T_1[$ and $t \in [T_1, 24]$ and let $\bar{t}_c$ denote

[16]See Appendix B. 1.2 for details on the derivation of the covered market condition (3.6).

[17]If these conditions are not met, the markets are fully separated and each carrier acts as a monopolist on its own segment. This case is not considered in this chapter.

[18]Given that travellers have density one, $f(x) = 1$, over the [0,1] geographic line, and that each traveller consumes a single unit of the good, we have $D_0(t) = \int_0^{\widetilde{x}(t)} 1\, f(x)\, \mathrm{d}x = \widetilde{x}(t)$ and $D_1(t) = \int_{\widetilde{x}(t)}^1 1\, f(x)\, \mathrm{d}x = 1 - \widetilde{x}(t)$.

the expected departure time of individuals with t in the $]T_0, T_1[$ interval, such that

$$m_\ell = \int_0^{T_0} \rho(t)dt, \; m_c = \int_{T_0}^{T_1} \rho(t)dt, \; m_r = \int_{T_1}^{24} \rho(t)dt, \; \bar{t}_c = \int_{T_0}^{T_1} t\rho(t)dt. \tag{3.7}$$

Aggregating the demand over the geographic and time lines, the market demand at each facility is given by:[19]

$$\begin{aligned} D_0(\mathbf{p}, \mathbf{T}) &= \int_0^{24} \widetilde{x}(t)\rho(t)\,\mathrm{d}t = p_1 - p_0 + \frac{1+h}{2} + \Phi(\mathbf{T}), \\ D_1(\mathbf{p}, \mathbf{T}) &= 1 - D_0 = p_0 - p_1 + \frac{1-h}{2} - \Phi(\mathbf{T}) \end{aligned} \tag{3.8}$$

where $\mathbf{p} = (p_0, p_1)$ and $\mathbf{T} = (T_0, T_1)$ and $p_i = \frac{\widehat{p}_i}{\theta(1-h)}$ for $i = 0, 1$. Note first that the fares in demands (3.8) are divided by $\theta(1-h)$. In what follows, we often apply this normalization and 'drop the hats' to get more compact expressions. Term $\Phi(\mathbf{T})$ captures the difference in (normalized) schedule delay costs (shorthanded SDC hereafter) at the market level and aggregates the individual SDC differences between facility 1 and 0 through the shares m_ℓ, m_c, m_r and the average preferred time $\bar{t}_c$. The expression of $\Phi(\mathbf{T})$ and its first derivatives with respect to departure times $\mathbf{T}$ are given by:

$$\Phi(\mathbf{T}) = \gamma(T_1 - T_0)m_\ell + (\beta T_0 + \gamma T_1)m_c - \beta(T_1 - T_0)m_r - (\beta + \gamma)\bar{t}_c \tag{3.9}$$

$$\Phi_{T_0}(\mathbf{T}) = \beta - (\beta + \gamma)m_\ell, \quad \Phi_{T_1}(\mathbf{T}) = \gamma - (\beta + \gamma)m_r \tag{3.10}$$

where $\beta = \frac{\widehat{\beta}}{\theta(1-h)}$ and $\gamma = \frac{\widehat{\gamma}}{\theta(1-h)}$, m_ℓ, m_c, m_r and $\bar{t}_c$ are defined in (3.7). $\Phi_{T_i}(\mathbf{T})$ denotes the first derivative of $\Phi(\mathbf{T})$ with respect to T_i for $i = 0, 1$ i.e $\partial\Phi(\mathbf{T})/\partial T_i$. Notice that Φ_{T_i} plays central role for determining the sensitivity of demands and prices to departure times $\mathbf{T}$. When $T_0 = T_1 = T$, no SDC difference exists across facilities i.e., $\Phi(T, T) = 0$. Section B. 1.3 in Appendix B. 1.1 gives useful properties of $\Phi(\mathbf{T})$ that we use below. Consumers' demand at each facility is characterized by the following comparative statics:

$$\frac{\partial D_0}{\partial p_0} = \frac{\partial D_1}{\partial p_1} = -1 < 0, \quad \frac{\partial D_0}{\partial p_1} = \frac{\partial D_1}{\partial p_0} = 1 > 0, \tag{3.11}$$

$$\frac{\partial D_0}{\partial h} = \frac{1}{2} + \frac{p_1 - p_0 + \Phi(\mathbf{T})}{(1-h)}, \quad \frac{\partial D_1}{\partial h} = -\frac{1}{2} - \frac{p_1 - p_0 + \Phi(\mathbf{T})}{(1-h)} \tag{3.12}$$

$$\frac{\partial D_0}{\partial T_0} = -\frac{\partial D_1}{\partial T_0} = \Phi_{T_0}(\mathbf{T}), \quad \frac{\partial D_0}{\partial T_1} = -\frac{\partial D_1}{\partial T_1} = \Phi_{T_1}(\mathbf{T}), \tag{3.13}$$

where $\Phi_{T_i} \equiv \frac{\partial\Phi(\mathbf{T})}{\partial T_i}$ for $i = 0, 1$. As expected, consumers' demand at each facility is decreasing in the fare of its carrier and increasing in the fare of the carrier operating at the rival facility. From (3.12), one can show that consumers' demand at facility 0/1 increases in h if the transportation cost of going from facility 0 to 1 for consumers located at h is larger/lower than the

[19] Appendix B. 1.1 provides a detailed derivation of the demand functions.

difference in service costs between facilities.[20] Demands' sensitivity to changes in departure times are further developed in Proposition 1.

Proposition 1 *Consider market demands D_0 and D_1 for a travel service delivered at times T_0 at facility 0 and T_1 at facility 1 where $T_0 \leq T_1$. Let $\rho(t) > 0$ be the distribution of consumers' desired departure times over the $[0, 24]$ schedule, and let β/γ with $0 < \beta < \gamma$ designate consumers' (normalized) unit early/late schedule delay costs. Then,*

$$\frac{\partial D_0}{\partial T_0} > 0 \quad \textit{iff} \quad \frac{\beta}{\beta + \gamma} > m_\ell, \quad \frac{\partial D_0}{\partial T_1} > 0 \quad \textit{iff} \quad \frac{\gamma}{\beta + \gamma} > m_r, \tag{3.14}$$

$$\frac{\partial D_1}{\partial T_0} > 0 \quad \textit{iff} \quad \frac{\beta}{\beta + \gamma} < m_\ell, \quad \frac{\partial D_1}{\partial T_1} > 0 \quad \textit{iff} \quad \frac{\gamma}{\beta + \gamma} < m_r, \tag{3.15}$$

where $m_\ell = \int_0^{T_0} \rho(t)dt$, $m_r = \int_{T_1}^{24} \rho(t)dt$. Symmetric results hold when $T_0 \geq T_1$.

Proof. Set the first derivatives of demands with respect to departure times $\mathbf{T}$ in (3.13) strictly larger than 0 and use (3.10). For the symmetry when $T_0 \geq T_1$, see Appendix B. 2. □

Proposition 1 shows that when the (earliest) departure time proposed at facility 0 is delayed, D_0 increases if the share of consumers who prefer to depart earlier than the time scheduled at facility 0 (m_ℓ) is low enough and below a threshold given by the unit schedule delay cost share $\frac{\beta}{\beta+\gamma}$. Similarly, D_0 increases with T_1 when the share of consumers who prefer to depart later than the time scheduled at facility 1 (m_r) is below the unit schedule delay cost share $\frac{\gamma}{\beta+\gamma}$. Reversing the inequality, the same reasoning applies regarding the changes in D_1 when departure times are delayed.[21] Note that equalizing the departure times and fares across carriers makes the location advantage of facility 0 explicit, its demand is $D_0 = h + \frac{1}{2}(1 - h)$ while demand at the rival facility is $D_1 = \frac{1}{2}(1-h)$. Having characterized consumers' problem, we turn to model carriers' rivalry in fares and scheduling.

3.2.2 Carriers' problem

We consider two carriers that compete with each other across facilities to attract consumers. Below, we examine two market structures : (i) when carriers compete only in fares and departure times are exogenously set by a regulator, and (ii) when departure times are chosen before fares and carriers compete both in departure times and fares.

Exogenous departure times

Transport services' scheduling is often regulated by transport authorities to improve the social welfare or to correct market failures (limited capacities creating congestion, nuisance to

[20]See Appendix B. 1.3.

[21]Using Lemma 1, we can show that D_0 is strictly concave in T_0 and strictly convex in T_1 while D_1 is strictly convex in T_0 and strictly concave in T_1.

neighbours, labour regulation, safety). This section analyzes the regulated framework from carriers' perspective. We assume that carriers' load factors are exogenous, hence, their operational costs and fees are directly given per passenger. The profit function of each carrier is given by:

$$\widehat{\pi}_i(\mathbf{p}, \mathbf{T}, \boldsymbol{\tau}) = (\widehat{p}_i - \widehat{c}_i - \widehat{\tau}_i) D_i(\mathbf{p}, \mathbf{T}) - \widehat{K}(T_i), \quad i = 0, 1, \tag{3.16}$$

where $\widehat{c}_i \geq 0$ is the marginal operational cost of the carrier located at facility i, $\widehat{\tau}_i \geq 0$ is the (aeronautical) per passenger fee charged by facility i to its carrier and $\widehat{K}(T_i)$ is the cost incurred by carrier i for scheduling the service at time T_i referred to as 'time costs'[22]. Given departure times $\mathbf{T}$, carriers choose their fare $\widehat{\mathbf{p}} = (\widehat{p}_0, \widehat{p}_1)$ to maximize profits (3.16), taking the fare of their rival as given. The first-order conditions $\partial\widehat{\pi}_i/\partial\widehat{p}_i = 0$ for $i = 0, 1$ represent the 'best response or reaction' function of each carrier to its rival's pricing, and are given by:

$$\begin{aligned} p_0^* &= \frac{1}{2}\left[p_1 + c_0 + \tau_0 + \frac{1+h}{2} + \Phi(\mathbf{T})\right], \\ p_1^* &= \frac{1}{2}\left[p_0 + c_1 + \tau_1 + \frac{1-h}{2} - \Phi(\mathbf{T})\right], \end{aligned} \tag{3.17}$$

where p_i^*, c_i and τ_i are the variables $\widehat{p}_i^*, \widehat{c}_i$ and $\widehat{\tau}_i$ divided by $\theta(1-h)$. If carrier 1 increases its own fare p_1, the best response of its rival is to increase its fare p_0, and vice versa. Solving the system of first-order conditions (FOCs) $\partial\widehat{\pi}_i/\partial\widehat{p}_i = 0$ for $i = 0, 1$ with respect to the fares leads to:

$$\begin{aligned} p_0^* &= \frac{2}{3}(c_0 + \tau_0) + \frac{1}{3}(c_1 + \tau_1) + \frac{3+h}{6} + \frac{1}{3}\Phi(\mathbf{T}), \\ p_1^* &= \frac{2}{3}(c_1 + \tau_1) + \frac{1}{3}(c_0 + \tau_0) + \frac{3-h}{6} - \frac{1}{3}\Phi(\mathbf{T}), \end{aligned} \tag{3.18}$$

The combination of the two best strategies results in vector of (normalized) *equilibrium* fares, denoted $\mathbf{p}^* \equiv (p_0^*, p_1^*)$ and represents a Nash equilibrium.[23] The first two terms on the RHS of Eqs. (3.18) are the (normalized) marginal costs of carrier i plus a duopolistic markup/markdown that depends positively on the marginal costs of the rival carrier.[24] The third term is a monopoly penalty/premium stemming from the location (dis)advantage of the facility at which carriers operate. The last terms represent a markdown/markup related to a SDC (dis)advantage of the carriers due to differences in departure times. We can further explore the impact of an increase in h and T_i on carriers' optimal fares with the following expressions:

$$\frac{\partial\widehat{p}_0^*}{\partial h} = -\frac{\theta(1+h)}{3} < 0, \quad \frac{\partial\widehat{p}_1^*}{\partial h} = -\frac{\theta(2-h)}{3} < 0, \tag{3.19}$$

$$\frac{\partial p_0^*}{\partial T_i} = \frac{1}{3}\Phi_{T_i}, \quad \frac{\partial p_1^*}{\partial T_i} = -\frac{1}{3}\Phi_{T_i}, \quad i = 0, 1. \tag{3.20}$$

[22]Carriers' time costs play little role for now but further details are provided in the next section.

[23]Formally, a Nash equilibrium satisfies $\pi_i(p_i^*, p_{-i}^*) \geq \pi_i(p_i, p_{-i}^*)$, $\forall i$ and for $p_i \geq 0$. One can check that $\frac{\partial^2\widehat{\pi}_0}{\partial\widehat{p}_0^2} = \frac{\partial^2\widehat{\pi}_1}{\partial\widehat{p}_1^2} < 0, \forall\widehat{p}_i$, so the concavity of the profit function is guaranteed for each carrier.

[24]If $c_i + \tau_i < c_{-i} + \tau_{-i}$ carrier i will be able to charge above its own marginal costs (before accounting for the location and SDC components), which is the definition of a price markup.

Notice that derivatives (3.19) are calculated on $\widehat{\mathbf{p}}$, and not on $\mathbf{p}$.[25] Given that $h \in [0, 1[$, the optimal fares are decreasing in h. Thus, increasing h in a profit maximizing environment with exogenous departure times increases rivalry between carriers and decreases the equilibrium fares at both facilities. The sensitivity of the fares to changes in departure times can be analyzed in light of Proposition 1: $\widehat{p}_0^*/\widehat{p}_1^*$ increases in T_0 (T_1) if the share of consumers m_ℓ (m_r) is below/above the unit schedule delay cost share $\frac{\beta}{\beta+\gamma}$ ($\frac{\gamma}{\beta+\gamma}$).

Fares' equations (3.18) can be further used to explore the differences in pricing and markups across carriers. Focusing on pricing first, we get:

$$p_0^* > p_1^* \quad \textit{iff} \quad \Delta\widetilde{c} < h + 2\Phi(\mathbf{T}), \tag{3.21}$$

where

$$\Delta\widetilde{c} = (c_1 + \tau_1) - (c_0 + \tau_0). \tag{3.22}$$

Term (3.22) is the difference between the marginal costs of carrier 1 and carrier 0, and represents a marginal costs advantage (disadvantage) for carrier 0 when $\Delta\widetilde{c} > 0$ ($\Delta\widetilde{c} < 0$). Proposition 2 summarizes the results.

Proposition 2 *Consider two carriers (0 and 1) that compete in fares on a linear geographic market with fixed scheduled times (T_0 and T_1) and null time costs $K(T_i)$, $i = 0, 1$.*

1. *There exists a unique Nash equilibrium in fares given by Eqs.* (3.18)*.*

2. *In equilibrium, carrier* 0 *charges a higher fare than its rival if its location and schedule delay costs' advantage offsets its marginal costs advantage, see Eq.* (3.21)*.*

Proof. Proof of 1 follows from the concavity in fares of the profit functions in (3.16) and from solving system (3.17) with respect to normalized fares. To prove 2, set p_0^* in (3.18) strictly larger than p_1^* and rearrange terms. □

Equalizing the departure times across facilities and assuming no location advantage at facility 0,[26] Proposition 2.2 shows that carrier 0 will charge a higher fare than its rival if its marginal costs are higher ($\Delta\widetilde{c} < 0$). This situation typically occurs when a legacy carrier (with a marginal costs disadvantage) competes with a rival low-cost carrier operating at the other facility over a shared market. Further accounting for the captive market, term h being positive, the location advantage of facility 0 allows its carrier to charge a higher fare than its rival, even when carrier 0 has lower marginal costs ($\Delta\widetilde{c} > 0$). This occurs when carrier 0's location advantage exceeds its marginal costs advantage. Hence, a carrier located at facility

[25] Recalling that $\widehat{p}_i^* = p_i^*\theta(1-h)$, derivatives (3.19) follow immediately from (3.18).

[26] Note that setting $h = 0$ implies *maximal* geographic differentiation while $T_0 = T_1$ implies *minimal* scheduling differentiation.

0 with lower marginal costs may well charge a higher fare than a rival operating at the other facility, due to its location advantage. A SDC advantage to carrier 0 would add to the location advantage and give carrier 0 further incentives to charge a higher fare in order to maximize its profits. Clearly, a SCD advantage for a carrier benefiting from a location advantage at its facility gives this carrier additional market power, increases its equilibrium fare and widens fares' gap across carriers.

Defining carriers' price markup as $p_i - (c_i + \tau_i)$ for $i = 0, 1$, using fares' expressions in (3.18) and rearranging, carrier 0's markup is higher than its rival if:

$$\Delta\widetilde{c} > -\frac{h}{2} - \Phi(\mathbf{T}). \tag{3.23}$$

Again, cancelling the location and SCD advantage, (3.23) becomes positive, hence the markup of carrier 0 exceeds its rival at the other facility if its marginal costs are lower. Thus, a legacy carrier (with higher marginal costs) serving facility 0 and competing on a shared market with a low-cost carrier serving facility 1 would have a lower markup than its rival. Accounting for the location advantage of facility 0, (3.23) becomes $\Delta\widetilde{c} > -\frac{h}{2}$. Term h being positive, carrier 0 can get a larger markup than its rival even if its marginal costs are higher (i.e., when $\Delta\widetilde{c} < 0$). Therefore, the business of a legacy carrier operating from a facility with a location advantage would be more profitable than the business of the rival low-cost carrier located at facility 1 if its marginal costs disadvantage is not excessive (above $-h/2$). Further considering the full expression in (3.23), the difference in markups between carrier 0 and its rival expands in proportion to its SDC advantage ($\Phi(\mathbf{T}) > 0$) and shrinks in proportion to its SDC disadvantage ($\Phi(\mathbf{T}) < 0$).

Substituting the equilibrium fares $\mathbf{p}^*$ into consumers' demands (3.8), we can obtain carriers' *equilibrium* demands as:

$$\begin{aligned} D_0^*(\mathbf{T}, \boldsymbol{\tau}) &= \frac{1}{6}[3 + h + 2\Delta\widetilde{c} + 2\Phi(\mathbf{T})], \\ D_1^*(\mathbf{T}, \boldsymbol{\tau}) &= \frac{1}{6}[3 - h - 2\Delta\widetilde{c} - 2\Phi(\mathbf{T})]. \end{aligned} \tag{3.24}$$

We denote carriers' equilibrium demands as $\mathbf{D}^*(\mathbf{T}, \boldsymbol{\tau})$ below.[27] One can verify that carrier 0's equilibrium demand is higher than its rival's when its markup is higher. Therefore a larger equilibrium demand for carrier 0 goes hand-in-hand with a more profitable business with respect to its rival at the other facility. Cancelling the location and SCD advantage terms in (3.24), and setting the marginal costs equal across carriers, as expected in equilibrium, the market is evenly shared between carriers.

In equilibrium, the profits (3.16) can be written as:

$$\pi_i^*(\mathbf{T}, \boldsymbol{\tau}) = D_i^{*2}(\mathbf{T}, \boldsymbol{\tau}) - K(T_i), \quad i = 0, 1, \tag{3.25}$$

[27] Note that $D_0^*(\mathbf{p}^*, \mathbf{T}) \in]0, 1[$ requires $|\frac{1}{3}[h + 2\Delta\widetilde{c} + 2\Phi(\mathbf{T})]| < 1$ and implies $D_1^*(\mathbf{p}^*, \mathbf{T}) \in]0, 1[$ when the latter restriction holds.

where $\pi_i^* = \widehat{\pi}_i/\theta(1-h)$ and $K(T_i) = \widehat{K}(T_i)/\theta(1-h)$. As expected, carriers' profit depend upon all determinants of carriers' demands minus their scheduling costs. Ignoring the scheduling costs, we can readily apply the results obtained for the equilibrium demands : $\pi_0^* > \pi_1^*$ if the markup of carrier 0 exceeds carrier 1's markup. A larger markup for carrier i implies a larger demand and profit than its rival at equilibrium. With the markup expression (3.23) in mind, one can deduce how differences in departure times across carriers affect their (equilibrium) profit, see Proposition 3.

Proposition 3 *Consider two carriers (0 and 1) that compete in fares on a linear geographic market with a fixed departure times T_0 and T_1 and null time costs $K(T_i)$, $i = 0, 1$. The markup fare of carrier 0, its demand and profit are higher than its rival's if its marginal costs advantage $(c_0 + \tau_0) - (c_1 + \tau_1)$ offsets the sum of (half of) its location advantage ($\frac{h}{2}$) and its schedule delay costs advantage $\Phi(\mathbf{T})$.*

Proof. To prove, use inequality (3.23). For the demands and profits, set D_0^* in (3.24) superior to D_1^* and π_0^* in (3.25) superior to π_1^* to get (3.23). □

Proposition 3 implies that when there is no differentiation in departure times across the facilities, the markup fare of carrier 0, its demand and profit are higher than its rival's if carrier 0's marginal costs advantage offsets (half of) its location advantage.

The sensitivity of carriers' equilibrium demands to h and $\mathbf{T}$ is given by:

$$\frac{\partial D_0^*(\mathbf{T},\boldsymbol{\tau})}{\partial h} = \frac{1}{6} + \frac{\Delta\widetilde{c} + \Phi(\mathbf{T})}{3(1-h)}, \quad \frac{\partial D_1^*(\mathbf{T},\boldsymbol{\tau})}{\partial h} = -\frac{1}{6} - \frac{\Delta\widetilde{c} + \Phi(\mathbf{T})}{3(1-h)}, \tag{3.26}$$

$$\frac{\partial D_0^*(\mathbf{T},\boldsymbol{\tau})}{\partial T_i} = \frac{\partial p_0^*}{\partial T_i}, \quad \frac{\partial D_1^*(\mathbf{T},\boldsymbol{\tau})}{\partial T_i} = \frac{\partial p_1^*}{\partial T_i}, \quad i = 0, 1. \tag{3.27}$$

Equilibrium demands react to changes in departure times as optimal fares $\mathbf{p}_i^*$ do. Thus, Proposition 1 applies here as well. Regarding the impact of the location of facility 0 on carriers' demands, setting (3.26) strictly larger than zero and rearranging, we get:

$$\begin{aligned} \frac{\partial D_0^*(\mathbf{T},\boldsymbol{\tau})}{\partial h} > 0 \quad & \textit{iff} \quad \frac{\theta}{2}(1-h)^2 > -\Delta\widehat{\widetilde{c}} - \widehat{\Phi}(\mathbf{T}), \\ \frac{\partial D_1^*(\mathbf{T},\boldsymbol{\tau})}{\partial h} > 0 \quad & \textit{iff} \quad \frac{\theta}{2}(1-h)^2 < -\Delta\widehat{\widetilde{c}} - \widehat{\Phi}(\mathbf{T}), \end{aligned} \tag{3.28}$$

where $\Delta\widehat{\widetilde{c}} = \theta(1-h)\Delta\widetilde{c}$ and $\widehat{\Phi}(\mathbf{T}) = \theta(1-h)\Phi(\mathbf{T})$. Notice that if carrier 0 is more competitive in marginal and schedule delay costs than its rival (both $\Delta\widehat{\widetilde{c}}$ and $\widehat{\Phi}(\mathbf{T}) > 0$), it will always prevent consumers from its captive market to fly with the rival carrier at the competing facility. If carrier 0 is less competitive in marginal and schedule delay costs (both $\Delta\widehat{\widetilde{c}}$ and $\widehat{\Phi}(\mathbf{T}) < 0$), increasing h increases carrier 0's equilibrium demand if the transportation costs of going from facility 0 to 1 for the consumers located at h are larger than carrier 0's costs disadvantage.[28] Taking the perspective of carrier 1, its marginal costs and SDC advantages must fully compensate the transportation cost from facility 0 to 1 for the consumers located at h to capture part of its rival's captive demand.

The effect of a change in the location of facility 0 on carriers' (equilibrium) profits establishes whether the 'competition' effect offsets the 'demand' effect. The competition and demand effects are given by:

$$\frac{\partial \widehat{\pi}_i^*(\mathbf{T},\boldsymbol{\tau})}{\partial h} = \frac{\partial}{\partial h}\left[(\widehat{p}_i^* - \widehat{\widetilde{c}}_i)D_i^*\right] = \underbrace{D_i^*\frac{\partial \widehat{p}_i^*}{\partial h}}_{\text{competition effect}} + \underbrace{(\widehat{p}_i^* - \widehat{\widetilde{c}}_i)\frac{\partial D_i^*}{\partial h}}_{\text{demand effect}}. \tag{3.29}$$

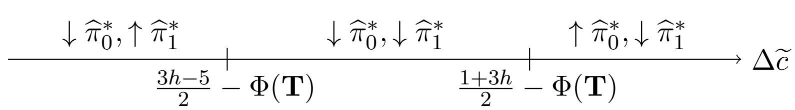
While optimal fares $\mathbf{p}^*$ are decreasing in h, carriers' equilibrium demands move in opposite directions when h varies depending the costs' conditions in (3.26). Whether a demand increase for a carrier compensates the decrease in optimal fares depends on the relative (dis)advantages identified above. Hence, we get:

$$\frac{\partial \widehat{\pi}_0^*(\mathbf{T},\boldsymbol{\tau})}{\partial h} = \frac{\theta}{6}\left[-(1+3h) + 2\Delta\widetilde{c} + 2\Phi(\mathbf{T})\right] D_0^*(\mathbf{T},\boldsymbol{\tau}), \tag{3.30}$$

$$\frac{\partial \widehat{\pi}_1^*(\mathbf{p}^*,\mathbf{T})}{\partial h} = \frac{\theta}{6}\left[3h - 5 - 2\Delta\widetilde{c} - 2\Phi(\mathbf{T})\right] D_1^*(\mathbf{T},\boldsymbol{\tau}),. \tag{3.31}$$

Assuming strictly positive transportation cost parameter θ and equilibrium demands, we can focus on the terms within brackets in (3.30)-(3.31) to determine under which conditions the demand effect dominates the competition effect for each carrier. From (3.30), we deduce that $\widehat{\pi}_0^*$ increases in h if $\Delta\widetilde{c} > (1+3h)/2 - \Phi(\mathbf{T})$. Hence, a (normalized) marginal costs advantage is needed for carrier 0 to increase its profits when h increases, unless its (normalized) SDC advantage is strong enough. Similarly, we deduce from (3.31) that carrier 1's marginal costs advantage must be strong enough, i.e., $\Delta\widetilde{c} < (3h-5)/2 - \Phi(\mathbf{T})$, for its profit to increase with h unless its schedule delay cost advantage is strong enough. Figure 3.4 summarizes these results along the $\Delta\tilde{c}$ line.

Figure 3.4 – Effect of a positive change of h on $\hat{\pi}_i^*$.



Furthermore, for carrier 1's demand effect to dominate the competition effect, a *lower* fare and a higher markup (higher demand and profit) than its rival carrier at facility 0 are required.[29]

[28] Notice that, in equilibrium, derivatives (3.28) are similar those obtained for consumers' demands, see Eq. (B. 1.15) in the Appendix, and the difference in fares are replaced by differences in carriers' marginal costs.

[29] To prove this, one can check that $\frac{3h-5}{2} - \Phi(\mathbf{T})$ lies below $-\frac{h}{2} - \Phi(\mathbf{T})$. Comparing both terms results in $h < \frac{5}{4}$.

Similarly, for carrier 0's demand effect to dominate the competition effect, its markup must be higher than its rival but its equilibrium fare need not be necessarily larger than its rival.[30]

Focusing now on the impact of a positive change of the departure times on profits, we obtain:

$$\frac{\partial \pi_0^*(\mathbf{T},\boldsymbol{\tau})}{\partial T_i} = \frac{2}{3}\Phi_{T_i} D_0^*(\mathbf{T},\boldsymbol{\tau}) - \frac{\partial K(T_0)}{\partial T_i}, \quad i = 0,1 \tag{3.32}$$

$$\frac{\partial \pi_1^*(\mathbf{T},\boldsymbol{\tau})}{\partial T_i} = -\frac{2}{3}\Phi_{T_i} D_1^*(\mathbf{T},\boldsymbol{\tau}) - \frac{\partial K(T_1)}{\partial T_i}, \quad i = 0,1 \tag{3.33}$$

Ignoring $\frac{\partial K(T_i)}{\partial T_i}$ and assuming positive equilibrium demands, term Φ_{T_i} is the key determinant of the signs and we can again resort on Proposition 1.

Having characterized carriers' problem for exogenous departure times, we proceed to consider a two-stage carrier-rivalry game where carriers simultaneously choose their departure times first and set their fares at a second stage.

Departure times chosen before fares

Setting departure times before fares is the most common behaviour for carriers offering (air, rail, road, water) transportation services to individuals, in particular for long distance trips. In air transportation, carriers typically commit toward consumers on departure times first and compete in fares with their rival at a second stage. Moreover, fares are easier to adjust than departure times. The two-stage decision process is solved backward : we first maximize carriers' profit with respect to fares for a given vector $\mathbf{T}$, and then find the optimal departure times $\mathbf{T}^* = (T_0^*, T_1^*)$ given the equilibrium fares $\mathbf{p}^*$. Since the *pricing* stage has already been solved, see (3.18), we can focus on the second stage. The maximization problem of carriers is:

$$\max_{T_i} \ \pi_i^*(\mathbf{T},\boldsymbol{\tau}) = D_i^{*2}(\mathbf{T},\boldsymbol{\tau}) - K(T_i), \quad i = 0,1 \tag{3.34}$$

and the first-order conditions (FOCs) are given by:

$$\begin{aligned} \frac{\partial \pi_0^*(\mathbf{T},\boldsymbol{\tau})}{\partial T_0} &= \frac{2}{3}\left[\beta - (\beta+\gamma)m_\ell\right] D_0^*(\mathbf{T},\boldsymbol{\tau}) - \frac{\partial K(T_0)}{\partial T_0} = 0, \\ \frac{\partial \pi_1^*(\mathbf{T},\boldsymbol{\tau})}{\partial T_1} &= -\frac{2}{3}\left[\gamma - (\beta+\gamma)m_r\right] D_1^*(\mathbf{T},\boldsymbol{\tau}) - \frac{\partial K(T_1)}{\partial T_1} = 0. \end{aligned} \tag{3.35}$$

Terms m_ℓ/m_r in the FOCs are the usual shares of consumers with desired departure time below/above T_0/T_1 (see Eqs. 3.7) while $\frac{\partial K(T_i)}{\partial T_i}$ denotes the marginal time costs of carrier i along the day.

Scheduling a transport service is a central element of carriers' planning. Etschmaier and Mathaisel (1985) describe airline scheduling process in simple terms: given (1) demand functions

[30] This result follows from noting that $\frac{1+3h}{2} - \Phi(\mathbf{T})$ lies above $-\frac{h}{2} - \Phi(\mathbf{T})$. Notice that $\frac{1+3h}{2} - \Phi(\mathbf{T})$ is not necessarily above $h + 2\Phi(\mathbf{T})$. Whether carrier 0's fare is lower or higher than its rival depend on the magnitude of its location and SDC advantages, i.e., $p_0^* \gtreqless p_1^*$ when $h \gtreqless 6\Phi(\mathbf{T}) - 1$.

and associated revenues for every passenger origin-destination pair market over the time of day, (2) route characteristics (distance, times and operating restrictions), (3) aircraft characteristics and operating costs, and (4) operational and managerial constraints; find a set of flights with associated assignments of aircraft and times of departure and arrival which maximizes profits. Clearly, carriers are not always free to locate their departure or arrival times where they wish over the $[0, 24]$ schedule and departure/arrival times are often constrained to lie during departure/arrival facilities operating hours (night flying restrictions). Moreover, scheduling a transport service early or late in the time of day may be more costly in terms of logistics, and may depend on carriers' business model.[31] In air transportation, the timing of the service can be subject to important monetary costs, such as the peak/off-peak charges or slot acquisition in congested or coordinated airports, which add up to other operating costs that do not depend directly on the time of departure (fuel, aircraft amortization, overflight charges).[32] Accounting for the time costs faced by carriers is of paramount importance to understand their scheduling decisions.

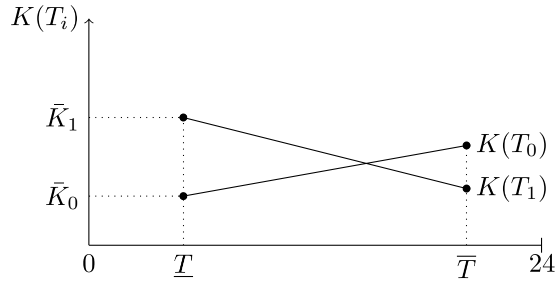
We assume that carriers can decompose their operational costs $K(T_i)$ additively into a fixed component and a cost that varies along the time of the day over all feasible times $T_i \in [\underline{T}, \overline{T}]$ at their departure facility. We posit that the time-varying component is either null or linearly increasing/decreasing in T_i. This simple functional form allows to explore analytically how time costs of carriers affect their timing decision.

Figure 3.5 shows the specific case of an increasing marginal cost in the time of day for the carrier serving facility 0 and a decreasing one for the carrier located at facility 1.

[31] The business of low-cost airlines is often characterized by a more intense daily use of their fleet as compared to legacy carriers, shorter turnaround time between operations, and aircrafts and crew returned back to a base airport, which reduces aircraft maintenance costs or overnight accommodation costs, see Gross and Schroeder (2007).This, in turn, favours the scheduling of flights at the earliest and latest available times at the airports they serve; see Bley and Buermann (2007, pp.59-62) for a discussion on the strategic use of schedules by low-cost airlines to reduce their operating costs.

[32] Peak/off-peak landing fees are usually charged per weight and aircraft type. The process for acquiring a slot under IATA regulation is described in Ulrich (2008) and Gillen (2008), and involves a well regulated but complex bargaining process between parties (slot coordinator, carriers, airport authorities) that results in slot swaps between carriers, leases, new slot allocation or slot trading depending on the regulatory frameworks. These costs are far from being negligible at congested or coordinated airports. Greater Toronto Airports Authority (2016) charges \$145 per 1000kg of maximum permissible takeoff weight during the peak period (Mon-Fri 0700-1000 & Sun-Fri 1430-2100) while the non-peak period fee is \$82.50 per 1000kg. As reported by Done (2008), Continental airlines paid \$116m for its summer season slots at Heathrow.

Figure 3.5 – A specific case of carriers' linear time cost functions $K(T_i)$



Clearly, an increasing cost in the time of day for carrier 0 favours departure times located at the opening hour at the facility it serves. Conversely, the decreasing cost for its rival would push the carrier serving facility 1 to schedule its service at the closing hour. Heterogeneity in consumers' desired service time would prevent such extreme outcomes.

Consider first case (i), where carriers' time cost is constant along the time of day, such as:

$$K(T_i) \quad = \quad \bar{K}_i \quad \text{with} \quad \bar{K}_i > 0, \quad T_i \in [\underline{T}, \overline{T}]. \tag{3.36}$$

Under the maintained assumptions that carriers' equilibrium demands are strictly positive, solving the FOCs in (3.35) yields to the optimal scheduling response function of the carriers to their rival's scheduling, i.e.,

$$\begin{aligned} m_\ell|_{k_0=0} &= \frac{\beta}{\beta+\gamma} \Rightarrow T_0^*|_{k_0=0} = F^{-1}\left(\frac{\beta}{\beta+\gamma}\right), \\ m_r|_{k_1=0} &= \frac{\gamma}{\beta+\gamma} \Rightarrow T_1^*|_{k_1=0} = F^{-1}\left(\frac{\beta}{\beta+\gamma}\right), \end{aligned} \tag{3.37}$$

where $F(t)$ denotes the cumulative distribution function of consumers' preferred departure time and $\frac{\partial K(T_i)}{\partial T_i} = k_i = 0$ for $i = 0, 1$ emphasizes that the related magnitudes have been computed assuming null (normalized) marginal time costs. Solving FOCs in (3.37), we get

$$T_0^*|_{k_0=0} = T_1^*|_{k_1=0} = T^*|_{k_i=0} = F^{-1}\left(\frac{\beta}{\beta+\gamma}\right). \tag{3.38}$$

The results are summarized in the following Proposition.

Proposition 4 *Consider two carriers (0 and 1) that compete in a single departure time $T_i \in [\underline{T}, \overline{T}]$ prior setting fares. Let carriers' cost for scheduling their service be constant along the time of day, i.e., $K(T_i) = \bar{K}_i$ with $K'(T_i) = k_i = 0$ for $i = 0, 1$. Let β (γ) with $0 < \beta < \gamma$ be consumers' unit early (late) schedule delay costs and F be the cumulative distribution of the consumers' preferred departure times. When carriers' time costs do not vary along the time of day, there exists a unique Nash equilibrium in departure times given by (3.38) and carriers schedule their service at the same time, at the $\beta/(\beta+\gamma)$th quantile of consumers' desired time distribution.*

Proof. The existence and unicity of solution $\mathbf{T}^*$ follows from solving FOCs in (3.37) with respect to the departure times and from the concavity in departure times of the profit functions in (3.34) when $\frac{\partial K(T_i)}{\partial T_i} = k_i = 0$ for $i = 0, 1$. Indeed, to ensure that the chosen departure times are profit-maximizing, note that the second-order conditions (SOCs) for each carrier are given by:

$$\begin{aligned}
\frac{\partial \pi_0^{*2}(\mathbf{T}, \boldsymbol{\tau})}{\partial T_0^2} &= -\frac{2}{3}(\beta + \gamma)\rho(T_0)D_0^*(\mathbf{T}, \boldsymbol{\tau}) + \frac{2}{9}[\beta - (\beta + \gamma)\ m_\ell]^2, \\
\frac{\partial \pi_1^{*2}(\mathbf{T}, \boldsymbol{\tau})}{\partial T_1^2} &= -\frac{2}{3}(\beta + \gamma)\rho(T_1)D_1^*(\mathbf{T}, \boldsymbol{\tau}) + \frac{2}{9}[\gamma - (\beta + \gamma)\ m_r]^2.
\end{aligned} \tag{3.39}$$

The last terms on the RHS of Eqs. (3.39) being null when the related FOCs are satisfied, and given that $D_i^*, \rho(T_i), \beta$ and γ are strictly positive, the second derivatives of the profit functions with respect to the departure times are negative. Thus, the optimal departure time $T_i^*|_{k_i=0}$ in (3.38) is unique and maximizes carriers' profit. Further, each carrier has a dominant strategy which is a Nash equilibrium because the optimal departure time of a carrier does not depend on the time scheduled by its rival. To prove that Proposition 4 holds when $T0 \geq T1$, use the equilibrium demands (B. 2.5) and (B. 2.6) in Appendix B. 2 in the profit functions (3.34) and follow the same steps. □

Proposition 4 establishes that when the time costs do not vary with the time of the day and when time schedules are chosen before fares, the optimal departure times are equal across carriers and depend on consumers' unit schedule delay costs' share $\frac{\beta}{\beta+\gamma}$ along with the distribution of their preferred departure time. Hence, the principle of minimal differentiation in departure times applies here. Profit-maximizing carriers locate their time over the $[\underline{T}, \overline{T}]$ schedule as close as possible and compete in fares only in order to exploit the spatial differentiation dimension.

Turning to case (ii), where the time costs of the carriers vary in the time of day, we posit the following linear structure:

$$K(T_i) = \bar{K}_i + k_i\ T_i, \quad \text{where} \quad \bar{K}_i > 0, \quad k_i \neq 0, \quad T_i \in [\underline{T}, \overline{T}],\ i = 0, 1 \tag{3.40}$$

Substituting (3.40) into (3.35) and solving the FOCs with respect to departure times when $T_0 \leq T1$, we obtain:

$$m_\ell = \frac{\beta}{\beta + \gamma} - \frac{3k_0}{2(\beta + \gamma)D_0^*(\mathbf{T}, \boldsymbol{\tau})} = m_\ell|_{k_0=0} - \frac{3k_0}{2(\beta + \gamma)D_0^*(\mathbf{T}, \boldsymbol{\tau})}, \tag{3.41}$$

$$m_r = \frac{\gamma}{\beta + \gamma} + \frac{3k_1}{2(\beta + \gamma)D_1^*(\mathbf{T}, \boldsymbol{\tau})} = m_r|_{k_1=0} + \frac{3k_1}{2(\beta + \gamma)D_1^*(\mathbf{T}, \boldsymbol{\tau})}. \tag{3.42}$$

where $m_\ell|_{k_0=0}$ and $m_r|_{k_1=0}$ are obtained in (3.37) for the null marginal time costs case. Note that T_i, $i = 0, 1$ appears on both sides of Eqs. (3.41) and (3.42). Solving FOCs with respect to departure times $\mathbf{T}$, we get:

$$\begin{aligned} T_0^*(\mathbf{k}) &= F^{-1}\left(\frac{\beta}{\beta+\gamma} - \frac{3k_0}{2(\beta+\gamma)D_0^*(\mathbf{T},\boldsymbol{\tau})}\right), \\ T_1^*(\mathbf{k}) &= F^{-1}\left(\frac{\beta}{\beta+\gamma} - \frac{3k_1}{2(\beta+\gamma)D_1^*(\mathbf{T},\boldsymbol{\tau})}\right). \end{aligned} \tag{3.43}$$

where $\mathbf{k} = (k_0, k_1)$. The results are summarized in Proposition 5.

Proposition 5 *Consider two carriers (0 and 1) that compete in a single departure time* $T_i \in [\underline{T}, \overline{T}]$ *prior setting fares. Let carriers' cost for scheduling their service be linear in the time of day, i.e.,* $K(T_i) = \bar{K}_i + k_i T_i$ *with* $K'(T_i) = k_i$ *for* $i = 0, 1$*, and* F *be the cumulative distribution of the consumers' preferred departure times. When carriers' time costs vary along the time of day, and if a unique Nash equilibrium in time scheduling exists, carriers schedule their service at the same time if the marginal time cost across carriers is of same proportion as the equilibrium demand at their departure facility, i.e,* $k_0/k_1 = D_0^*/D_1^*$*; and at different times in all other time cost and equilibrium demand configurations.*

Proof. The existence of solution T_i^* follows from solving FOCs in (3.41) and (3.42) with respect to the departure times $\mathbf{T}$ and from the concavity in $\mathbf{T}$ of the profit functions in (3.34) when $\frac{\partial K(T_i)}{\partial T_i} = k_i \neq 0$ for $i = 0, 1$. Indeed, when a (possibly) unique solution exists over the $[0, 24]$ interval, they are the solutions of Eqs.(3.43). To ensure that the second derivatives of the profit functions with respect to $\mathbf{T}$ are negative, the SOCs (3.39) require

$$\begin{aligned} k_0^2 &< \frac{4}{3}\rho(T_0^*)(\beta+\gamma)D_0^{*3}(\mathbf{T},\boldsymbol{\tau}), \\ k_1^2 &< \frac{4}{3}\rho(T_1^*)(\beta+\gamma)D_1^{*3}(\mathbf{T},\boldsymbol{\tau}). \end{aligned} \tag{3.44}$$

The Simulation section shows that profit-maximizing departure times exist when $\rho(t)$ is uniform and for reasonable parameter values. To prove that Proposition 5 holds when $T_0 \geq T1$, solve system (B. 2.17)-(B. 2.18) in Appendix B. 2.4 under restriction (B. 2.19). □

Proposition 5 implies that, unless demands are symmetric ($D_0^* = D_1^*$) *and* marginal time costs are equal across carriers ($k_1 = k_0$), the existence of such costs ($k_i > 0$) always drives to differentiated service times across carriers. For example, consider that the cost of scheduling a flight is increasing in the time of day for carrier 0 but null for carrier 1 ($k_0 > 0, k_1 = 0$), carrier 0 would schedule its service earlier.[33] Thus, $T_0^* < T_1^*$, with $T_1^* = T_1^*|_{k_1=0}$. We get a similar outcome, i.e., $T_0^* < T_1^*$, when carrier 1's time cost is decreasing in the time of day instead of constant, as in Figure 3.5 (or when $k_0 = 0, k_1 < 0$). When carriers' marginal time costs induce $T_0^* > T_1^*$, one needs to consider the carrier-rivalry game with demands derived assuming $T_0 \geq T_1$. One can verify in Appendix B. 2.4 that when $T_0^* \geq T_1^*$, we

[33]The k_0 term of T_0^* in (3.43) is necessarily negative while the k_1 term in T_1^* vanishes

obtain symmetric results. Borenstein and Netz (1999) and Salvanes et al. (2005) find that the principle of minimal differentiation in departure times applies in the air transport industry. If airlines' time costs do not vary in the time of day across carriers, we shall expect minimal differentiation in departures times. More precisely, our model predicts no differentiation at all in departure times in two situations: when the time costs do not vary in the time of day across carriers or when the marginal time costs are identical and the equilibrium demands are equal for both carriers. Differentiated service times should be observed in all other cases. Given IATA (2016)'s statement in footnote 7, competing carriers across congested and uncongested facilities are likely to face differentiated marginal costs for scheduling their service at specific time of the day. In such case, our model predicts that differentiation in departure times is what we should observe. The level of scheduling differentiation will depend on the differences in marginal time costs across carriers, facility demands along with the distribution of travellers' desired departure times.

The sensitivity of *equilibrium* fares to carriers' time costs $K(T_i)$ depend on the structure of these costs. Substituting $\mathbf{T}$ by $\mathbf{T}^* = (T_0^*, T_1^*)$ into the *equilibrium* fares in (3.18) yields:

$$\begin{aligned} p_0^* &= \frac{2}{3}(c_0 + \tau_0) + \frac{1}{3}(c_1 + \tau_1) + \frac{3+h}{6} + \frac{1}{3}\Phi(\mathbf{T}^*), \\ p_1^* &= \frac{2}{3}(c_1 + \tau_1) + \frac{1}{3}(c_0 + \tau_0) + \frac{3-h}{6} - \frac{1}{3}\Phi(\mathbf{T}^*), \end{aligned} \tag{3.45}$$

When carriers' time cost is constant along the time of day, departure times competition results in minimal differentiation such that $T_0^* = T_1^*$. Thus, term $\Phi(\mathbf{T}^*)$ in (3.45) vanishes i.e. $\Phi(\mathbf{T}^*) = 0$ (see Lemma 1). Compared to the case where departure times are exogenously set and are differentiated, allowing carriers to optimize their time scheduling further increases price competition. As the services offered are not differentiated in the time scheduling dimension anymore, carrier 0 has to decrease its fare p_0^* to attract more passengers while carrier 1 increases its price p_1^*. Note that symmetric demands ($D_0^* = D_1^*$) and identical marginal time costs ($k_1 = k_0$) also lead to similar results. Other configurations of time costs affect the equilibrium fares through term $\Phi(\mathbf{T}^*)$ in (3.45).

Having characterized carriers' market, we can now focus on the facilities' problem.

3.2.3 Facilities' problem

We consider two profit-maximizing facilities that compete with each other in the fees they charge to their downstream carrier. In general, facilities' revenues are derived from rental activities and services offered to their final service providers and from commercial activities proposed to consumers of the final service. For airports, they derive revenues both from aeronautical services (per seat terminal charges, landing fees for air traffic control and runway maintenance, services offered to carriers) and non-aeronautical activities (restaurants, car parking, banks) offered by concessionaires to the final consumers. In what follows, we follow Basso and Zhang (2007) and consider that aeronautical revenues are derived from a per passenger global fee charged to carriers. Further, we include an exogenous per passenger non-aeronautical revenue. We posit that facilities' capacity is fixed, their marginal operational costs are null and their fixed operational costs are given, i.e., $\widehat{F}_i \geq 0$ for $i = 0, 1$. Hence, the facility maximization problem reads:

$$\max_{\widehat{\tau}_i} \widehat{\Pi}_i(\mathbf{T}, \widehat{\boldsymbol{\tau}}) = (\widehat{\tau}_i + \widehat{\omega}_i) D_i^*(\mathbf{T}, \boldsymbol{\tau}) - \widehat{F}_i \qquad i = 0, 1, \tag{3.46}$$

where $\widehat{\tau}_i \geq 0$, $i = 0, 1$ denotes facility (aeronautical) fee per passenger and $\widehat{\omega}_\mathbf{i} \geq 0$, $i = 0, 1$ represents the commercial (or non-aeronautical) revenue per passenger (both measured in monetary units). Note that we use the normalized τ_i^* and ω_i, which are $\widehat{\tau}_i^*$ and $\widehat{\omega}_i$ divided by $\theta(1-h)$. Departure times can be either given to the carriers (as in Section 3.2.2) or optimally chosen (as in Section 3.2.2). In the latter case, when the time cost varies with the time of day for a carrier ($k_i \neq 0$), its optimal service time is an implicit expression which depends on the (normalized) fees $\boldsymbol{\tau}$. Solving the maximization problem in (3.46) analytically is not tractable, so we need to rely on the Simulation section for the solutions. In all other cases, the maximization problem for the competing facilties with respect to fees is straightforward and follows the same exact steps as maximizing the profits of carriers with respect to fares.

Solving the FOCs from (3.46) with respect to fees, we obtain the *equilibrium* fees $\boldsymbol{\tau} = (\tau_0^*, \tau_1^*)$ given by:

$$\begin{aligned} \tau_0^* &= \frac{1}{3}\left[(c_1 - c_0) - (2\omega_0 + \omega_1)\right] + \frac{9+h}{6} + \frac{1}{3}\Phi(\mathbf{T}), \\ \tau_1^* &= \frac{1}{3}\left[(c_0 - c_1) - (\omega_0 + 2\omega_1)\right] + \frac{9-h}{6} - \frac{1}{3}\Phi(\mathbf{T}), \end{aligned} \tag{3.47}$$

The results are summarized in Proposition 6.

Proposition 6 *Consider two profit-maximizing facilities (i=0,1) that compete in fees charged to their carrier. Let $h \geq 0$ represent the magnitude of the spatial asymmetry that gives facility 0 a location advantage over facility 1, $\Delta c = (c_1 - c_0)$ the difference in carriers' (normalized) marginal operational costs, $\Delta\omega = (\omega_0 - \omega_1)$ the difference in facilities' (normalized) commercial revenue per consumer, $\Phi(\boldsymbol{T})$ the (normalized) schedule delay cost difference of the market related to the scheduled service times T_1 and T_0 at facility 1 and 0, respectively. Then, there exists a unique Nash Equilibrium in fees given by* (3.47)*.*

Proof. The proofs follow from solving FOCs with respect to fees and from the concavity in fees of the profit functions in (3.46). To prove that Proposition 6 holds when $T0 \geq T1$, use the equilibrium demands (B. 2.5) and (B. 2.6) in Appendix B. 2 in the profit functions in (3.46) and follow the same step. □

Proposition 6 implies that the *equilibrium* fee of facility i is decreasing in the marginal operational cost of its carrier and increasing in that of the carrier serving the rival facility. Larger commerical revenues at both facilities help to keep aeronautical fees lower at each facility. The h term is a monopoly premium/penalty related to the location (dis)advantage and $\Phi(\mathbf{T})$ captures the SDC (dis)advantage due to potential differences in departure times.[34]

Substituting the *equilibrium* fees into carriers' demands (3.24), we obtain the facilities' *equilibrium* demands, which are:

$$\begin{aligned} D_0^{f,*}(\mathbf{T}) &= \frac{1}{18}\,[9 + h + 2(c_1 - c_0) + 2(\omega_0 - \omega_1) + 2\Phi(\mathbf{T})], \\ D_1^{f,*}(\mathbf{T}) &= \frac{1}{18}\,[9 - h - 2(c_1 - c_0) + 2(\omega_1 - \omega_0) - 2\Phi(\mathbf{T})]. \end{aligned} \tag{3.48}$$

Note that c_i, ω_i are, respectively, $\hat{c}_i$ and $\hat{\omega}_i$ divided by $\theta(1-h)$. Facilities' demands are affected by the location (dis)advantage of the facilities and differences in carriers' operational marginal costs, in commercial revenues and in schedule delay costs with respect to the rival facility. Transportation costs are also implicitly accounted for through the normalized parameters.

With facilities' optimal fees and demands in hand, facilities' profit at equilibrium is given by:

$$\Pi_i^*(\mathbf{T}) = 3D_i^{*2}(\mathbf{T}) - F_i, \quad i = 0, 1. \tag{3.49}$$

Similarly to carriers' market analysis, we can compare the *equilibrium* aeronautical fees, demands and profits of the competing facilities. Using expressions in (3.47), (3.48) and (3.49), differences in fees, demands and profits across facilities are given by:

$$\begin{aligned} \tau_0^* > \ \tau_1^* \quad &\textit{iff} \quad \Delta c \ > -\frac{h}{2} - \Phi(\mathbf{T}) + \frac{\Delta\omega}{2}, \\ D_0^{f,*}(\mathbf{T}) > \ D_1^{f,*}(\mathbf{T}) \quad &\textit{iff} \quad \Delta c \ > -\frac{h}{2} - \Phi(\mathbf{T}) - \Delta\omega, \\ \Pi_0^*(\mathbf{T}) > \ \Pi_1^*(\mathbf{T}) \quad &\textit{iff} \quad \Delta c \ > -\frac{h}{2} - \Phi(\mathbf{T}) - \Delta\omega - \frac{3}{2}\Delta F, \end{aligned} \tag{3.50}$$

where $\Delta c = c_1 - c_0$, $\Delta\omega = \omega_0 - \omega_1$, $\Delta F = F_1 - F_0$. The delta terms (3.2.3) represent normalized cost and commercial revenue (dis)advantages for facility 0 when they are positive (negative) while $\Phi(\mathbf{T})$ captures the usual SDC (dis)advantage. Proposition 7 summarizes the results.

Proposition 7 *Consider two profit-maximizing facilities (i=0,1) that compete in the fees charged to their carrier. Let* $h \geq 0$ *represent the magnitude of the spatial asymmetry that gives facility 0 a location advantage over facility 1,* $\Delta c = (c_1 - c_0)$ *the difference in carriers' (normalized) marginal operational costs,* $\Delta\omega = (\omega_0 - \omega_1)$ *the difference in facilities' (normalized) commercial revenue per consumer,* $\Phi(\mathbf{T})$ *the (normalized) schedule delay cost difference*

[34] Note that, using (3.47) in the markup of the carriers, $p_i^* - (c_i + \tau_i^*)$, one can further identify how carriers' equilibrium markup is related to per passenger non-aeronautical revenues at *both* facilities.

of the market related to the scheduled service times T_1 and T_0 at facility 1 and 0, respectively, and $\Delta F = (F_1 - F_0)$ the difference in facilities' fixed costs. Then, facility 0 charges a higher fee, receives a larger demand and profit than its rival when expressions in (3.50) hold.

Proof. To prove, set $\tau_0^*, D_0^{f,*}$ and Π_0^* strictly larger than, respectively, $\tau_1^*, D_1^{f,*}$ and Π_1^* and rearrange terms. To prove that Proposition 7 holds when $T0 \geq T1$, use the equilibrium demands (B. 2.5) and (B. 2.6) in Appendix B. 2 in the profit functions in (3.46) and follow the same step. □

The first implication of Proposition 7 is that an operational cost advantage for its carrier is required for facility 0 to have higher optimal aeronautical fee, demand and profit than its rival. This can be shown by setting all RHS terms in Eqs. (3.50) to zero. Introducing a location advantage $h > 0$, facility 0 can have a higher fee, demand and profit even when its carrier's marginal operational cost is larger than its rival carrier. A (dis)advantage in per passenger commercial revenue drives up (down) the difference in optimal fees across facilities but reduces the difference in equilibrium demands and profits. By setting $h = \Phi(\mathbf{T}) = \Delta F = 0$ in (3.50), we conclude that a facility charges a higher fee than the rival facility if the marginal operational cost advantage of its carrier with respect to the carrier serving the rival facility outweighs (half of) its per passenger commercial revenue advantage; a facility receives a larger demand and profit than the rival facility if the marginal operational cost *disadvantage* of its carrier with respect to the carrier serving the rival facility offsets its per passenger commercial revenue advantage. All other costs advantages (in SCD and in fixed operational costs) help facility 0 to get a higher demand and profit.

Having fully characterized the duopolistic outcome of the three stage game, we now explore the minimization of the social costs.

3.2.4 Social cost minimization

This section investigates the optimal location of the facilities and the optimal departure times from a viewpoint of authorities that are seeking for social cost minimization. In the transportation industry, the location of large facilities is essentially made by regional authorities in order to minimize consumers' access cost. Scheduling decisions often require broad coordination between a variety of agents (carriers, facilities' owners, regional and national authorities, international transport regulator) and may need to obey international standards. In air transportation, local and national entities decide where to locate the airports, while IATA provides the global air transport community a single set of rules for the management of airport slots worldwide. Hence, we treat the location and scheduling decisions independently of one another.

Choosing the location of firms over the linear city in order to minimize the average total transportation cost (denoted TC^S below) is a standard social planner problem in Hotelling models. In our context, the problem amounts to minimizing the area below the transportation costs function in Figure 3.2, ignoring all costs related to scheduling, that is:

$$\min_{a,b} TC^S(a,b) = \frac{\theta}{2}\left[\int_0^a (a-x)^2 dx + \int_a^{\tilde{x}^S=\frac{1-b+a}{2}} (x-a)^2 dx + \int_{\tilde{x}^S=\frac{1-b+a}{2}}^{1-b} ((1-b)-x)^2 dx\right], \tag{3.51}$$

where $\tilde{x}^S$ is the usual 'socially indifferent' consumer and a and $1-b$ are the locations of, respectively, facility 0 and 1 over the unit line, with $a+b \leq 1$ and $a, b \in [0,1]$. Detailed derivations are provided in Appendix B. 4.1 but note that the analysis assumes equal operational marginal costs across carriers and equal marginal revenues across facilities. It is well-known that the optimal location of two firms (or facilities) when consumers are uniformly distributed over the $[0,1]$ market is the middle of segments $[0,\frac{1}{2}]$ and $[\frac{1}{2},1]$, at $\frac{1}{4}$ and $\frac{3}{4}$, respectively. Consumers located at the extreme of facilities' catchment areas, at 0, $\frac{1}{2}$ and 1, would incur the same transportation cost and the average total transportation cost is minimized. The social planner may rather want to relocate only one facility, given the location of the other, at $1-b=1$ for facility 1 or at $a=h$ for facility 0. Under our assumptions, the optimal location rules (denoted by the superscript S) are given by:

$$(a^S, 1-b^S) = \left(\frac{1}{4}, \frac{3}{4}\right), \quad a^S\big|_{b=1} = \frac{1}{3}, \quad 1-b^S\big|_{a=h} = \frac{2+h}{3}. \tag{3.52}$$

For the scheduling authority, minimizing the scheduling costs for the whole society (denoted SC^S below) requires finding the departure times at each facility that minimize the area under consumers' schedule delay cost functions in Figure 3.1, plus carriers' scheduling costs (3.40), such as:

$$\min_{T_0,T_1} SC^S = SDC^S(\mathbf{T}) + K^S(\mathbf{T}) \tag{3.53}$$

where

$$\begin{aligned} SDC^S(\mathbf{T}) = &\int_0^{T_0} \widehat{\gamma}(T_0-t)\rho(t)\,\mathrm{d}t + \int_{T_0}^{\widetilde{t}} \widehat{\beta}(t-T_0)\rho(t)\,\mathrm{d}t + \\ &\int_{\widetilde{t}}^{T_1} \widehat{\gamma}(T_1-t)\rho(t)\,\mathrm{d}t + \int_{T_1}^{24} \widehat{\beta}(t-T_1)\rho(t)\,\mathrm{d}t, \\ K^S(\mathbf{T}) = &\,\widehat{k}_0 T_0 + \widehat{k}_1 T_1. \end{aligned} \tag{3.54}$$

Term $\widetilde{t} = \frac{\widehat{\beta}T_0+\widehat{\gamma}T_1}{\widehat{\beta}+\widehat{\gamma}}$ in the integration bounds of (3.54) is the abscissa of the intersection between the dotted and the bold schedule delay cost function in Figure 3.1, while the first/last two RHS expressions capture the area to the left/right of $\widetilde{t}$ in Figure 3.1 and represent the schedule delay cost of consumers that prefer departing early/late with respect to T_0 and T_1.

Solving the FOCs of (3.53), we get:

$$\frac{\partial SC^S(\mathbf{T})}{\partial T_0} = \widehat{\gamma} m_\ell - \widetilde{m}_\ell \widehat{\beta} + \widehat{k}_0 = 0, \tag{3.55}$$

$$\frac{\partial SC^S(\mathbf{T})}{\partial T_1} = \widetilde{m}_r \widehat{\gamma} - \widehat{\beta} m_r + \widehat{k}_1 = 0, \tag{3.56}$$

where terms $\widetilde{m}_\ell = \int_{T_0}^{\widetilde{t}} \rho(t)dt$ and $\widetilde{m}_r = \int_{\widetilde{t}}^{T_1} \rho(t)dt$ have now a familiar interpretation. Using $\rho(t) \sim \mathcal{U}[0, 24]$ as an analytically tractable choice and assuming that carriers incur no scheduling costs ($k_0 = k_1 = 0$), the SC^S function is given by:

$$SC^S = \frac{(2\widehat{\beta}\widehat{\gamma} + \widehat{\gamma}^2)T_0^2 + (2\widehat{\beta}\widehat{\gamma} + \widehat{\beta}^2)T_1^2 - 48\widehat{\beta}^2 T_1 - 2\widehat{\beta}\widehat{\gamma} T_0 T_1 + 576(\widehat{\beta}\widehat{\gamma} + \widehat{\beta}^2)}{48(\widehat{\beta} + \widehat{\gamma})} \tag{3.57}$$

and solving the FOCs with respect to T_0 and T_1, we obtain the socially optimal departure times:

$$T_0^S = \frac{12\widehat{\beta}}{\widehat{\beta} + \widehat{\gamma}}, \qquad T_1^S = 12\left[1 + \frac{\widehat{\beta}}{\widehat{\beta} + \widehat{\gamma}}\right]. \tag{3.58}$$

The results are given in Proposition 8.

Proposition 8 *Consider two regulators, each of which chooses independently the location of two facilities (denoted a and 1-b with a $\leq$ 1-b) over a linear city of unit length in order to minimize the social transportation costs, and the departure times at each facility (denoted T_0^S and T_1^S) in order to minimize social schedule delay costs. Let $\widehat{\beta}$ and $\widehat{\gamma}$ designate the shadow costs of departing earlier and later than desired per unit of time. When carriers' marginal scheduling costs do not vary in the time of day and consumers are uniformly distributed over the linear city and over the $[0, 24]$ time schedule,*

1. *the optimal locations of the facilities along the [0,1] line are at coordinates ($a^S = \frac{1}{4}, 1 - b^S = \frac{3}{4}$) when the are simultaneously chosen, $a^S = \frac{1}{3}$ when facility 1 is located at 1, and at $1 - b^S = \frac{2+h}{3}$, when facility 0 is located at $a = h$.*

2. *the optimal departure times T_0^S at facility 0 and T_1^S at facility 1 are such that $T_0^S < T_1^S$ and are given by (3.58).*

Proof. The proof of 1. is given in Appendix B. 4.1. The proof of 2. follows from solving the FOCs of (3.53) using the same tools[35] as in Lemma 1 and from the convexity of the objective function in (3.53).□

[35] Using a symbolic mathematical software is useful here as the expressions become cumbersome to manipulate. We used `Mathematica 10.4.0`.

Proposition 8 clearly shows that 'socially' optimal departure times are located at the left- and right-hand side of the middle of the $[0, 24]$ line.[36] As expected, these service times depend on consumers' unit schedule delay cost share $\frac{\widehat{\beta}}{\widehat{\beta}+\widehat{\gamma}}$. Further recalling Proposition 4, where the duopolistic competition leads to identical departure times across facilities, using the uniform distribution, we get:[37]

$$\Delta T_0 = T_0^S - T_0^*|_{k_0=0} = -12\frac{\widehat{\beta}}{\widehat{\beta}+\widehat{\gamma}}, \quad \Delta T_1 = T_1^S - T_1^*|_{k_1=0} = 12\frac{\widehat{\gamma}}{\widehat{\beta}+\widehat{\gamma}}.$$

Therefore, duopolistic competition results in departure times which are later than socially optimal at facility 0 and earlier than socially optimal at facility 1. The scheduling authority could either impose the optimal departure times or set a schedule pricing scheme that drives the market outcome to socially optimal times. Using T_0^S and T_1^S in the FOCs of carriers' profit maximization (3.43), with the uniform distribution, we get an explicit pricing rule for the service time at both facilities with the linear scheduling costs (3.40), i.e.,

$$k_0^S = \frac{\widehat{\beta} D_0^*}{3}, \quad k_1^S = -\frac{\widehat{\gamma} D_1^*}{3}. \tag{3.59}$$

The above results indicate that the scheduling authority should set an increasing scheduling cost in the time of day for the carrier serving facility 0 to get the early socially optimal service time and a decreasing one at facility 1 to incentive its carrier to schedule service later in the day. The distributional impacts of a scheduling regulation from the social planners' viewpoint are further analyzed in the Simulations section.

3.3 Numerical Results

This section illustrates numerically the analytical results found in the previous sections and verifies the validity of our propositions. All parameters of the simulations are expressed in monetary units. We assume that travellers' desired departure times are uniformly distributed, such that $t \sim \mathcal{U}[0, 24]$, and we set consumers' unit schedule delay costs to $\widehat{\beta} = \$5$ and $\widehat{\gamma} = \$7$. The latter values are slightly lower than those used in van der Weijde et al. (2014) but closer to the willingness to pay found by Brey and Walker (2011) for air travellers. We posit a unit transportation cost of $\frac{\theta}{2} = \$130$, which ensures that our covered market conditions are satisfied.[38] This implies a cost of 73\$ for a traveller going from a facility 1 to facility 0, which is reasonable with respect to other parameters values and the equilibrium fares computed in the simulations. We set a higher marginal operational cost for the carrier located at facility

[36] Appendix B. 4.2 establish that all second-order conditions are satisfied for a global minimum for $T_i \in [0, 24]$.

[37] Note that $T_1^S = 12\left[1 + \frac{\widehat{\beta}}{\widehat{\beta}+\widehat{\gamma}}\right] \equiv \frac{24\widehat{\beta}}{\widehat{\beta}+\widehat{\gamma}} + \frac{12\widehat{\gamma}}{\widehat{\beta}+\widehat{\gamma}}$.

[38] See conditions (3.6). More specifically, one can verify that for all equilibrium fares and scheduled times found in the simulations, these conditions hold.

0 than its rival's at facility 1: $\widehat{c}_0 = \$10$ while $\widehat{c}_1 = \$8$. Again, one can think of carrier 0 as a legacy carrier operating at a primary facility that competes with a low cost carrier serving a secondary facility. Per passenger revenues derived from commercial activities are, however, higher in the facility where the legacy carrier operates: $\hat{\omega}_0 = 20\$$ at facility 0 and $\hat{\omega}_1 = 18$ at facility 1. Without loss of generality, we consider that all fixed costs are null ($\bar{K}_i = \widehat{F}_i = 0$ for $i = 0, 1$).

3.3.1 Equilibria when carriers' time costs do not vary in the time of day

We first analyze the market equilibria when the (marginal) scheduling costs of the carriers are null in the time of day (both $\widehat{k}_0 = \widehat{k}_1 = 0$). Solving the three-stage game with the above parameters values, duopolistic competition drives to no differentiation in service times across carriers. Applying (3.38), we immediately get a unique departure time at both facilities in the morning, at $T_0^* = T_1^* = 10$.

Table 3.1 analyzes the market equilibrium (consumers' demands and costs, carriers' fares and profits; and facilities' aeronautical fees and profits) under a variety of situations: (*i*) when facility 0 has no location advantage and its carrier differentiate minimally their departure times to maximize their profit ($h = 0$ and $T_0^* = T_1^* = 10$), (*ii*) when facility 0 (and its carrier) possess a location advantage which represents 25% of market share and departure times are optimal and minimally differentiated ($h = 0.25$ and $T_0^* = T_1^* = 10$), (*iii*) when a schedule regulator forces carrier 0 to depart earlier than optimal ($h = 0.25$, $T_0 = 7$ and $T_1^* = 10$) and carrier 1 can set its profit-maximizing service time, (*iv*) when a schedule regulator forces carrier 0 to depart at a time that offsets the location advantage of the facility it serves ($h = 0.25$, $T_0 = 0$ and $T_1^* = 10$), and (*v*) when a local regulator optimizes the location of facility 0 only and an independent scheduling coordinator sets the service times at both facilities to minimize social scheduling costs ($h^S = 0.33$, $T_0^S = 5$ and $T_1^S = 17$). Note that cases (*iii*) and (*iv*) would capture the case of a legacy carrier that is granted for free a slot which is not optimal while its rival carrier at the other facility can choose its departure time free of timing costs. Case (*v*) would represent a fully regulated market in service times, in which carriers are granted specific slots free of timing costs.

Table 3.1 – Market Equilibrium and Social Optimum

	Market Equilibrium				Social Optimum
	$T_0^* = T_1^* = 10$ $h = 0$ $\widehat{\Phi} = 0$	$T_0^* = T_1^* = 10$ $h = 0.25$ $\widehat{\Phi} = 0$	$T_0 = 7$; $T_1^* = 10$ $h = 0.25$ $\widehat{\Phi} = -0.012$	$T_0 = 0$; $T_1^* = 10$ $h = 0.25$ $\widehat{\Phi} = -0.128$	$T_0^S = 5$; $T_1^S = 17$ $h^S = 0.33$ $\widehat{\Phi} = 0.034$
Facilities					
$(\widehat{\tau}_0^*; \widehat{\tau}_1^*)$	(370 ; 372)	(280.6 ; 266.4)	(279.9 ; 267.1)	(272.3 ; 274.7)	$(252.9, 231.7)$
$(\widehat{\Pi}_0^*; \widehat{\Pi}_1^*)$	(195 ; 195)	(154.5 ; 138.2)	(153.7 ; 139.0)	(146.0 ; 146.5)	$(142.5, 119.3)$
Carriers					
$(\widehat{p}_0^*; \widehat{p}_1^*)$	(510 ; 510)	(390.8 ; 369.2)	(389.8 ; 370.2)	(379.7 ; 380.3)	$(353.8, 323)$
$(\widehat{\pi}_0^*; \widehat{\pi}_1^*)$	(65 ; 65)	(51.5 ; 46.1)	(51.2 ; 46.3)	(48.7 ; 48.8)	$(47.5, 39.8)$
Consumers					
Demands $(D_0^*; D_1^*)$	(0.5 ; 0.5)	(0.514 ; 0.486)	$(0.513, 0.487)$	(0.499 ; 0.501)	$(0.522, 0.478)$
Schedule delay cost†	35	35	28.11	26.49	17.5
Transportation cost†	10.83	5.25	5.25	5.25	4.82
Total Cost	45.83	40.25	33.36	31.74	22.32

† The schedule delay and transportation costs of consumers are computed with (3.51) and (3.53), respectively.
The simulations assume: $t \sim \mathcal{U}[0, 24]$, $\widehat{\beta} = 5, \widehat{\gamma} = 7$, $\frac{\theta}{2} = 130$, $\widehat{c}_0 = 10$, $\widehat{c}_1 = 8$, $\widehat{k}_0 = \widehat{k}_1 = 0$, $\widehat{\omega}_0 = 20$, $\widehat{\omega}_1 = 18$.

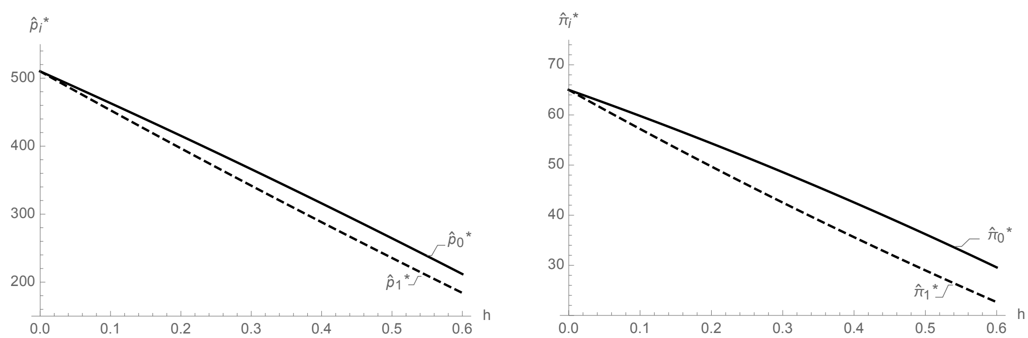
Consider first the case where no location advantage exists in column 1 of Table 3.1. When we combine maximal differentiation in facilities' location with minimal differentiation in scheduling, duopolistic competition results in the highest transportation and scheduling costs for consumers as compared to all other cases. It is worth checking that the prices and profits obtained are consistent with our propositions. By Proposition 5.1, facility 0 charges a lower aeronautical fee than its rival facility if $\Delta\widehat{c} < \frac{\Delta\widehat{\omega}}{2}$. The carrier serving facility 0 has an operational marginal cost disadvantage ($\Delta\widehat{c} = -2$), which is lower than (half of) the commercial revenue advantage of facility 0 ($\frac{\Delta\widehat{\omega}}{2} = \frac{2}{2}$). Notice that $\widehat{\tau}_0^* = \$370 < \widehat{\tau}_1^* = \$372$ in column 1. Thus our proposition is verified. Proposition 5.5 states that profits are equal across facilities when $\Delta\widehat{c} = -\Delta\widehat{\omega}$, which holds here as well. Carriers' outcome also corroborates Proposition 3.1: in the absence of location advantage, fares and profits are identical across carriers when the marginal costs advantage of carrier 0 is null. As one can verify, $(\widehat{c}_1 + \widehat{\tau}_1) - (\widehat{c}_0 + \widehat{\tau}_0) = 380 - 380 = 0$ and $\widehat{\pi}_0^* = \widehat{\pi}_1^*$.

Turning to column 2 of Table 3.1, we introduce a captive market of size 25% for facility 0 into the analysis and let the carriers set their optimal service time. As expected, consumers' transportation cost decreases as compared to the former case (75% of the travellers are now closer to facility 0) and their schedule delay cost remain steady as service times are not affected. Recall that equilibrium fares (and the equilibrium fees by symmetry) are decreasing in h for both carriers (facilities) due to the competition effect and consumers' demand at each facility moves in the opposite direction with h.[39] Comparing column 2 with column 3, increasing h from 0 to 0.25, we notice that D_0^* expands while D_1^* reduces. Moreover, facilities and carriers profits are also decreasing with h. This was expected for facility 1 and its carrier as fare, fee and demand decrease with h. For facility 0 and its carrier, the decrease in profits indicates

[39]To check that market conditions are such that D_0^* increases in h at $h = 0$ and $h = 0.25$, so that D_1^* decreases in h, note that the marginal consumer located at $h = 0$ and $h = 0.25$ is better off departing from facility 0. By using (B. 1.15), we have $130(1 - 0) > 510 - 510$ and $130(1 - 0.25) > 390.8 - 369.2$, respectively.

that the competition effect dominates the demand effect.[40] Figure 3.6 illustrates the effect of increasing h on fares and carriers' profits for the chosen parameters. Notice that the fares and profits of carrier 0 are always above that of its competitor as h increases. In addition, introducing a captive market that benefits facility 0 and its carrier hurts more the profits of their rivals (-7.8% for facility 0 and its carrier and -13.8% for their rivals).

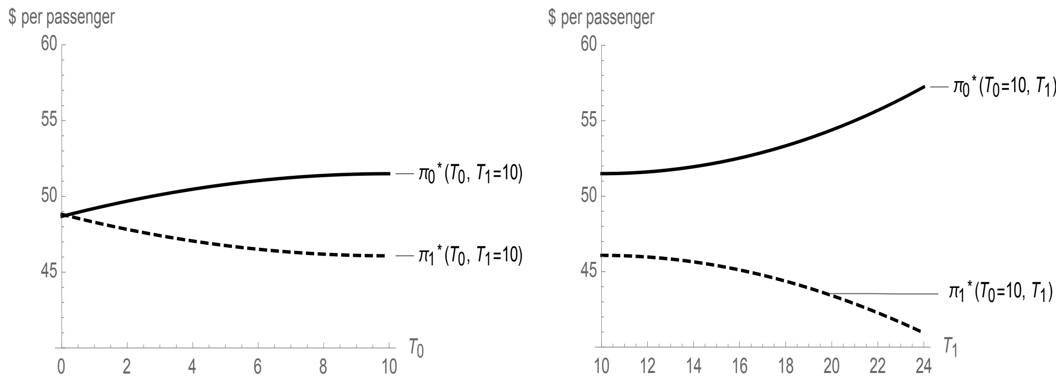
Figure 3.6 – Carrier fares, profits as a function of h when service times are equal



In column 3 of Table 3.1, we combine the 25% location advantage to a 'small' SDC disadvantage for facility 0 and its carrier. Note first that small differentiation in departure times reduces the schedule delay costs of consumers. Then, demand at facility 1 increases, and so do the fee and profit of facility 1, and the fare and profit of its carrier as compared to the case where $\widehat{\Phi} = 0$. If we were to draw the fares and profits with respect to h in this case, we would get Figure 3.6 with the decreasing curves slightly closer together. In other words, the competition and demand effects identified assuming no SDC advantage remain valid here, the differences in fares and profits across carriers (and facilities by symmetry) slightly shrink along h but remain higher for carrier 0 (and the facility it serves). The reader can check that all relevant propositions derived in the theoretical section hold here as well. In Figure 3.7, we further explore how carriers' profits vary when their departure time change, under the provision that $T_0 \leq T_1$ and that the other carrier schedules optimally its service. The left-hand side plot shows carriers' profits over the range $T_0 \in [0, 10]$ when $T_1^* = 10$ and the right-hand side plot depicts these profits over the range $T_1 \in [10, 24]$ when $T_0^* = 10$.

[40]This stresses that, for the given parameters, carriers' marginal costs advantage always lies in the interval where the competition effect dominates the demand effect in Figure 3.4 when h varies.

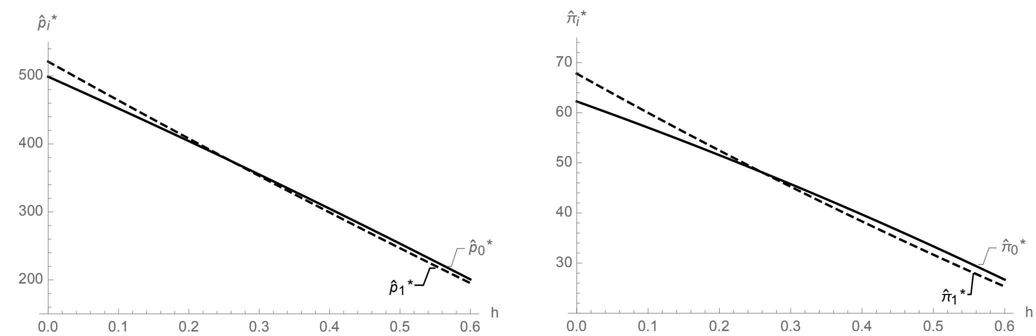
Figure 3.7 – Carriers profits and service timing



Carrier 0's profit is increasing in T_0 while the profit of its rival decreases in T_0. This result is related to Proposition 1, where the demand of facility 0 (facility 1) increases (decreases) with T_0 if the share of consumers preferring to depart before T_0 is large (low) enough. The threshold value is given by $\frac{\widehat{\beta}}{\widehat{\beta}+\widehat{\gamma}} = \frac{5}{5+7} = 41.6\%$ and the share of consumers preferring departing before 10 $a.m.$ is $m_\ell = \int_0^{T_0^*} = \frac{10}{24} = 41.6\%$. Thus, π_0^* is increasing in T_0 until $T_0^* = 10$ while π_1^* decreases. A similar argument can be used to explain the relationships drawn in the right-hand side plot. This result corroborates Proposition 1 for the given parameters.

In column 4 of Table 3.1, we consider the case where we combine the 25% location advantage of facility 0 to a 'large' SDC disadvantage for facility 0 and its carrier while the rival carrier schedules its optimal time. Note first that this configuration further reduces consumers' schedule delay costs. Using column 3 as the benchmark, we notice that demand at facility 1 decreases and falls below that of its rival, and so do the prices and profits of facility 0 and its home carrier. Again, all relevant Propositions of the theoretical section are verified. Figure 3.8 displays the fares and profits when h varies in this particular configuration. We notice that, when the location advantage at facility 0 becomes sufficiently high, we are back to the situation described in column 3, where facility 0 and its carrier can set higher prices and make higher profits.

Figure 3.8 – Carriers' fares and profits and advantage in location when service times are strongly differentiated

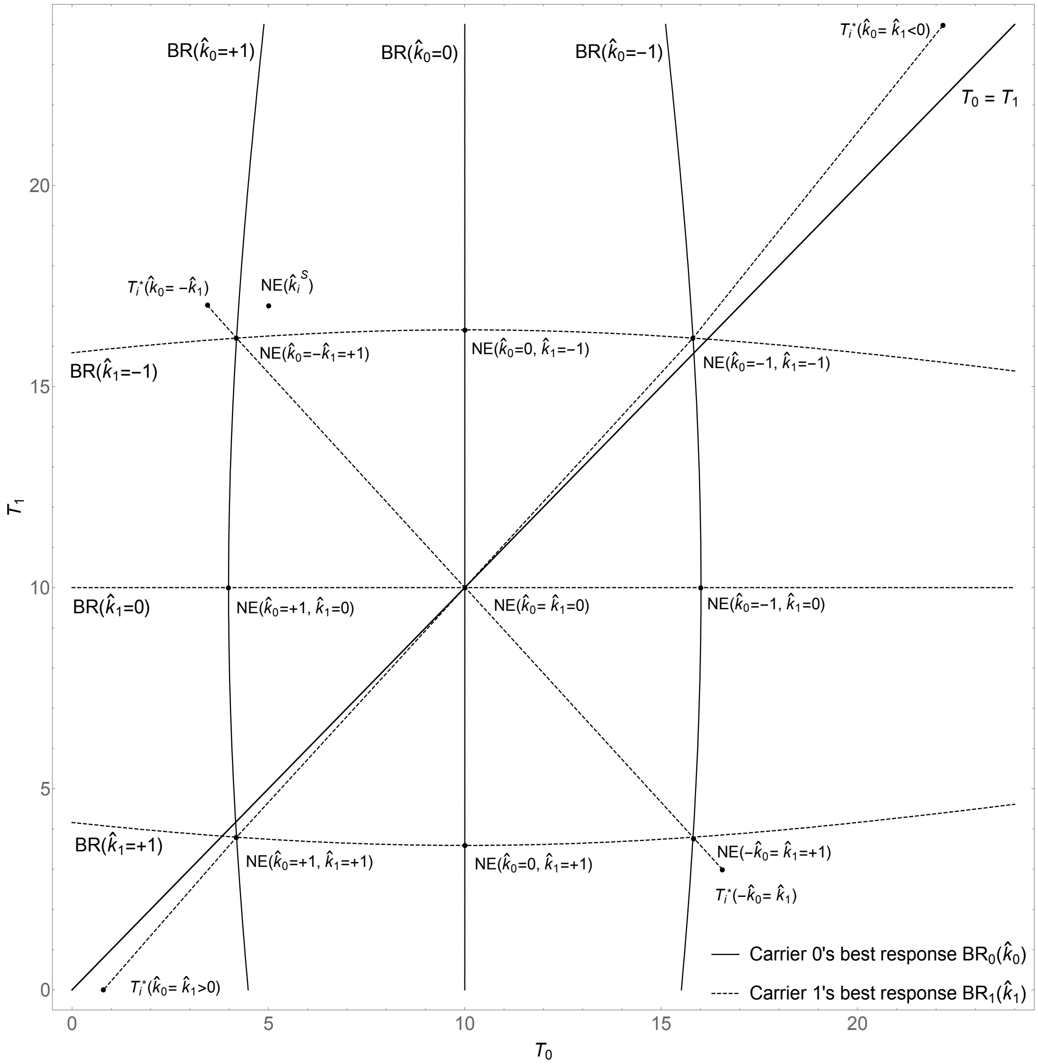


We now focus on the social optimum. Using Eqs. (3.52) and (3.58), we obtain $h^S = 0.33$, $T_0^S = 5$ and $T_1^S = 17$ and the related demands, prices and profits are given in column 5 of Table 3.1. As compared to the outcome obtained in a fully unregulated market in column 1, the total cost of consumers is 51.3% lower. Demand at facility 0 increases as its captive market is now larger. The fees at both facilities decrease and so do the fares (due to the competition effect). The profits of the suppliers all decrease: the profits at facility 0 diminish by 7.8% while that of its rival decreases by 13.8%. Again, the competition effect dominates the demand effect of the suppliers located at h. So the social optimum has an asymmetric impact across facilities and its carriers. The scheduling regulator would achieve the same optimal departure times by setting the marginal scheduling costs in the time of day as in (3.59), as outlined in Proposition 6.3. The case where marginal scheduling costs are not null is analyzed in detail below.

3.3.2 Equilibria when carriers' time costs vary in the time of day

In this section, we focus on the carrier-rivalry game and explore the existence of sequential equilibria in service times and fares over the range of admissible values of marginal time costs (see below) and departure times. We leave facilities' problem aside and set the aeronautical fees to $\widehat{\tau}_0^* = \$280$, $\widehat{\tau}_1^* = \$266$. These aeronautical fees are chosen based on Column 2 of Table 3.1, that we use as a benchmark to explore the effects of introducing marginal costs that depend on the time of day. We assume that both facilities operate 24h/day. Figure 3.9 shows the 'best response' functions of each carrier to their rival's scheduling, denoted $BR_i(\widehat{k}_i)$ with $i = 0, 1$, for all possible combinations of marginal time costs across carriers.

Figure 3.9 – Nash Equilibria in service time and reaction functions for the carrier-rivalry game



Notes: We assume $h = 0.25$, $t \sim \mathcal{U}[0, 24]$, $\widehat{\beta} = 5, \widehat{\gamma} = 7$, $\frac{\theta}{2} = 130$, $\widehat{c}_0 = 10$, $\widehat{c}_1 = 8$, $\widehat{\tau}_0 = 280$, $\widehat{\tau}_1 = 266$, $\widehat{K}_i = 0$ for $i = 0, 1$.

As outlined in Section 3.2.2, the results *above* the $T_0 = T_1$ diagonale rely on expressions valid when $T_0^* \leq T_1^*$ holds while those *below* the $T_0 = T_1$ are based the symmetric expressions in Appendix B. 2, which posit that $T_0^* \geq T_1^*$. Table 3.2 presented in the end of this section displays the numerical values of the subgame Nash equilibria in fares and scheduling for selected levels of $\widehat{k}_i$, for the benchmark parameters along with the equilibria obtained for alternative values of consumers' unit schedule delay costs.
Starting with the null and identical marginal time costs ($\widehat{k}_0 = \widehat{k}_1 = 0$) in Figure 3.9, the reaction functions of the carriers are given by $BR_0(\widehat{k}_0 = 0)$ and $BR_1(\widehat{k}_1 = 0)$. As expected, they are constant in T_{-i} and intersect at point $NE(\widehat{k}_0, \widehat{k}_1 = 0) = (10, 10)$, corroborating the results of Column 2 in Table 3.1.

As outlined in Proposition 5, given that $D_0^* \neq D_1^*$, introducing a non null marginal time costs for at least one of the carriers should drive to differentiated service times. Consider first the case where $(\widehat{k}_0 = +1, \widehat{k}_1 = 0)$, the reaction function of carrier 0 moves the left of $BR_0(\widehat{k}_0 = 0)$ in Figure 3.9 while that of carrier 1 remains steady at $BR_1(\widehat{k}_1 = 0)$. The resulting Nash equilibrium is point $NE(\widehat{k}_0 = +1, \widehat{k}_1 = 0)$, located *above* the $T_0 = T_1$ line. Thus, carrier 0 schedules its service earlier in the morning at facility 0 while carrier 1 keeps its departure time unchanged, such that $T_0^* < T_1^*$. Following the same reasoning for the rest of Nash equilibria, we notice that the combinations of $(\widehat{k}_0 > 0, \widehat{k}_1 \leq 0)$ and $(\widehat{k}_0 = 0, \widehat{k}_1 < 0)$ always result in equilibria *above* the $T_0 = T_1$ diagonale, while $(\widehat{k}_0 < 0, \widehat{k}_1 \leq 0)$ and $(\widehat{k}_0 = 0, \widehat{k}_1 > 0)$ always induce equilibria *below* the $T_0 = T_1$ line.

Moreover, when the marginal time costs are identical but non null $(\widehat{k}_0 = \widehat{k}_1 \neq 0)$, departure times are slightly differentiated (close to the $T_0 = T_1$ diagonale) as equilibrium demands are quite close. By contrast, $(\widehat{k}_i = -\widehat{k}_{-i} \neq 0)$ induces large differentiation in scheduling.[41]

Figure 3.9 also shows that no 'undercutting' in service times is profitable for a carrier as the rival will respond to an earlier (later) service time with an earlier (later) service time. This deviation being suboptimal for both carriers, market forces push the service times back toward the equilibrium. Thus, we also find that service times are strategic substitutes.

As outlined in the Social cost minimization section, a regulator could set a pricing scheme for the time of the day which is opposite in signs at the facilities to achieve socially optimal times, see Eq. (3.59). In our context, setting $\widehat{k}_0^S = 0.83$ and $\widehat{k}_1^S = -1.17$ would make carriers' scheduling socially optimal, i.e., $T_0^* = T_0^S = 5$ and $T_1^* = T_1^S = 17$. Table 3.2 further explores the equilibrium departure times and fares of the carrier-rivalry game when the unit schedule delay cost values are such that $\widehat{\beta} = \widehat{\gamma} = 7$ and $\widehat{\beta} = 7 > \widehat{\gamma} = 5$. Again, the differences in fares are not commented in detail to save space but remember that they are driven by expression (3.21). Considering other types of asymmetries in consumers' schedule delay costs preserves the differentiation patterns in scheduling (and fares), the main changes being the location of the optimal departure times. When consumers are indifferent between early or late schedule delays, carriers schedule their service closer to the center of $[0, 24]$ interval. When travellers are willing to pay more for departing earlier (later) than desired, carriers schedule their service earlier (later) in the time of day.

[41] When marginal schedule delay costs have opposite signs across carriers, departure times are located at the RHS and at the LHS of $T_i^*|_{k_i=0}$ for $i = 0, 1$.

Table 3.2 – Carrier-rivalry equilibria with time-varying marginal costs for the carriers

	$T_0 \leq T_1$				
	Carrier marginal time costs				
	$\widehat{k}_0 = 0$ $\widehat{k}_1 = 0$	$\widehat{k}_0 = 0$ $\widehat{k}_1 = -1$	$\widehat{k}_0 = +1$ $\widehat{k}_1 = 0$	$\widehat{k}_0 = +1$ $\widehat{k}_1 = -1$	$\widehat{k}_0 = -1$ $\widehat{k}_1 = -1$
			$\widehat{\beta} = 5, \widehat{\gamma} = 7$		
(T_0^*, T_1^*)	$(10, 10)$	$(10, 16.4)$	$(4, 10)$	$(4.2, 16.2)$	$(15.8, 16.2)$
$(\widehat{p}_0^*, \widehat{p}_1^*)$	$(390.3, 368.7)$	$(393.7, 365.3)$	$(387.3, 371.7)$	$(390.7, 368.3)$	$(390.7, 368.3)$
(D_0^*, D_1^*)	$(0.514, 0.486)$	$(0.532, 0.468)$	$(0.499, 0.501)$	$(0.516, 0.484)$	$(0.516, 0.484)$
$(\widehat{\pi}_0^*, \widehat{\pi}_1^*)$	$(51.6, 46.0)$	$(55.2, 59.1)$	$(44.5, 49.0)$	$(47.8, 61.8)$	$(67.8, 61.8)$
			$\widehat{\beta} = 7, \widehat{\gamma} = 7$		
(T_0^*, T_1^*)	$(12, 12)$	$(12, 17.5)$	$(6.9, 12)$	$(7, 17.3)$	$(17.0, 17.3)$
$(\widehat{p}_0^*, \widehat{p}_1^*)$	$(390.3, 368.7)$	$(393.2, 365.8)$	$(387.7, 371.3)$	$(390.6, 368.4)$	$(390.6, 368.4)$
(D_0^*, D_1^*)	$(0.514, 0.486)$	$(0.529, 0.471)$	$(0.501, 0.499)$	$(0.516, 0.484)$	$(0.516, 0.484)$
$(\widehat{\pi}_0^*, \widehat{\pi}_1^*)$	$(51.6, 46.0)$	$(54.6, 60.7)$	$(42.1, 48.5)$	$(44.9, 63.0)$	$(68.9, 63.0)$
			$\widehat{\beta} = 7, \widehat{\gamma} = 5$		
(T_0^*, T_1^*)	$(14, 14)$	$(14, 20.4)$	$(8, 14)$	$(8.2, 20.2)$	$(19.8, 20.2)$
$(\widehat{p}_0^*, \widehat{p}_1^*)$	$(390.3, 368.7)$	$(393.7, 365.3)$	$(387.3, 371.7)$	$(390.7, 368.3)$	$(390.7, 368.3)$
(D_0^*, D_1^*)	$(0.514, 0.486)$	$(0.532, 0.468)$	$(0.499, 0.501)$	$(0.516, 0.484)$	$(0.516, 0.484)$
$(\widehat{\pi}_0^*, \widehat{\pi}_1^*)$	$(51.6, 46.0)$	$(55.2, 63.1)$	$(40.5, 49.0)$	$(43.8, 65.8)$	$(71.8, 65.8)$
			$T_0 \geq T_1^{\dagger}$		
	Carrier marginal time costs				
	$\widehat{k}_0 = 0$ $\widehat{k}_1 = 0$	$\widehat{k}_0 = 0$ $\widehat{k}_1 = +1$	$\widehat{k}_0 = -1$ $\widehat{k}_1 = 0$	$\widehat{k}_0 = -1$ $\widehat{k}_1 = +1$	$\widehat{k}_0 = +1$ $\widehat{k}_1 = +1$
			$\widehat{\beta} = 5, \widehat{\gamma} = 7$		
$(T_{0,sym}^*, T_{1,sym}^*)$	$(10, 10)$	$(10, 3.6)$	$(16, 10)$	$(15.8, 3.8)$	$(4.2, 3.8)$
$(\widehat{\pi}_0^*, \widehat{\pi}_1^*)$	$(51.6, 46.0)$	$(55.2, 39.1)$	$(64.5, 49.0)$	$(67.8, 41.8)$	$(47.8, 41.8)$
			$\widehat{\beta} = 7, \widehat{\gamma} = 7$		
$(T_{0,sym}^*, T_{1,sym}^*)$	$(12, 12)$	$(12, 6.5)$	$(17.1, 12)$	$(17, 6.7)$	$(7, 6.7)$
$(\widehat{\pi}_0^*, \widehat{\pi}_1^*)$	$(51.6, 46.0)$	$(54.6, 36.7)$	$(66.1, 48.5)$	$(68.9, 39.0)$	$(44.9, 39.0)$
			$\widehat{\beta} = 7, \widehat{\gamma} = 5$		
$(T_{0,sym}^*, T_{1,sym}^*)$	$(14, 14)$	$(14, 7.6)$	$(20, 14)$	$(19.8, 7.8)$	$(8.2, 7.8)$
$(\widehat{\pi}_0^*, \widehat{\pi}_1^*)$	$(51.6, 46.0)$	$(55.2, 35.1)$	$(49.0, 68.5)$	$(71.8, 37.8)$	$(43.8, 37.8)$

Notes: all simulations assume: $h = 0.25$, $t \sim \mathcal{U}[0, 24]$, $\frac{\theta}{2} = 130$, $\widehat{c}_0 = 10$, $\widehat{c}_1 = 8$, $\widehat{\tau}_0 = 280$, $\widehat{\tau}_1 = 266$, $\widehat{K}_i = 0$ for $i = 0, 1$. † The equilibrium fares $(\widehat{p}_0^*, \widehat{p}_1^*)$ and demands (D_0^*, D_1^*) when $T_0 \geq T_1$ are identical to those reported in the same column for $T_0 \leq T_1$ due to the symmetry of the uniform distribution.

3.4 Conclusion of Essay 3

The aim of this paper is to provide a framework to analyze the rivalry in prices and time scheduling between facilities, for the case in which the facilities provide an input to downstream firms that sell the final product to consumers (vertical structure). The model incorporates asymmetries in the location of the facilities and in the schedule delay costs of consumers, and includes heterogeneous time costs across downstream firms. This setup is used to analyze how a primary airport and its carrier, located within a linear city, compete with a rival secondary airport (and its carrier) located in a remote place (the extremity) of the city. We assume that each carrier schedules a single flight toward the same destination, operates alone at its home facility and sets a single time of departure. In contrast to other spatial models, we use a general distribution of the desired departure times of consumers.

Our results extend those obtained by others under more restrictive assumptions, and appear to be in line with empirical evidence found on scheduling competition in air transportation. In unregulated markets, duopolistic competition results in services scheduled closer than optimal for travellers. However, the principle of minimal differentiation in scheduling (equal departure times across carriers) appears to be valid only when carriers' operational costs do not vary with the time of departure along the day or when these costs are the same across carriers and consumers' demand is equally shared between rival firms. By using a linear cost function in the time of departure for the downstream firms, we show that these costs are important for identifying the level of differentiation in the timing of the service in duopolistic competitive markets: (i) when operational costs do not vary in the time of day for both carriers, minimal differentiation in scheduling applies, (ii) when these costs vary in the time of day but are identical across carriers, differences in equilibrium demands suffice to generate slightly differentiated departure times, (iii) when marginal time costs differ across carriers, the service time is differentiated and the level of differentiation is proportional to the marginal time costs of the firms. Socially optimal schedules require well separated service times along the time clock. The regulator can set increasing cost in the time of day at one facility and decreasing ones at the other to achieve the social optimum. The level of the charge depends on consumers' unit schedule delay costs and on the distribution of their desired departure time.

In addition, the paper identifies all price markups of the vertical structure. Ignoring the location advantage of the primary airport and the differences in departure times across carriers, airports' fees depend upon their own commercial marginal revenues and those of their rival, and upon marginal operational costs of the carriers serving both facilities. When the primary facility benefits from a location advantage, it can set a higher fee and its downstream carrier can charge a higher fare. Differentiation in departure times allows the suppliers to compete in an additional differentiation dimension that can reduce or strengthen the advantage in location.

This model could be extended in a number of directions. Stackelberg games would clearly refine our results regarding strategic behaviours in scheduling and their impact on unregulated markets. Considering heterogeneous transportation costs toward the facilities would allow to better characterize the role played by the location advantage. Allowing a wider range of departure times in the spirit of Lindsey and Tomaszewska (1999) would help to design realistic scheduling policies to improve the social welfare. Future research may want to explore more realistic distributions of the travellers' desired service times as our simulations focuses on the uniform shape.

Conclusion

This dissertation examines important issues in the aviation industry that have been ignored in the economics literature. In the first chapter, we establish a link between the level of corruption in the country and economic efficiency of airports under different forms of ownership and management (private, public and mixed private-public). The empirical exercise is conducted on data on 47 major European airports observed over the 2003-2009 period and the country-level corruption index from International Country Risk Guide. We find strong evidence that corruption has negative impact on airport's operating efficiency, which is measured by the residual (or net) variable factor productivity index in our analysis. We also prove that the impact of corruption depends upon the forms of management and ownership of airports. Indeed, airports owned and operated by mixed public-private enterprises with private majority (including 100% private) appear to be the most efficient in a society where corruption is low. However, they exhibit lower levels of efficiency compared with publicly owned- airports (including mixed ownership with government majority and 100% government) in very corrupt countries. We conclude that efficiency gains from privatization may be cancelled out by the negative corruption effects.

The second and third chapters of this dissertation analyze competition between medium and large facilities at the empirical and theoretical levels. The second chapter investigates the determinants of travellers' choice between a regional airport and the closest airline-hub; and explores several functional forms for the choice probability. The empirical model relies on original data from the 2010 Airport Service Quality survey conducted at Canadian airports, including Quebec city Jean-Lesage (YQB) and Montreal Pierre-Elliot Trudeau (YUL) international airports. Because including our proxy of airfares may bias the estimates of all marginal effects, we estimate two versions of each model: one with airfares and another one without this variable. Including airfares among the predictors has little impact on the signs and significance levels of the coefficients of the other predictors but the magnitude of the impact may vary. Empirical findings from the conventional fixed- and random- coefficients logistic models highlight the importance of accessibility (access time and access mode) and flight frequency for travellers' choice. We also found that the probability of choosing a regional facility is strongly linked to flight destination, reason of flight, departure times along with travellers' characteristics (age and gender). The more flexible Generalized Additive models provide similar results as the parametric logit ones. Though the logistic and GAM models rely on the economic theory of random utility model, formal specification tests appear to reject these specifications. The alternative nonparametric kernel estimators provide attractive tools to better capture individuals' behaviour and represent interaction effects of access time and airfare according to the flight destination and purpose without shape constraints.

The third chapter of this dissertation provides a unified framework allowing to explain the pricing mechanism of a medium airport that competes with the closest airline-hub airport. The impacts of differentiation resulting from geographic location and time scheduling on carrier prices, facility charges and social optimum are highlighted with a combination of Hotelling and Vickrey models. Based on the empirical evidence, we assume that the demand for services at an airport depends upon the airlines' ticket price, transportation cost and a schedule delay cost, which is the monetary cost of departing earlier or later than desired. Two cases are investigated: when the departure times are exogenously set and carriers compete only in fares and when time schedules are chosen before fares. For the exogenous case, we find that a location advantage allows the facility (and its on-site carrier) to charge higher aeronautical fee (and higher fare) than its rival. However, differentiation in scheduling reduces the ability of the facility (and its on-site carrier) to exploit its location advantage. When carriers are allowed to compete in departure times, the scheduling game drives to identical departure times if the airlines' marginal time costs do not vary with the time of the day, but generally leads to differentiated times if these costs depend on the time of departure. The market outcome differs from the social optimum.

This dissertation, however, has some limitations. The first chapter explores the link between corruption and efficiency in the aviation industry. This question is also relevant when it comes to large infrastructures that require significant resources such as roads, ports and telecommunications. Second, this study employs a short and medium-term measure of airport efficiency, which excludes capital investment. If available data on capital costs of airports exist, future research may consider to use different measures of efficiency that account for this variable, and can even extend the analysis to other regions (Pacific Asia, Latina America and Africa). The second chapter of this dissertation explores competition between regional and airline-hub airports, focusing on the case of airports located in the Quebec province. This study can be extended to other regional airports (basically located in Europe and US) that host low cost carriers and offer very competitive services, both in terms of departure times and ticket prices. The airline deregulation has spurred the growth of low cost carriers, which in turn have promoted development of regional airports, and created opportunity for competition between medium regional and large airline-hub airports. Besides, it is well-known that low-cost carriers rather choose secondary (less congested) facilities to compete with legacy carriers, usually based in primary airports. Finally, the third chapter of this dissertation assumes that each carrier schedules one departure time at each airport; and travellers incur a homogenous transportation cost. Future research may consider to include two or more departure times at each facility to be more realistic, and explore heterogenous transportation costs.

Though my dissertation is in general more descriptive rather than normative, the empirical results from the first and second chapters have important policy implications for governments and airport authorities. The first policy implication concerns governments that are willing to transfer management and ownership of airports to private sectors in order to improve their efficiency. Indeed, the privatization policy should be accompanied by strategies aiming at reducing the levels of corruption in the country. For example, the governments may want to allocate adequate resources to set up clean bidding and tendering processes with proper checks and balances, educate and train officials and employees, and implement regular audits. As for the implications for the airport authority, the empirical estimates from the second chapter regarding travellers' sensitivity to a change in each determinant of airport choice may help the local authorities and managers of medium airports on their investment decision making.

Appendix A

A. 1 Descriptive statistics

Variable	Observation	Mean	Std. Deviation	Min	Max
ICRG Corruption Index	254	4.998	2.649	0	10
Corruption Perception Index (CPI)	253	5.843	1.671	3.4	9.7
Control of Corruption Index (CCI)	254	2.251	1.386	0.000	5.719
GDP per capita (in current US Dollars)	254	35204.5	16199.18	2641.79	95189.9
Openness to trade (in %)	254	43.099	17.175	23.875	91.575
Share of central government revenues in GDP (in %)	252	34.014	6.398	17.955	51.234
Quality of Bureaucracy	254	2.323	3.032	0	10
Law and Order	254	2.550	2.019	0	10
Ethnical tension	254	5.057	2.419	0	10
Internal Conflict	254	3.679	2.227	0	10
External Conflict	254	3.502	2.749	0	10
Government Stability	254	3.887	1.567	0	10
Dummy variables	Frequency	Percent	Cumulative	Min	Max
Ownership form					
100% government or public corporation	126	49.61	49.61	0	1
Mixed ownership with government majority($>$ 50%)	56	22.04	71.65	0	1
Mixed ownership with private majority (including 100% private)	72	28.35	100	0	1
Form of regulation					
Unregulated	51	20.08	20.08	0	1
Cost-plus, single till	50	19.69	39.76	0	1
Cost-plus, dual till	29	11.42	51.18	0	1
Incentive, single till	55	21.65	72.83	0	1
Incentive, dual till	33	12.99	85.83	0	1
Charges set by airports (single & dual till)	21	8.27	94.09	0	1
Belongs to an airport group from a management perspective					
Yes	111	43.70	43.70	0	1
No	143	56.3	100	0	1
Competition					
Strong	164	64.57	64.57	0	1
Weak	90	35.43	100	0	1
Hub Status					
Yes	215	84.65	84.65	0	1
No	39	15.35	100	0	1

Appendix B

B. 1 Derivations assuming $T_0 \leq T_1$

B. 1.1 Consumers' demands (3.8)

To get (3.8), assuming that $T_0 \leq T_1$, we can identify three category of consumers: those with $t \in [0, T_0[$, $t \in]T_0, T_1[$ and $t \in [T_1, 24]$. Each category incurs a specific schedule delay cost. Thus, we account for these differences when we aggregate the individual demands over the dimension t. The net benefits of travelling for a consumer located at $x \in [0, 1]$ with desired consumption time $\underline{t \in [0, T_0]}$ is :

$$\widehat{U}_0^\ell = \widehat{U} - \widehat{p}_0 - \frac{\theta}{2}(x-h)^2 - \widehat{\gamma}(T_0 - t)$$
$$\widehat{U}_1^\ell = \widehat{U} - \widehat{p}_1 - \frac{\theta}{2}(1-x)^2 - \widehat{\gamma}(T_1 - t)$$

where the exponent ℓ indicates that we focus on consumers with t located at the 'left-hand side' of T_0 on the $[0, 24]$ interval. Calculating $\widehat{U}_0^\ell - \widehat{U}_1^\ell$ and solving for x, the indifferent consumer is given by :

$$\tilde{x}^\ell(t) = \frac{1}{\theta(1-h)}[\widehat{p}_1 - \widehat{p}_0 + \widehat{\gamma}(T_1 - T_0)] + \frac{1+h}{2}. \tag{B. 1.1}$$

Given that all consumers are uniformly distributed with density one, $f(x) = 1$, along the geographic space, consume a single unit of the good, and given the distribution $\rho(t)$ of desired departure times, market demands at both facilities for this category of consumers, denoted D_0^ℓ and D_1^ℓ, are given by :

$$D_0^\ell = \int_0^{T_0} \int_0^{\tilde{x}^\ell(t)} 1\, f(x)\rho(t)\,\mathrm{d}x\mathrm{d}t = \int_0^{T_0} \tilde{x}^\ell(t)\rho(t)\,\mathrm{d}t \tag{B. 1.2}$$

$$= \left[p_1 - p_0 + \gamma(T_1 - T_0) + \frac{1+h}{2}\right] m_\ell, \tag{B. 1.3}$$

$$D_1^\ell = m_\ell - D_0^\ell = \left[p_0 - p_1 - \gamma(T_1 - T_0) + \frac{1-h}{2}\right] m_\ell. \tag{B. 1.4}$$

where m_ℓ denotes the share of consumers with $t \in [0, T_0]$:

$$m_\ell = \int_0^{T_0} \rho(t)\,\mathrm{d}t. \tag{B. 1.5}$$

and where

$$p_0 = \frac{\widehat{p}_0}{\theta(1-h)}, \quad p_1 = \frac{\widehat{p}_1}{\theta(1-h)}, \quad \beta = \frac{\widehat{\beta}}{\theta(1-h)}, \quad \gamma = \frac{\widehat{\gamma}}{\theta(1-h)}.$$

Following the same reasoning for consumers with $t \in]T_0, T_1[$, we get :

$$\widehat{U}_0^c = \widehat{U} - \widehat{p}_0 - \frac{\theta}{2}(x-h)^2 - \widehat{\beta}(t - T_0)$$

$$\widehat{U}_1^c = \widehat{U} - \widehat{p}_1 - \frac{\theta}{2}(1-x)^2 - \widehat{\gamma}(T_1 - t)$$

$$\tilde{x}^c(t) = \frac{1}{\theta(1-h)}(\widehat{p}_1 - \widehat{p}_0) + \frac{\widehat{\beta}T_0 + \widehat{\gamma}T_1 - (\widehat{\gamma} + \widehat{\beta})t}{\theta(1-h)} + \frac{(1+h)}{2} \tag{B. 1.6}$$

$$D_0^c = \int_{T_0}^{T_1} \tilde{x}^c(t)\rho(t)\,\mathrm{d}t = \left[p_1 - p_0 + (\gamma T_1 + \beta T_0) + \frac{1+h}{2}\right] m_c - (\beta + \gamma)\bar{t}_c, \tag{B. 1.7}$$

$$D_1^c = m_c - D_0^c = \left[p_0 - p_1 - (\gamma T_1 + \beta T_0) + \frac{1-h}{2}\right] m_c + (\beta + \gamma)\bar{t}_c, \tag{B. 1.8}$$

where the exponent c identifies consumers with t between T_0 and T_1 on the $[0, 24]$ interval, m_c is the share of consumers with $t \in]T_0, T_1[$, and $\bar{t}_c$ is their expected desired departure time, i.e.,

$$m_c = \int_{T_0}^{T_1} \rho(t)\,\mathrm{d}t \quad ; \quad \bar{t}_c = \int_{T_0}^{T_1} t\rho(t)\,\mathrm{d}t. \tag{B. 1.9}$$

Regarding the consumers with $t \in [T_1, 24]$, we get :

$$\widehat{U}_0^r = \widehat{U} - \widehat{p}_0 - \frac{\theta}{2}(x-h)^2 - \widehat{\beta}(t - T_0)$$

$$\widehat{U}_1^r = \widehat{U} - \widehat{p}_1 - \frac{\theta}{2}(1-x)^2 - \widehat{\beta}(t - T_1)$$

$$\tilde{x}^r(t) = \frac{1}{\theta(1-h)}[\widehat{p}_1 - \widehat{p}_0 - \widehat{\beta}(T_1 - T_0)] + \frac{(1+h)}{2} \tag{B. 1.10}$$

$$D_0^r = \int_{T_1}^{24} \tilde{x}^c(t)\rho(t)\,\mathrm{d}t = \left[p_1 - p_0 - \beta(T_1 - T_0) + \frac{1+h}{2}\right] m_r \tag{B. 1.11}$$

$$D_1^r = \left[p_0 - p_1 + \beta(T_1 - T_0) + \frac{1-h}{2}\right] m_r \tag{B. 1.12}$$

where the exponent r identifies consumers with t located at the 'right-hand side' of T_1 on the $[0, 24]$ interval and m_r refers to the share of consumers with $t \in [T_1, 24]$, i.e.,

$$m_r = \int_{T_1}^{24} \rho(t)\,\mathrm{d}t. \tag{B. 1.13}$$

Using (B. 1.3), (B. 1.7) and (B. 1.11) in $D_0 = D_0^\ell + D_0^c + D_0^r$ and given that $m_\ell + m_c + m_r = 1$, we get D_0 in (3.8). Further using the full covered markets assumption $D_1 = 1 - D_0$, we get D_1 in (3.8).

B. 1.2 Derivations of the covered market conditions (3.6)

To find when $0 < \widetilde{x}(t) < 1$ for $t \in [0, 24]$, use (B. 1.1), (B. 1.6) and (B. 1.10) and note that $\tilde{x}^{\ell}(t) \leq \tilde{x}^{c}(t) \leq \tilde{x}^{r}(t)$. Thus, $0 < \tilde{x}^{\ell}(t) < 1$ drives to the first condition and $0 < \tilde{x}^{r}(t) < 1$ gives the second condition in (3.6).

B. 1.3 Properties of function $\phi(\mathbf{T})$ (3.9)

Eq. (3.9) can be rewritten as:

$$\Phi(\mathbf{T}) = \underbrace{(\gamma m_\ell + \gamma m_c - \beta m_r)T_1 - \gamma \bar{t}_c}_{C_1^M} - \underbrace{[(\gamma m_\ell - \beta m_c - \beta m_r)T_0 + \beta \bar{t}_c]}_{C_0^M}, \tag{B. 1.14}$$

where C_i^M is the average *normalized* schedule delay cost difference associated with the time offered at facility i. Recalling that $\Phi(\mathbf{T}) = \frac{\widehat{\Phi}(\mathbf{T})}{\theta(1-h)}$, we have $\Phi(\mathbf{T}) = \frac{1}{\theta(1-h)} \left[\widehat{C}_1^M - \widehat{C}_0^M \right]$, where $\widehat{C}_i^M$ is the counterpart of C_i^M expressed *in monetary units*. With this in mind, we can rewrite (3.12) as

$$\frac{\partial D_0}{\partial h} > 0 \quad \textit{iff} \quad \frac{\theta}{2}(1-h)^2 > \widehat{p}_0 + \widehat{C}_0^M - (\widehat{p}_1 + \widehat{C}_1^M), \tag{B. 1.15}$$

and $\frac{\partial D_1}{\partial h} > 0$ when the RHS inequality is reversed. The link between (B. 1.15) and the related result on $\widetilde{x}(t)$ under (3.4) should be apparent. Useful properties of (B. 1.14) are given below.

Lemma 1 *Consider $\rho(t) > 0$ the density function of consumers' desired departure time, and the related shares and expected departure time given by*

$$m_\ell = \int_0^{T_0} \rho(t)dt, \quad m_c = \int_{T_0}^{T_1} \rho(t)dt, \quad m_r \int_{T_1}^{24} \rho(t)dt, \quad \bar{t}_c = \int_{T_0}^{T_1} t\rho(t)dt$$

for $T_0 < T_1$ over the $[0, 24]$ schedule. Then,

1. *by the fundamental theorem of calculus, it follows that*

$$\begin{aligned}
\frac{\partial m_l}{\partial T_0} &= \rho(T_0) > 0, & \frac{\partial m_l}{\partial T_1} &= 0, \\
\frac{\partial m_c}{\partial T_0} &= -\rho(T_0) < 0, & \frac{\partial m_c}{\partial T_1} &= \rho(T_1) > 0, \\
\frac{\partial m_r}{\partial T_0} &= 0, & \frac{\partial m_r}{\partial T_1} &= -\rho(T_1) < 0, \\
\frac{\partial \bar{t}_c}{\partial T_0} &= -T_0\rho(T_0) < 0, & \frac{\partial \bar{t}_c}{\partial T_1} &= T_1\rho(T_1) > 0.
\end{aligned}$$

2. *Consider the schedule delay cost function* (3.9) *and Lemma 1.1, then*

$$\frac{\partial \Phi(\mathbf{T})}{\partial T_0} = \beta - (\beta+\gamma)m_\ell, \qquad \frac{\partial \Phi(\mathbf{T})}{\partial T_1} = \gamma - (\beta+\gamma)m_r, \tag{B. 1.16}$$

$$\frac{\partial^2 \Phi(\mathbf{T})}{\partial T_0^2} = -(\beta+\gamma)\rho(T_0) < 0 \quad \frac{\partial^2 \Phi(\mathbf{T})}{\partial T_1^2} = (\beta+\gamma)\rho(T_1) > 0. \tag{B. 1.17}$$

$$\frac{\partial^2 \Phi(\mathbf{T})}{\partial T_0 \partial T_1} = \frac{\partial^2 \Phi(\mathbf{T})}{\partial T_1 \partial T_0} = 0. \tag{B. 1.18}$$

Setting Eqs. (B. 1.16) *equal to zero and solving with respect to* T_0 *and* T_1 *leads to*

$$T_0^* = F^{-1}\left(\frac{\beta}{\beta+\gamma}\right), \quad T_1^* = F^{-1}\left(\frac{\beta}{\beta+\gamma}\right), \tag{B. 1.19}$$

where $F(a) = \int_0^a \rho(t)dt$ *denotes the cumulative distribution function of* t.

3. *Coordinate* (T_0^*, T_1^*) *in* (B. 1.19) *is a saddle point that maximizes* $\Phi(T_0, \bar{T}_1)$ *for a given value* $\bar{T}_1 \in [T_0, 24]$ *and minimizes* $\Phi(\bar{T}_0, T_1)$ *for a given value* $\bar{T}_0 \in [0, T_1]$.

4. *Assuming that* $t \sim \mathcal{U}[0, 24]$, *so that* $\rho(t) = 1/24$, *expressions* (3.9), (B. 1.16), (B. 1.17) *and* (B. 1.19) *are given by:*

$$\Phi^U(\mathbf{T}) = \frac{\gamma+\beta}{48}T_1^2 - \beta T_1 + \beta T_0 - \frac{\gamma+\beta}{48}T_0^2,$$

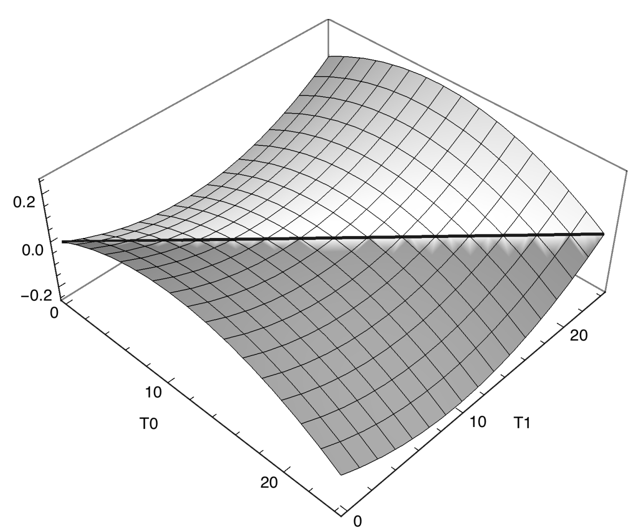
$$\frac{\partial \Phi^U(\mathbf{T})}{\partial T_0} = \beta - \frac{\beta+\gamma}{24}T_0, \quad \frac{\partial \Phi^U(\mathbf{T})}{\partial T_1} = \gamma - \frac{\beta+\gamma}{24}T_1,$$

$$\frac{\partial^2 \Phi^U(\mathbf{T})}{\partial T_0^2} = -\frac{\beta+\gamma}{24} < 0, \quad \frac{\partial^2 \Phi^U(\mathbf{T})}{\partial T_1^2} = \frac{\beta+\gamma}{24} > 0,$$

$$T_0^{*U} = T_1^{*U} = \frac{24\beta}{\beta+\gamma}.$$

Setting $\theta = 260$, $h = 0.25$, $\widehat{\beta} = 5$, $\widehat{\gamma} = 7$, *we get* $T_0^{*U} = T_1^{*U} = 10$ *and the schedule delay cost function is shown below.*

Figure B. 1.1 – $\Phi^U(\mathbf{T})$ when $t \sim \mathcal{U}[0, 24]$



B. 2 Derivations assuming $T_0 \geq T_1$

B. 2.1 Symmetry of demands (3.8)

When $T_0 \geq T_1$, D_i^ℓ and D_i^r for $i = 0, 1$ are given by replacing the shares m_ℓ in (B. 1.3)-(B. 1.4) and m_r in (B. 1.11)-(B. 1.12) by:

$$m_\ell = \int_0^{T_1} \rho(t)\,\mathrm{d}t, \quad \text{and} \quad m_r = \int_{T_0}^{24} \rho(t)\,\mathrm{d}t. \tag{B. 2.1}$$

Regarding D_i^c for $i = 0, 1$, applying the same reasoning as in Appendix B. 1.1, we get:

$$\begin{aligned}
\widehat{U}_0^c &= \widehat{U} - \widehat{p}_0 - \frac{\theta}{2}(x-h)^2 - \widehat{\gamma}(T_0 - t) \\
\widehat{U}_1^c &= \widehat{U} - \widehat{p}_1 - \frac{\theta}{2}(1-x)^2 - \widehat{\beta}(t - T_1) \\
\tilde{x}^c(t) &= \frac{1}{\theta(1-h)}(\widehat{p}_1 - \widehat{p}_0) - \frac{(\widehat{\beta}T_1 + \widehat{\gamma}T_0) - (\widehat{\beta} + \widehat{\gamma})t}{\theta(1-h)} + \frac{(1+h)}{2} \\
D_0^c &= \left[p_1 - p_0 - (\beta T_1 + \gamma T_0) + \frac{1+h}{2}\right] m_c + (\beta + \gamma)\bar{t}_c & \text{(B. 2.2)} \\
D_1^c &= \left[p_0 - p_1 + (\beta T_1 + \gamma T_0) + \frac{1-h}{2}\right] m_c - (\beta + \gamma)\bar{t}_c & \text{(B. 2.3)}
\end{aligned}$$

where

$$m_c = \int_{T_1}^{T_0} \rho(t)\,\mathrm{d}t, \quad \bar{t}_c = \int_{T_1}^{T_0} t\;\rho(t)\,\mathrm{d}t \tag{B. 2.4}$$

Given that $D_0 = D_0^l + D_0^c + D_0^r$ and $D_1 = 1 - D_1$, we have the following symmetric aggregate demands:

$$\begin{aligned}
D_0^{sym} &= (p_1 - p_0) + \Phi_{sym}(\mathbf{T}) + \frac{1+h}{2} & \text{(B. 2.5)} \\
D_1^{sym} &= (p_0 - p_1) - \Phi_{sym}(\mathbf{T}) + \frac{1-h}{2} & \text{(B. 2.6)}
\end{aligned}$$

where

$$\Phi_{sym}(\mathbf{T}) \quad = \quad [\gamma(T_1 - T_0)m_l - (\beta T_1 + \gamma T_0)m_c + \beta(T_0 - T_1)m_r + (\beta + \gamma)\bar{t}_c] \tag{B. 2.7}$$

where $m_l + m_c + m_r = 1$.

B. 2.2 Symmetry of the covered market conditions (3.6)

Following the same steps as in Appendix B. 1.2, conditions (3.6) become:

$$\begin{aligned}
-\frac{\theta}{2}(1-h^2) &< \widehat{p}_1 - \widehat{p}_0 + \widehat{\beta}(T_0 - T_1) < \frac{\theta}{2}(1-h)^2 \\
-\frac{\theta}{2}(1-h^2) &< \widehat{p}_1 - \widehat{p}_0 - \widehat{\gamma}(T_0 - T_1) < \frac{\theta}{2}(1-h)^2.
\end{aligned} \tag{B. 2.8}$$

B. 2.3 Symmetry of Lemma 1

Consider $\rho(t)$ the density function of the consumers' desired departure time t and terms m_ℓ, m_c, m_r and $\bar{t}_c$ defined in (B. 2.1) and (B. 2.4). Then,

1. by the fundamental theorem of calculus, it follows that

$$
\begin{aligned}
\frac{\partial m_l}{\partial T_1} &= \rho(T_1) > 0, & \frac{\partial m_l}{\partial T_0} &= 0,\\
\frac{\partial m_c}{\partial T_1} &= -\rho(T_1) < 0, & \frac{\partial m_c}{\partial T_0} &= \rho(T_0) > 0,\\
\frac{\partial m_r}{\partial T_1} &= 0, & \frac{\partial m_r}{\partial T_0} &= -\rho(T_0) < 0,\\
\frac{\partial \bar{t}_c}{\partial T_1} &= -T_1\rho(T_1) < 0, & \frac{\partial \bar{t}_c}{\partial T_0} &= T_0\rho(T_0) > 0.
\end{aligned} \tag{B. 2.9}
$$

2. Consider $\Phi_{sym}(\mathbf{T})$ given in (B. 2.7), using Lemma (B. 2.3).1, it follows that

$$
\frac{\partial \Phi_{sym}(\mathbf{T})}{\partial T_0} = -\gamma + (\beta+\gamma)m_r, \quad \frac{\partial \Phi_{sym}(\mathbf{T})}{\partial T_1} = -\beta + (\beta+\gamma)m_\ell., \tag{B. 2.10}
$$

$$
\frac{\partial^2 \Phi_{sym}(\mathbf{T})}{\partial T_0^2} = -(\beta+\gamma)\rho(T_0), \quad \frac{\partial^2 \Phi_{sym}(\mathbf{T})}{\partial T_1^2} = (\beta+\gamma)\rho(T_1) \tag{B. 2.11}
$$

$$
\frac{\partial^2 \Phi_{sym}(\mathbf{T})}{\partial T_0 \partial T_1} = \frac{\partial^2 \Phi_{sym}(\mathbf{T})}{\partial T_1 \partial T_0} = 0. \tag{B. 2.12}
$$

Setting Eqs. (B. 2.10) equal to zero and solving with respect to T_0 and T_1 leads to

$$
T^*_{0,sym} = F^{-1}\left(\frac{\beta}{\beta+\gamma}\right), \quad T^*_{1,sym} = F^{-1}\left(\frac{\beta}{\beta+\gamma}\right), \tag{B. 2.13}
$$

where $F(a) = \int_0^a \rho(t)dt$ denotes the cumulative distribution function of t.

3. Coordinates $(T^*_{0,sym}, T^*_{1,sym})$ in (B. 2.13) is a saddle point that maximizes $\Phi_{sym}(T_0, \bar{T}_1)$ for a given value $\bar{T}_1 \in [0, T_1]$ and minimizes $\Phi_{sym}(\bar{T}_0, T_1)$ for a given value $\bar{T}_0 \in [T_0, 24]$.

B. 2.4 Symmetry of the carrier-rivalry game (3.41)-(3.42)

When $T_0 \geq T_1$, the first-order conditions of problem (3.34) are:

$$
\begin{aligned}
\frac{\partial \pi_0^{sym,*}(\mathbf{T},\boldsymbol{\tau})}{\partial T_0} &= \frac{2}{3}\left[-\gamma + (\beta+\gamma)\ m_r\right] D_0^{sym,*}(\mathbf{T},\boldsymbol{\tau}) - \frac{\partial K(T_0)}{\partial T_0} = 0,\\
\frac{\partial \pi_1^{sym,*}(\mathbf{T},\boldsymbol{\tau})}{\partial T_1} &= -\frac{2}{3}\left[-\beta + (\beta+\gamma)\ m_l\right] D_1^{sym,*}(\mathbf{T},\boldsymbol{\tau}) - \frac{\partial K(T_1)}{\partial T_1} = 0,
\end{aligned} \tag{B. 2.14}
$$

which are the symmetric counterparts of (3.35). Consider the case where we assume that carriers' scheduling cost is constant along the time of day, i.e., (3.36) holds. Solving system $\frac{\partial \pi_i^*(\mathbf{p}^*,\mathbf{T})}{\partial T_i} = 0$ for $i = 0, 1$ with respect to T_i gives symmetric expressions to Eqs. (3.37), i.e.,

$$m_r|_{k_0=0} = \frac{\gamma}{\beta+\gamma} \Rightarrow T_0^*|_{k_0=0} = F^{-1}\left(\frac{\beta}{\beta+\gamma}\right),$$
$$m_\ell|_{k_0=0} = \frac{\beta}{\beta+\gamma} \Rightarrow T_1^*|_{k_0=0} = F^{-1}\left(\frac{\beta}{\beta+\gamma}\right), \tag{B. 2.15}$$

where m_r and m_l are given in (B. 2.1) and denote the share of travellers with desired departure times earlier than T_1 and later than T_0. Thus,

$$T^*_{0,sym}\big|_{k_0=0} = T^*_{1,sym}\big|_{k_1=0} = T^*|_{k_i=0} = F^{-1}\left(\frac{\beta}{\beta+\gamma}\right). \tag{B. 2.16}$$

Turning to case where we posit that carriers' scheduling costs are linear in the time of day, i.e., (3.40) holds, Eqs. (3.41)-(3.42) become:

$$m_r = \frac{\gamma}{\beta+\gamma} + \frac{3k_0}{2(\beta+\gamma)D_0^{sym,*}(\mathbf{T},\boldsymbol{\tau})} = m_r|_{k_0=0} + \frac{3k_0}{2(\beta+\gamma)D_0^{sym,*}(\mathbf{T},\boldsymbol{\tau})}, \tag{B. 2.17}$$
$$m_\ell = \frac{\beta}{\beta+\gamma} + \frac{3k_1}{2(\beta+\gamma)D_1^{sym,*}(\mathbf{T},\boldsymbol{\tau})} = m_\ell|_{k_1=0} + \frac{3k_1}{2(\beta+\gamma)D_1^{sym,*}(\mathbf{T},\boldsymbol{\tau})}. \tag{B. 2.18}$$

where $D_0^{sym,*}(\mathbf{T},\tau)$ and $D_1^{sym,*}(\mathbf{T},\boldsymbol{\tau})$ are (B. 2.5) and (B. 2.6), respectively. Profit maximization further requires:

$$k_0^2 < \frac{4}{3}\rho(T_0^*)(\beta+\gamma)D_0^{sym,*3}(\mathbf{T},\boldsymbol{\tau}),$$
$$k_1^2 < \frac{4}{3}\rho(T_1^*)(\beta+\gamma)D_1^{sym,*3}(\mathbf{T},\boldsymbol{\tau}). \tag{B. 2.19}$$

Then, using (B. 2.17)-(B. 2.18), we get the symmetric counterpart to (3.43), i.e.,

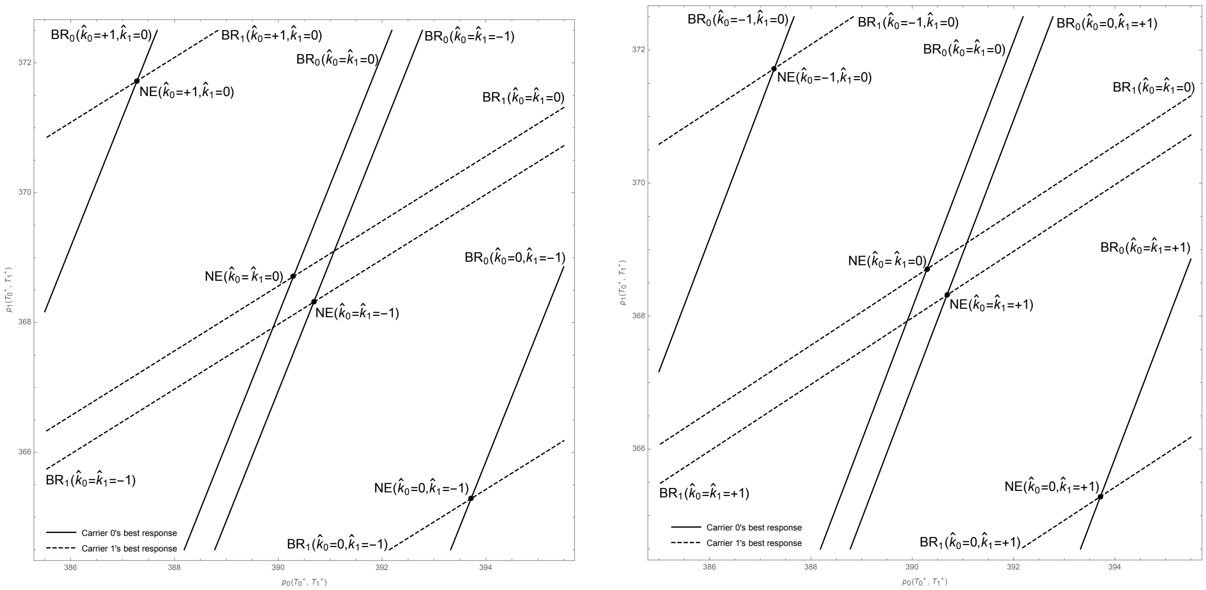
$$T^*_{0,sym} = F^{-1}\left(\frac{\beta}{\beta+\gamma} - \frac{3k_0}{2(\beta+\gamma)D_0^{sym,*}(\mathbf{T},\boldsymbol{\tau})}\right),$$
$$T^*_{1,sym} = F^{-1}\left(\frac{\beta}{\beta+\gamma} - \frac{3k_1}{2(\beta+\gamma)D_1^{sym,*}(\mathbf{T},\boldsymbol{\tau})}\right). \tag{B. 2.20}$$

B. 3 Nash equilibrium in fares

Fig. B. 3.1 shows fares' reaction functions for selected equilibria displayed in Fig. 3.9 of the paper. Nash equilibria in fares are denoted $NE(T_0^*, T_1^*, \widehat{k}_0, \widehat{k}_1)$ and the corresponding reaction functions by $BR_i(T_0^*, T_1^*)$ for $i = 0, 1$. Again, our representation distinguishes between $T_0^* \leq T_1^*$ and $T_0^* \leq T_1^*$. However, this distinction is useless here as, based on Table 3.2, we know that fares equilibria are equal in the converse situation. Note that we do not represent all fares equilibria from Fig. 3.9 to keep the plots readable.

Figure B. 3.1 – Nash Equilibria in fares: reaction functions for the carrier-rivalry game

Case $T_0 \leq T_1$ Case $T_0 \geq T_1$



Notes: all simulations assume: $h = 0.25$, $t \sim \mathcal{U}[0, 24]$, $\widehat{\beta} = 5, \widehat{\gamma} = 7$, $\frac{\theta}{2} = 130$, $\widehat{c}_0 = 10$, $\widehat{c}_1 = 8$, $\widehat{\tau}_0 = 280$, $\widehat{\tau}_1 = 266$, $\widehat{\omega}_0 = 20$ and $\widehat{\omega}_1 = 18$.

Fares' reaction functions are as expected: linear in fares, upward trending and intersecting at positive levels. Moreover, these plots establish graphically that there is stability in fares competition.

B. 4 Derivations related to the minimization of social costs

B. 4.1 Optimal locations (3.52)

Note first that the 'socially indifferent' consumer, denoted $\tilde{x}^S$, is obtained by adding $\pi_i = \widehat{p}_i - \widehat{c}_i - \widehat{\tau}_i$ and $\Pi_i = \widehat{\tau}_i + \widehat{\omega}_i$ to (3.2) and (3.3). Denoting these utilities U_0^S and U_1^S, respectively, solving $U_0^S - U_1^S$ for x, assuming that $\widetilde{c}_i$ and $\widehat{\omega}_i$ are equal across carriers/facilities and ignoring $\widehat{C}(T_i, t)$, we get $\tilde{x}^S = \frac{1-b+a}{2}$. Let $a \in [0, 1]$ be the location of facility 0 and $1 - b$ represent the 'backyard' of facility 1 for $b \in [0, 1]$. In the Hotelling model with quadratic transportation costs, the locations that minimize the average total transportation cost is given by solving:

$$\min_{a,b} TC^S = \frac{\theta}{2}\left[\int_0^a (a-x)^2 dx + \int_a^{\tilde{x}^S} (x-a)^2 dx + \int_{\tilde{x}^S}^{1-b} ((1-b)-x)^2 dx + \int_{1-b}^{1} (x-(1-b))^2 dx\right].$$

Integrating the above expressions, we get:

$$\frac{a^3}{3} + \frac{(1-b-a)^3}{12} + \frac{b^3}{3}. \tag{B. 4.1}$$

The first order conditions are

$$\frac{\partial TC^S}{\partial a} = 4a^2 - (1-b-a)^2 = 0, \tag{B. 4.2}$$

$$\frac{\partial TC^S}{\partial b} = 4b^2 - (1-b-a)^2 = 0. \tag{B. 4.3}$$

Solving the system of FOCs gives $a^* = b^*$. Replacing b^* in (B. 4.2) and a^* in (B. 4.3) drives to $(a^S, 1-b^S) = \left(\frac{1}{4}, \frac{3}{4}\right)$. Given that $\frac{\partial^2 TC^S}{\partial a^2} > 0, \frac{\partial^2 TC^S}{\partial b^2} > 0$ and $\frac{\partial^2 TC^S}{\partial a^2}\frac{\partial^2 TC^S}{\partial b^2} - \left(\frac{\partial^2 TC^S}{\partial a \partial b}\right)^2 > 0$ at the stationary points, the pair $(a^S, 1-b^S)$ minimizes $TC^S(a,b)$. If the social planner relocates only facility 0, setting $1-b=1$ and solving (B. 4.2) results in $a^S\big|_{b=1} = \frac{1}{3}$. Conducting the same exercise with (B. 4.3) when only facility 1 is relocated, given $a = h \geq 0$, we get the local minimum $1 - b^S\big|_{a=h} = \frac{2+h}{3}$.

B. 4.2 Minimizing the average total schedule delay costs (3.54)

Using Eqs. (3.55) and (3.56), the second-order derivatives are given by :

$$\frac{\partial^2 SC^S(\mathbf{T})}{\partial T_0^2} = (\widehat{\beta}+\widehat{\gamma})\rho(T_0) - \frac{\widehat{\beta}^2}{\widehat{\beta}+\widehat{\gamma}}\rho(\tilde{t}),$$

$$\frac{\partial^2 SC^S(\mathbf{T})}{\partial T_1^2} = (\widehat{\beta}+\widehat{\gamma})\rho(T_1) - \frac{\widehat{\gamma}^2}{\widehat{\beta}+\widehat{\gamma}}\rho(\tilde{t}),$$

$$\frac{\partial^2 SC^S(\mathbf{T})}{\partial T_i \partial T_{-i}} = -\frac{\widehat{\beta}\widehat{\gamma}}{\widehat{\beta}+\widehat{\gamma}}\rho(\tilde{t}), \quad i = 0, 1.$$

Rearranging the above, minimization requires

$$\frac{\partial^2 SC^S(\mathbf{T})}{\partial T_0^2} = (\widehat{\beta}+\widehat{\gamma})^2\rho(T_0) > \widehat{\beta}^2\rho(\tilde{t}), \tag{B. 4.4}$$

$$\frac{\partial^2 SC^S(\mathbf{T})}{\partial T_1^2} = (\widehat{\beta}+\widehat{\gamma})^2\rho(T_1) > \widehat{\gamma}^2\rho(\tilde{t}), \tag{B. 4.5}$$

and the Hessian determinant needs to be positive, i.e.,

$$2\widehat{\beta}\widehat{\gamma}\rho(T_0)\rho(T_1) + \widehat{\beta}^2\rho(T_1)[\rho(T_0) - \rho(\tilde{t})] + \widehat{\gamma}^2\rho(T_0)[\rho(T_1) - \rho(\tilde{t})] > 0. \tag{B. 4.6}$$

From the above, it is clear that if $\rho(t) \sim \mathcal{U}[0, 24]$, then $\rho(t) = 1/24, \forall t \in [0, 24]$ and (T_0^S, T_1^S) in (3.58) is a (global) minimum.

B. 5 Substituting the equilibrium fees in carriers' equilibrium fares and markups

Substituting the fees (3.47) in the fares (3.18) and rearranging, we get:

$$\begin{aligned} p_0^{**} &= \frac{1}{9}[(5c_0 + 4c_1) - (5\omega_0 + 4\omega_1)] + \frac{18+2h}{9} + \frac{4}{9}\Phi(\mathbf{T}), \\ p_1^{**} &= \frac{1}{9}[(4c_0 + 5c_1) - (4\omega_0 + 5\omega_1)] + \frac{18-2h}{9} - \frac{4}{9}\Phi(\mathbf{T}). \end{aligned} \tag{B. 5.1}$$

Substituting the fees (3.47) in carrier markups, $m_i^{**} = p_i^* - (c_i + \tau_i^*)$ for $i = 0, 1$, yields:

$$\begin{aligned} p_0^{**} - c_0 - \tau_0^* &= \frac{1}{9}[(c_1 - c_0) + (\omega_0 - \omega_1)] + \frac{9+h}{18} + \frac{1}{9}\Phi(\mathbf{T}), \\ p_1^{**} - c_1 - \tau_1^* &= \frac{1}{9}[(c_0 - c_1) + (\omega_1 - \omega_0)] + \frac{9-h}{18} - \frac{1}{9}\Phi(\mathbf{T}). \end{aligned} \quad \text{(B. 5.2)}$$

B. 6 Covered market condition in terms of model parameters

When the marginal time cost of the carriers is null ($\widehat{k}_0 = \widehat{k}_1 = 0$) or when the departure times are given, we can substitute the fares given in Appendix B. 5 and express the covered market condition in terms of the exogenous parameters of the model. That is,

$$-\frac{\theta}{2}(1-h^2) < \widehat{p}_1^{**} - \widehat{p}_0^{**} - \widehat{\beta}(T_1 - T_0) \leq \widehat{p}_1^{**} - \widehat{p}_0^{**} + \widehat{\gamma}(T_1 - T_0) < \frac{\theta}{2}(1-h)^2. \quad \text{(B. 6.1)}$$

leads to:

$$\begin{aligned} &-\frac{\theta}{2}(1-h)(9+h) < \\ &\Delta\widehat{c} + \Delta\widehat{\omega} - 8\widehat{\Phi}(\mathbf{T}) - 9\widehat{\beta}(T_1 - T_0) \leq \Delta\widehat{c} + \Delta\widehat{\omega} - 8\widehat{\Phi}(\mathbf{T}) + 9\widehat{\gamma}(T_1 - T_0) \\ &< \frac{\theta}{2}(1-h)(9-h), \end{aligned} \quad \text{(B. 6.2)}$$

with $\Delta\widehat{c} = \widehat{c}_1 - \widehat{c}_0$, $\Delta\widehat{\omega} = \widehat{\omega}_0 - \widehat{\omega}_1$. Keeping term $\widehat{\Phi}(\mathbf{T})$ as such, note that when $T_0 = T_1$, (B. 6.2) becomes:

$$-\frac{\theta}{2}(1-h)(9+h) < \Delta\widehat{c} + \Delta\widehat{\omega} < \frac{\theta}{2}(1-h)(9-h).$$

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